On the Performance of Projects under Uncertainty: An Agent-based Simulation Modeling

Abstract
This paper investigates the effects of environmental complexity on project performance by means of simulation modeling. There are few works that prepare a bottom-up, mechanism-based account of project-environment interactions. Rather, some statistical, top-down models have been developed which fall short of explaining how projects can handle uncertainties. This research is an attempt to fill this gap. The question is how environmental complexity affects project performance. The results of the model show that the complexity of environment can have positive effects on project performance. On the contrary, the results demonstrate that the internal complexity modeled as randomness in the activity times is detrimental to the project performance. To tackle environmental complexity, the model suggests that shorter memory cycles improve project performance in that projects give more priority to recent outcomes to offset effects of uncertainty. The results have been by empirical data from 18 infrastructure projects.

Keywords
Project management, Agent-based simulation, Complexity

1. Introduction

Projects are organized, goal seeking systems of people, technology and information. They have all characteristics of organizations except that they have comparatively a short life. This similarity facilitates application of organization theories and models for projects. Division of work, unity of commands, and teamwork are among management principles that have been widely adopted in project management. Projects as temporary organizations (Shenhar, 2001) are artificial entities that depend on their environments in a contingent way (Simon 1996). They are surrounded by physical, technological, cultural, and social environments that tended to be overlooked or underestimated; recently the importance of organization-environment linkages has drawn the attention of organization scholars, because every organization is dependent on its environment for survival (Scott, 1998). As Godwyn and Gittel (2012) cite, "organizations succeed to the extent that their structures match the requirements of their environments". In Herbert Simon's (1996) terms, environments act like a mold and affect organizations as artifacts. It is difficult to define the concept of fitness to environment for organizations but in the real world the match between organizational strategic orientation and that the environment requires is a measure of fitness (Sastry, 1997). Dynamics of business environments give rise to some changes in the ways organizations are formed (Siggelkow & Rivkin, 2005) as well as their operations (Lin & Carley 2003); this is what is called adaptation (or fitness) to changes.

To model project-environment interactions, three groups of models are generally used for advancing organization science: rational system, natural system and open system models (Scott, 1998; Thompson, 2003). Rational models of organizations assume that organizations are instruments that can be designed and controlled to accomplish certain goals and therefore the variables of model should be few and simple; the environment is difficult to be considered in such models. By contrast, natural system models are based on an organic metaphor of organizations, where the organization is a collective, controlled by spontaneous, indeterminate evolutionary processes towards the goal of survival (Thompson, 2003). This view accords to open system models where developments in system theory has opened new rooms for modeling organizations based on cybernetics. In open system models, organizations are identified as open systems with high level of complexity, reactivity, and looseness of coupling among system components (Morel & Ramanujam, 1999; Thompson, 2003). "From an open systems perspective, environments shape, support, and infiltrate organizations" (Scott, 1998: 25). This conception of organizations is consistent with natural system modeling approach, where adaptation to the environment is crucial (Thompson, 2003).

As a newer tradition, organizations are conceived as bounded-rational, problem-solving entities in Simon-March-Cyert stream of study (Thompson, 2003); instead of maximizing, organizations try to find feasible solutions for problems (March & Simon, 1993). In this conception, problems are deemed to be the course of actions that organizations should take to fulfill their own goals when confronting with the environmental influences (Chang & Harrington Jr, 2006; Thompson, 2003). The problem-solving behavior of organizations aim at acquiring intelligence which is achieved by search through the problem space (Masuch & Warglien, 1992). In projects, problem-solving is constrained by deadlines and limited budgets more strictly.

To realize its intelligence, a project like any other intelligent system, must have a goal and some candidates for the goal; furthermore, it must modify its response according to the task environment (Newell, 1980). In other words, a project acts like a complex adaptive system (Kuhn, 1974). In this paper, the project is conceived as an open information processor, interacting with the environment to achieve the objective of more fitness by virtue of learning.

There are two types of interrelation between a project and its environment: the environment can be conceived as a pool of resources or a source of information (Scott, 1998). Since in the open-system view of projects the focus is on the degree of information uncertainty, the environment is deemed to be the source of information in this research and the project tries to decode the environment and gain intelligence. By determining constraints, contingencies, and variables, the environment sets the stage for project team problem-solving.

As a source of information, the environment is subject to uncertainty. There are studies that differentiate between uncertainty and complexity (for example Daniel et al (2018)) but we use these terms interchangeably in this study. Scott (1998) proposes five dimensions for uncertainty in relation to the environment: (1) degree of homogeneity-heterogeneity of environmental entities, (2) degree of stability-variability of environmental entities, (3) degree of threat-security of the organization in the environment, (4) degree of interconnectedness-isolation to the environment, and (5) degree of coordination/non-coordination with the environment. The relationship between uncertainty and project performance is under-researched theoretically and empirically (Floricel, Michela, & Piperca, 2016). There is no thorough, empirically tested theoretical framework for analyzing changes and uncertainty for variety of projects (Shenhar, 2001) or understanding different approaches and their applicability to encounter uncertainty (Pich, Loch, & De Meyer, 2002). According to contingency theory, there is a direct link between environmental uncertainty and the internal structure of an organization for adaptation in that "the greater the uncertainty of the task, the greater the amount of information that has to be processed between decision makers during its execution" (Galbraith, 1973: 4). The amount of information needed to ensure effective performance of organizations is represented as f(u,n,c), where u is the degree of uncertainty concerning the task requirements such as resources needed, time to complete etc; n is the number of elements relevant for decision making; and c is interdependence and interrelatedness among the elements (Godwyn & Gittell, 2012). However, the effects of uncertainty on project performance is not straightforward because uncertainty/complexity are multi-faceted. The concept of environmental uncertainty is modeled by taking into account different aspects of uncertainty as outlined above that will be discussed later.

2. Projects as Complex Systems

Project management has been developed based on a reductionist approach by which systems are analyzed based on the properties of their parts. The rationale behind work breakdown structure or other breakdown structures (organization breakdown structure, risk breakdown structure, etc.) is rooted in a mechanistic view of the world. Projects as temporary organizations are collectives of intelligent, adaptive, and computational agents and thus are themselves intelligent, adaptive, and computational agents (Kathleen M. Carley, 2002; Kathleen M. Carley & Frantz, 2009). Traditional reductionist, Newtonian view of systems falls short of capturing the essence of complex systems (Bechtel & Richardson, 1993; Richardson, 2005). In a complex system like a project, as Carley (1994: XI) notes "rarely can generalized organizational behavior be explained by examining solely the characteristics of the component agents, the tasks or the situation networks in isolation". A bottom-up modeling paradigm like Agent-based Modeling (ABM) that takes into accounts both components and behaviors of a complex system seems to offer this possibility. ABM improves descriptive realism because it maps "objects, actors, or other natural entities in the target system onto agents in a multi-agent system, so that the 'boundary' of the entities correspond to those of the agents and that the interactions between entities correspond to interactions between agents" (Moss & Davidsson, 2001: 20). Therefore, processes of abstraction and application become easier and more transparent (ibid). ABM is highly suitable for distributed systems comprising of autonomous entities and, in particular, for evaluating the performance of decentralized decision policies (Paolucci & Sacile, 2005). Therefore, it seems that ABM is an appropriate modeling paradigm for projects.

A review of the literature reveals that ABM has been principally developed either describing/explaining a system or phenomenon (Banal-Estañol & Rupérez Micola, 2011; Bunn & Oliveira, 2007; Ma & Nakamori, 2005) or prescribing course of action for a special situation (i.e. optimization) (Akanle & Zhang, 2008; Anosike & Zhang, 2009). Among the explanatory applications of agent-based modeling, there are a few works that target theory building; one classical example is garbage can model (Cohen, March, & Olsen, 1972). Also, Siggelkow and Rivkin (2005) discuss the effects of environmental turbulence and complexity on the formal design of organizations by virtue of NK model. They define complexity as the degree of interdependence among the decisions a firm makes.

To model quasi-realistic artifacts like projects, a modeler requires some knowledge about how to represent underlying phenomena and also some data for estimating parameters within these representations; becoming more mature through further validation, calibration and refinement, computational models of organizations are claimed to be powerful computational labs for validating existing organization hypothesis and generating new theories (Levitt, 2004). From the viewpoint of complex adaptive systems, project adaptation in response to complexity of environment is a key survival strategy. Complexity may be structural, originating from different components of projects (i.e. individuals, teams, and companies) and their interactions or dynamic due to temporal emergence and unpredictable changes to external systems (Daniel & Daniel, 2018; Floricel et al., 2016). Another type of complexity is representational (Floricel et al., 2016) which relates to inability to represent the reality and absence of complete information (Floricel et al., 2016; Mitchell, 2007). Complexity in projects is attributed to factors like project size, scope, and experience with the technology (Mitchell, 2007) and is deemed to be negatively correlated with performance (Antoniadis, Edum-Fotwe, & Thorpe, 2011). There is complexity at program and portfolio level as well (Teller, Unger, Kock, & Gemünden, 2012) which is not the scope of this study.

This paper is intended to act as a computational laboratory for investigating the interaction between projects and their environments. A learning conception of project-environment interactions within the framework of complex adaptive systems is presented in this research. The question is how projects react to the external sources of complexity compared to the internal ones. There are two meanings of learning: (i) improvement in outcomes (e.g. learning curves in economics) and (ii) a particular process of reacting to information involving: beginning with the taking of an action, monitoring the outcome, and interpretation and then modification of the propensity to repeat the action which has the elements of intelligence (March, 2008). In this paper, the process conception of learning is considered, because it is consistent with behavioral theory of organizational learning and can be modeled as a reinforcement learning algorithm. The environmental complexity is defined based on Shannon's famous information entropy which is claimed to be a thorough conception of complexity, because it contains appropriately all facets of environmental uncertainty including degree of uncertainty, number of decision elements, and interdependence or interrelatedness among decision elements, discussed in Godwyn and Gittell (2012).

Among practical models for project complexity, the framework introduced by Transportation Research Board (2013) addresses different facets of complexity more thoroughly. In their conception, project complexity is related to project types, engineering complexity, size, modality, jurisdictional control, financing approach, contract type, and delivery method and is defined in five dimensions: cost, schedule, technical, context, and financing. The factors associated with each dimension have been summarized in Table 1.

Table 1: Complexity dimensions and associated factors (Transportation Research et al., 2013)

Dimension	Factors
Cost	Project estimates, uncertainty, contingency, project-related costs, Project cost drivers and constraints
Schedule	Time, schedule risk, prescribed milestones, resource availability
Technical	Scope of work, internal structure, contract, design, construction, technology, nature of constraints
Context	Stakeholders, project-specific issues, local issues, environmental conditions, legal and legislative requirements, global and national conditions, unexpected occurrences
Financing	public funding, bond and debt financing, loans and credit assistance, exploiting asset value, finance-driven project delivery methods

To understand project complexity, each dimension of complexity should be assessed by scoring based a scale from 0 to 100. In the scaling scheme, dimensions with scores below 25 have low complexity, those with scores between 25 and 75 are average and those with scores more than 75 are highly complex. In the next section, the structure of the developed model is explained followed by some results and discussions.

3. The computational model

As a fusion of learning concepts in organization science and multi-agent systems, the developed model is founded on the behavioral approach to study the firm (Cyert & March, 1963; March, 2008). In Figure 1, the developed model is depicted. The project, hereinafter called *project*, is comprised of two simple activities, each containing two roles connected in a simple network. There are four types of agents, each with different problem-solving capabilities. The initial layout seen in the figure is just an example as the computer program randomly assigns agents to the roles during initialization. *Project* manager hereinafter called *PM*, is responsible for improving performance. The environment consists of an agent, hereinafter called *environment*, challenging *project* by generating random problems. The objects generated by *environment* are problems comprised of a string of bits, representing *environment's* requirements. Accuracy of answers is a measure of effectiveness, while total processing time represents efficiency of *project*. Through solving different problems, *PM* and analyst agents learn how to improve their performance, respectively. *PM* has another RL algorithm in order for improving *project* as a whole by moving agents among roles. As Carley (2000) explains changes made in the design of organizations are actions for learning, therefore with changing positions (roles) of agents, *PM* tries to learn to improve *project*'s performance.

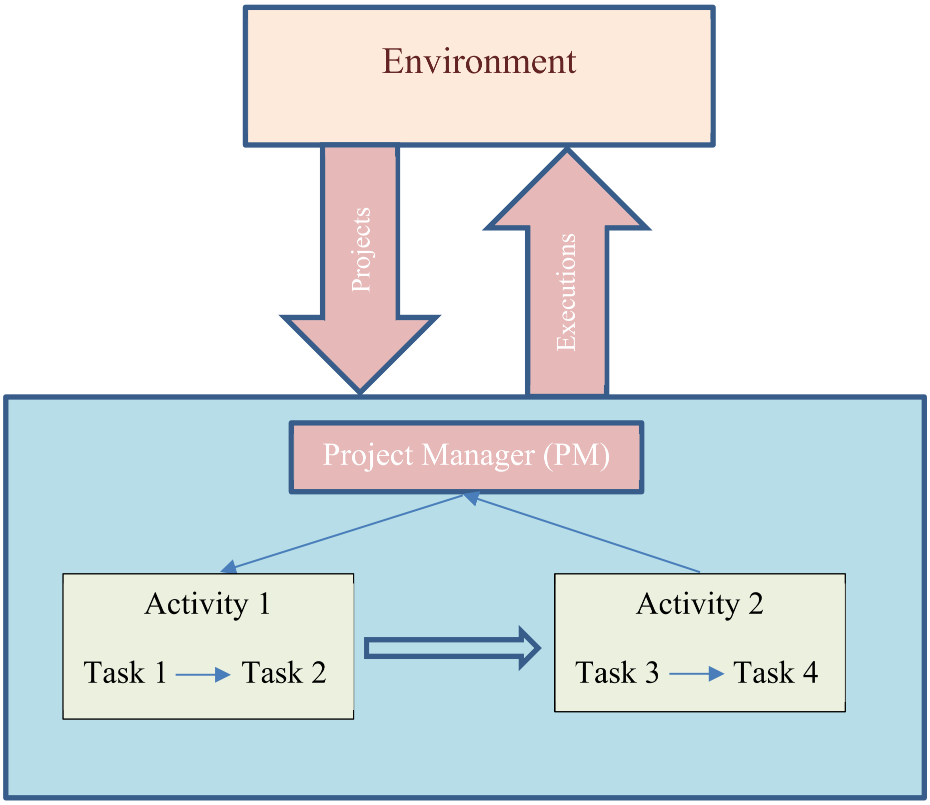

Figure 1: The Structure of the Computational Model

The dynamics of simulation is as follows: (1) *environment* generates random projects and sends them to *project*; (2) *PM* collects a problem and distributes it in the Activity 1. The agent at role one starts solving the problem through Task 1; (3) each agent receives the problem and depending on the task looks at certain bits to provide the solution from its memory and sends the solution to its successor. The duration of problem solving depends on the number of bits each agent processes; (4) *PM* provides the overall answer and passes it to *environment*; (5) according to a decision making rule, *environment* finds the current answer and updates *PM* and the other agents; (6) with a fixed frequency, *PM* tries to make some changes in *project* (based on a RL algorithm) to improve productivity (i.e. the ratio of accuracy of answers to total time spent).

Problems are classification choice tasks comprised of seven ternary variables X_0, X_1, X_2, X_3, X_4, X_5, X_6; each can take one or two or three as its value with equal probability. The size of problems can be selected more than seven, but it would increase the simulation time. The solution is "one" or "two" or "three" depending on the applied decision rule and cut-off values. The problem generation time is set at first and then is accumulated when a problem is processed at each role and pass through the network. The transfer time between agents is fixed at two simulation time units, called ticks. The difference between the generation time and the final time is a measure of efficiency. The performance measure defined here seems to be an appropriate measure because "the ratio of results achieved to resources consumed, is an appropriate and fundamental criterion for all of organizational decisions" (Simon, 1997: 277). Not every agent has access to all bits of a problem due to division of work in a project. The assignment of problem bits is shown in Table 2.

Project learning is modeled as a RL algorithm that operates based on a trial-and-error search and delayed reward. The appropriateness of RL comes from the fact that the overall objective of project managers is to align projects towards environmental requirements and thus the environment feedback plays a key role in the decision-making process within any organization. Pich et al (2002) apply the same idea to conceptualize projects based on payoff functions of actions within sequential decision making. *PM* tries to improve *project* by modifying activities 1 and 2, where it changes the agent roles within and between these activities. The list of its actions is presented in Table 3. For instance, assume the layout of a simulation run is DBCA, meaning agent D at Task 1; agent B at Task 2; agent C at Task 3; and agent A at Task 4. By taking action 3 for example, *PM* changes the layout of *project* to DCBA. The consequence of each action (the reward) appears in the form of a rise or decline of average productivity, incremented by the following equation:

$$\overline{r_{t+1}}= \overline{r_t}+ \alpha[r_t- \overline{r_t}] \tag{1}$$

where α is step-size parameter and r_t is the productivity level of current run. Each action has a numeric preference level ($p_t(a)$), incremented in each decision-making stage according to the following equation:

$$p_{t+1}(a)= p_t(a)+ \beta[r_t- \overline{r_t}] \tag{2}$$

where β is another step-size parameter. The preference of selecting successful actions rises gradually, which in turn increases the probability of their own selection according to the Gibbs distribution:

$$\Pr\{a_t=a\}= \frac{e^{p_t(a)}}{\sum_{b=1}^{n} e^{p_t(b)}} \tag{3}$$

The default parameters of the simulation are shown in Table 4. These show agent A processes data quickest but has a poor 'memory' for the consequences of past decisions, in contrast to agent D who is slow at decisions making but has a perfect memory. Cut-off values determine the correct answers of each problem. For all scenarios, they are set so that the probability of correct answers being "one", "two", or "three" be equal to 0.33. This guarantees that by changing decision rules, indifference of *environment* agent is maintained. For instance, the probability distribution of Linear decision rule is:

$$Y_{Linear}= \sum_{i=0}^{6} X_i$$

$$\Pr(Y_{Linear}=k_1+2k_2+3k_3) = \frac{7!}{k_1!k_2!k_3!} \left(\frac{1}{3}\right)^7$$

where k_1, k_2, and k_3 represent the number of "one"s, "two"s, and "three"s in the problem bits. Therefore, the lower cut-off can be calculated as follows:

$$\Pr\{Y_{Linear} \leq \text{Lower cut-off}\} = \frac{1}{3} \xrightarrow{\text{yields}} \text{Lower cut-off}=13$$

The upper cut-off value for Linear decision rule is calculated in the same way. For other decision rules, the cut-off value requires to be modified, because their probability function is different. The specifications of some arbitrary decision rules tested in this research (including entropy and cut-off values) are shown in Table 5. As another example, cut-off values of Nonlinear rule are calculated here:

$$\Pr(Y_{Nonlinear}=1^{k_1}2^{k_2}3^{k_3}) = \frac{7!}{k_1!k_2!k_3!} \left(\frac{1}{3}\right)^7$$

$$\Pr\{Y_{Nonlinear} \leq \text{Lower cut-off}\} = \frac{1}{3} \rightarrow \text{Lower cut-off} =36$$

Table 2: Problem decomposition structure

Task 1	x_0, x_1, x_2
Task 2	x5, output of Task 1
Task 3	x3, x4, output of Task 2
Task 4	x6, output of Task 3
PM	output of Task 3, output of Task 4

Table 3: PM Actions used for RL

Action	Description
1	Swap agents at Task 1 and Task 2.
2	Swap agents at Task 3 and Task 4.
3	Swap agents at Task 2 and Task 3.
4	Swap agents at Task 1 and Task 4.
5	Swap agents at Task 2 and Task 4.
6	Swap agents at Task 1 and Task 3.
7	No change

Table 4: Default parameters of simulation runs

Problem Solving Time (simulation ticks/bit):	Agent A = 1, Agent B = 2, Agent C = 3, Agent D = 4, PM = 1
Ratio of Memory Negligence (between 0 and 1)	Agent A = 0.3, Agent B = 0.2, Agent C = 0.1, Agent D = 0, PM = 0.3
Transfer Time between Agents (simulation ticks)	2 (constant for all activities)
Simulation Run Time (ticks)	8,000,000
Action Preference Step-size Parameter (β)	0.2
Reward Step-size Parameter (α)	0.1

Table 5: Specifications of different decision rules

Decision rules	Entropy	Lower cut-off	Upper cut-off
Linear: $Y = \sum_{i=0}^{6} X_i$	3.1564	13	15
Semi-Linear: $Y = X_0 + X_1X_2 + X_3X_4 + X_5X_6$	4.0932	12	16
Nonlinear: $Y = \prod_{i=0}^{6} X_i$	3.1564	36	108
Third Degree: $Y = X_0 + X_1X_2X_3 + X_4X_5X_6$	4.9667	13	21
Mixed Third Degree: $Y = X_0 + X_1 + X_2X_3 + X_4X_5X_6$	4.5889	12	17
Weighted Linear: $Y = X_0 + 2X_1 + 2X_2 + 3X_3 + 4X_4 + 3X_5 + 2X_6$	4.5256	31	36

4. Results and discussions

There are two sources of complexity in the model that are discussed here: *environment's* complexity and time complexity modeling the internal complexity of *project*. Also, the effects of learning parameters (i.e. α and β) are investigated in this section.

4.1 Effects of Environment's complexity

To examine the effects of complexity, *project* is exposed to different levels of environmental complexity, represented as decision rules. *Environment's* complexity has some counterintuitive effects on the performance. As seen in Figure 2, there exists a productivity gap between less complex solutions like Linear, Semi-Linear, and Nonlinear decision rules at the one hand and more complex decision rules such as Weighted Linear or Third Degree on the other hand. Discovering the cause of this pattern is complicated but the reason may be that when a less complex decision rule (with less entropy) is applied, solution space of the decision rule is smaller or put another way the difference among the frequency of solutions becomes greater according to Shannon (2001) (i.e. some solutions happen more frequently) and thus *project* should be more accurate in predicting these values. In other words, less complexity/randomness of the decision rules means less variation in the search space and thus finding correct answers require more prediction power. However, the knowledge level gained by *project* is bounded to agents' capabilities and consequently it has limited capabilities in targeting correct answers. In fact, since agents' learning in this model is incomplete there is always a degree of error and as a result, *PM*'s prediction accuracy is limited. That is why *project* has poorer performance with less complex decision rules, contrary to the intuitive expectation. Likewise, when the entropy of a decision rule rises, the range of decision rule is more than before (i.e. search space is bigger) and it is more probable for *PM* to hit the targets, considering its learning errors.

The RL algorithm is compared with random changing of agents among roles, called Random-Action algorithm. The comparison of RL performance versus Random-Action for various decision rules reveals that there is an interaction between *PM* actions defined as RL in this research and the environmental complexity. Figure 3 depicts an example where Linear as the least complex and Third Degree as the most complex decision rules are compared. The difference between RL and Random-Action algorithm, where *PM* randomly changes agents among roles is less with Linear rule in comparison to that of Third Degree rule. It means that RL algorithm performs more efficiently with more complex problems. The same trend is seen for Mixed Third Degree and Semi-Linear rules (See Figure 4). These results highlight the importance of leadership in complex environments. When the environment is more complex, intelligent behaviors of project managers (here modeled as RL) can be more productive for organizations.

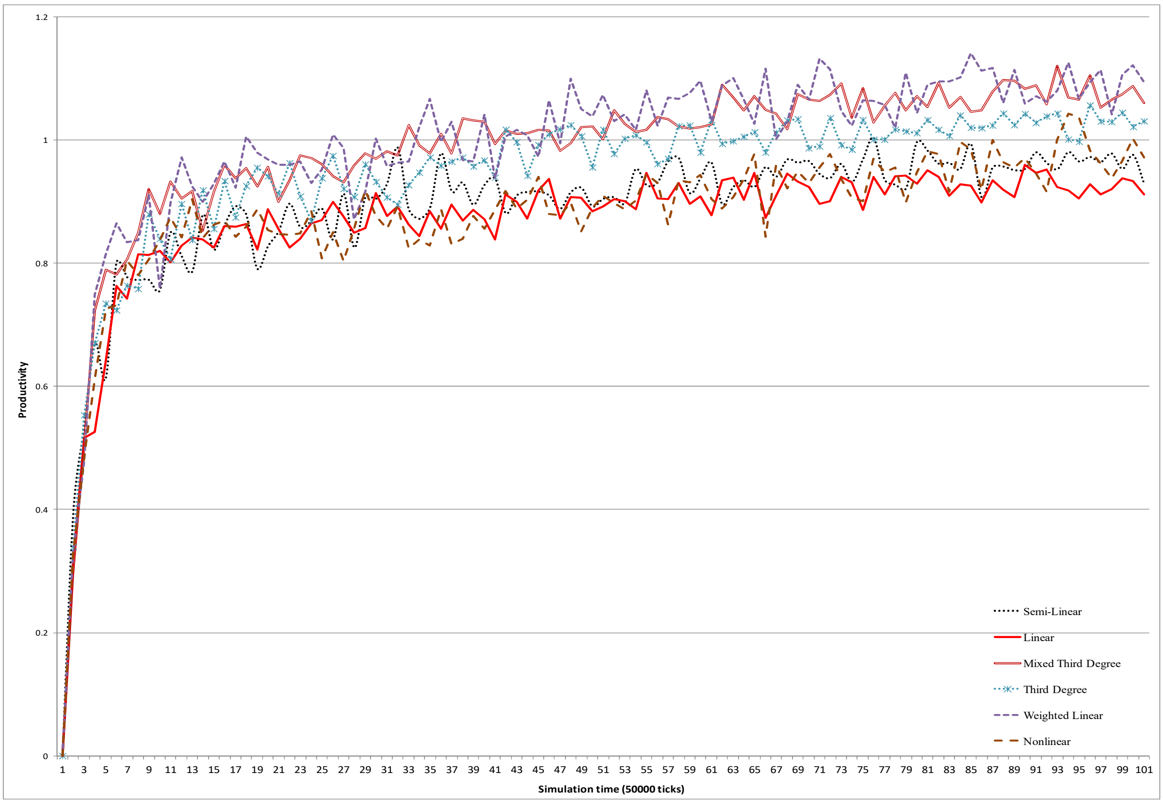

Figure 2: Comparison of the performance level for different decision rules

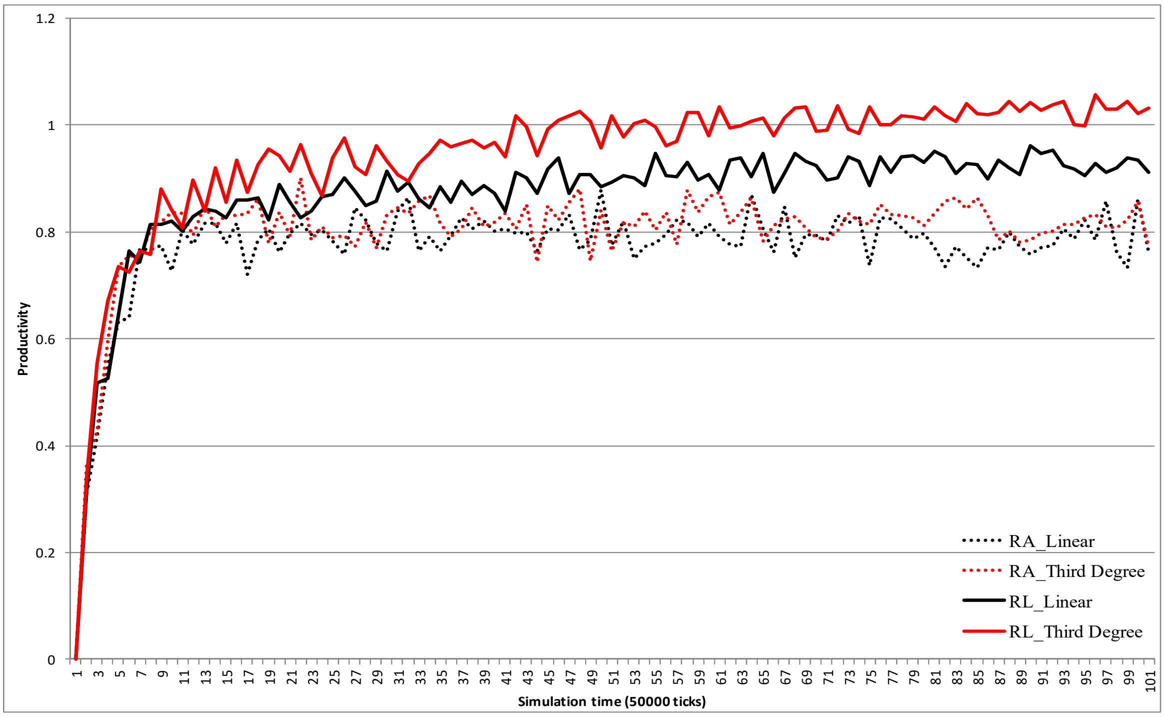

Figure 3: Comparison of performance levels with Linear and Third-Degree rules

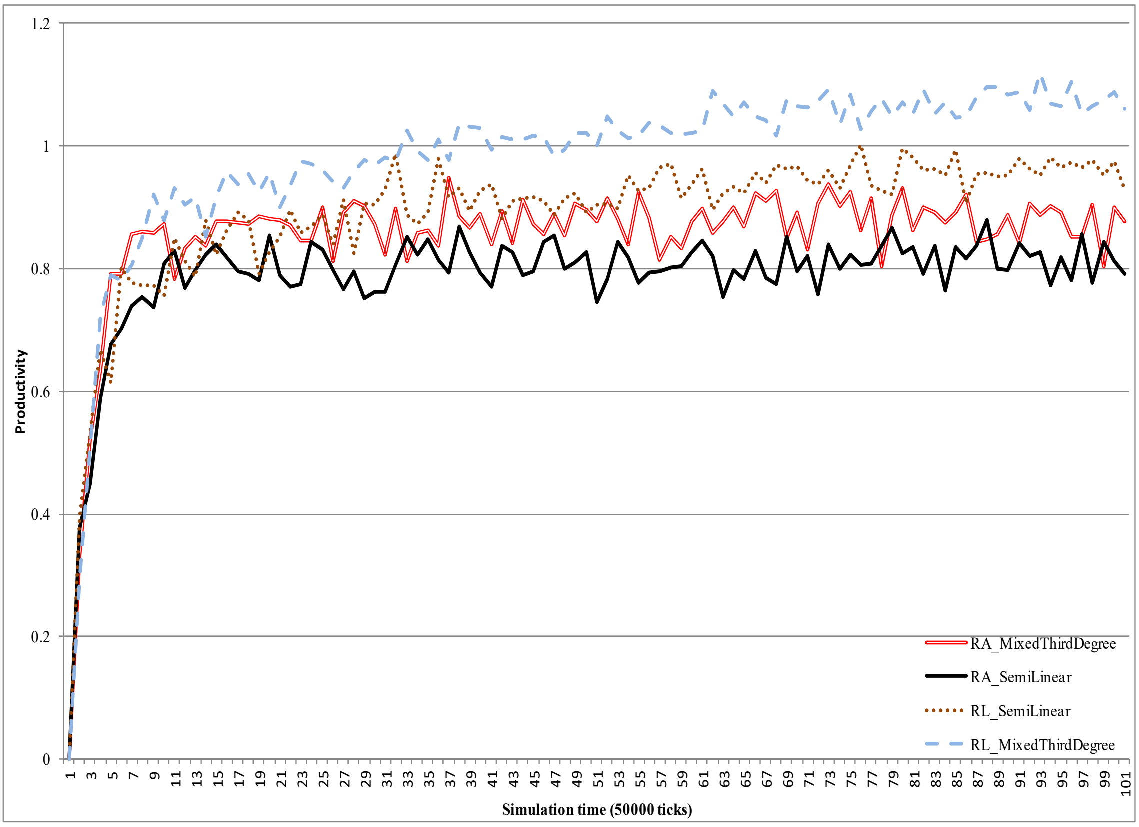

Figure 4:: Comparison of performance levels with Mixed Third Degree and Semi-Linear rules

Some empirical studies support the results presented in Figure 2 ,3, and 4 in that under certain conditions project team can take advantage of complexity and improve their performance by quick iteration and problem solving cycles and capability development (Iansiti & MacCormack, 1997; MacCormack, Verganti, & Iansiti, 2001; Pich et al., 2002). Successful taming of project complexity depends on organization's experience and problem solving capacity (Pich et al., 2002), flexibility (Mitchell, 2007) and knowledge production processes (Floricel et al., 2016). However, different dimensions of complexity may necessitate different approaches (Mitchell, 2007; Sommer & Loch, 2004). Mitchell and Nault (2007) in their empirical study found that greater uncertainty only partially lead to extra work. Floricel (2016) reports that complexity enhances innovation performance whereas there is no significant effect on completion, operation and value creation perforamnces.

4.2 Effects of learning memory

The learning algorithm has two step-size parameters: α and β. They represent the time horizon that previous experiences are considered. High levels of α and β stress the effects of recent *PM* actions, while low values consider *PM* actions over a longer period of time. In fact, they act as *PM*'s memory. The results of default parameters for various decision rules with high step-size parameters ($\alpha = 0.8$ and $\beta = 0.9$) are compared in Figure 5. As it is seen in this figure, the productivity level of Mixed Third-Degree rule with higher entropy is more than the others but the difference among the rest of decision rules is not statistically significant. The same thing happened in the default scenario with low α and β shown in Figure 2. Results with medium step-size parameters ($\alpha = 0.4$ and $\beta = 0.5$) show a similar trend as depicted in Figure 6. To sum up, the results show that learning memory parameters do not have any effect on *PM*'s taking advantage of environmental complexity by intelligent behavior through RL.

The comparison of results of a single decision rule with various step-size parameters reveals interesting findings. As shown in Figure 7 and Figure 8 for Mixed Third Degree and Linear rules, *project* performs better with the high levels of α and β. When high step-size parameters are used, the dependence of productivity levels to far past experiences diminishes that in turn facilitates effective handling of *environment's* complexity. This reflects in higher performance for more complex rules with high α and β, in comparison to the results acquired with the low levels of α and β. The implication of these results is that by emphasizing the recent results *project* can, to some degree, take advantage of more complex decision rules.

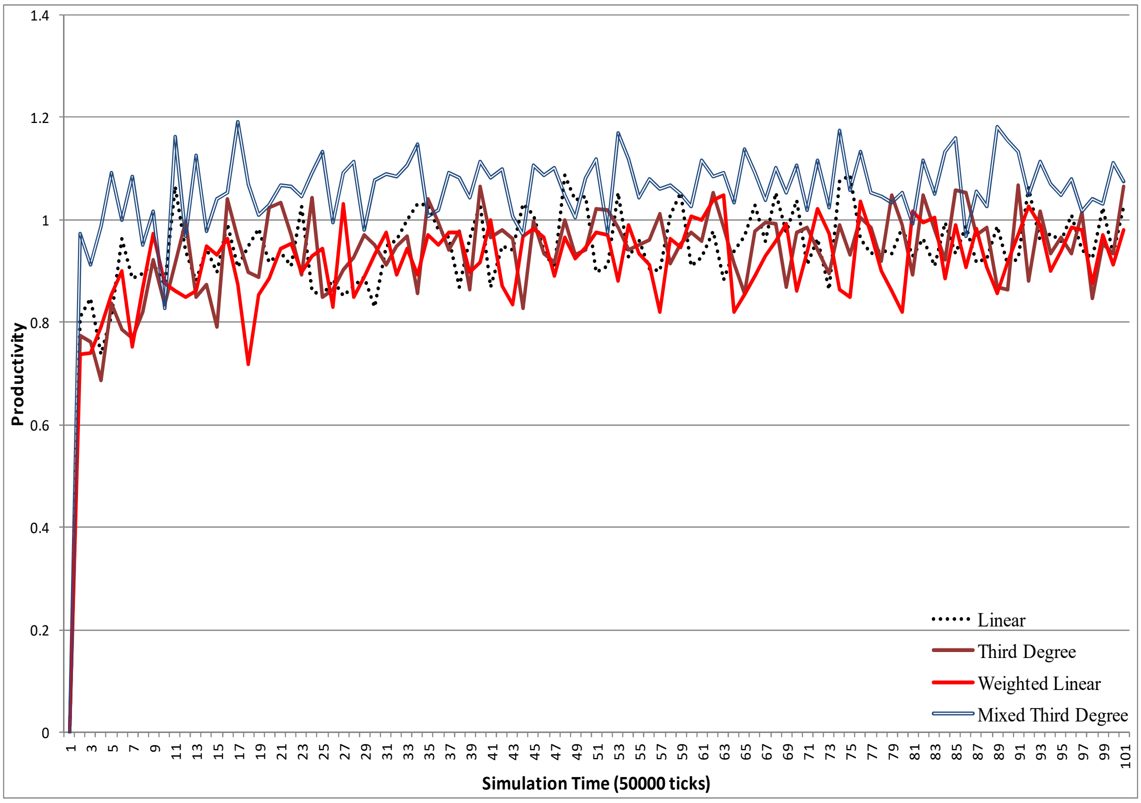

Figure 5: The comparison of different rules at high α and β

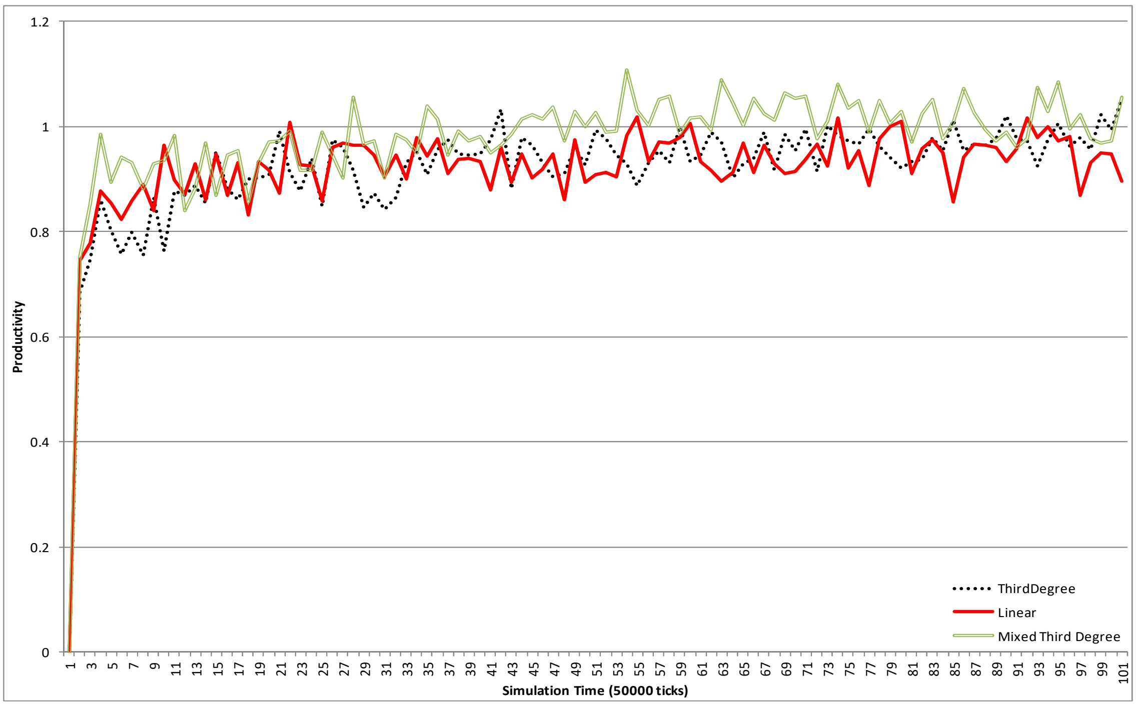

Figure 6: The comparison of different rules at medium α and β

4.3 Effects of time complexity

Aside from the environmental complexity modelled as the decision rules, another source of complexity is related to problem solving and transfer times. Remembering the productivity function being the ratio of correct answers over total time, time complexity affects the denominator. Thus far, all time parameters of the model have been determistic. As an attempt to examine effects of time complexity, all time parameters changed into random. Exponential distribution function is the most random among probability functions with the same mean but because of its hyperbolic shape, the frequency of lower-than-mean values is larger in comparison to other values that may affect *project*'s performance. Therefore, to avoid any bias, it is more plausible to apply uniform distribution which is the second most random probability function and has equal probablity for each value.

The experimental setting used has two independent variables: decision rules with three levels versus time complexity with two levels. The dependent variable is *project*'s performance. The result of equality of error variance test for 10 runs show that there is no evidence to reject the constancy of variance hypothesis with the significant level of 0.234. As can be seen in Table 6, the null hypotheses of equal performance among different decision rules and time complexity cannot be accepted at α=5%. It means that there is a significant difference between the random and the deterministic scenarios. However, there is no interaction effects between decision rules and time complexity.

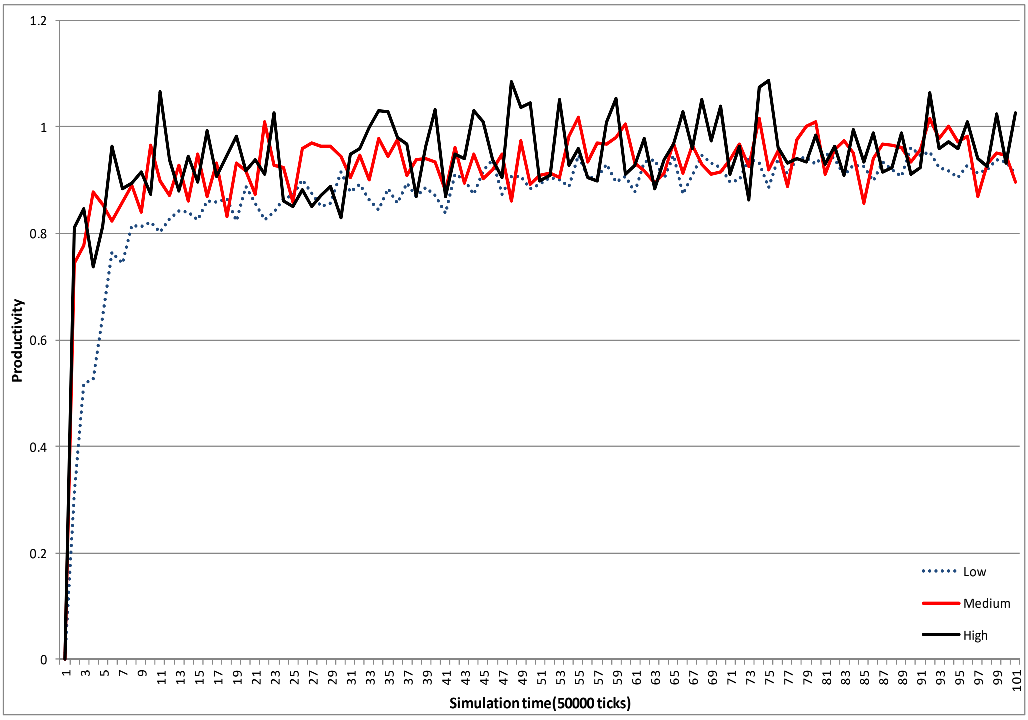

Figure 7: The performance of Mixed Third-Degree rule with different learning parameter levels

Table 6: Tests of Between-Subjects Effects

Source		Type III Sum of Squares	d. f.	Mean Square	F Value	Significance.
Corrected Model		.221[a]	5	.044	9.901	.000
Intercept		50.291	1	50.291	11242.519	.000
Decision Rule		.030	2	.015	3.327	.043
Random Time		.190	1	.190	42.487	.000
Decision Rule * Random Time		.002	2	.001	.182	.834
Error		.242	54	.004		
Total		50.754	60			
Corrected Total		.463	59			

a. R Squared = .478 (Adjusted R Squared = .430)

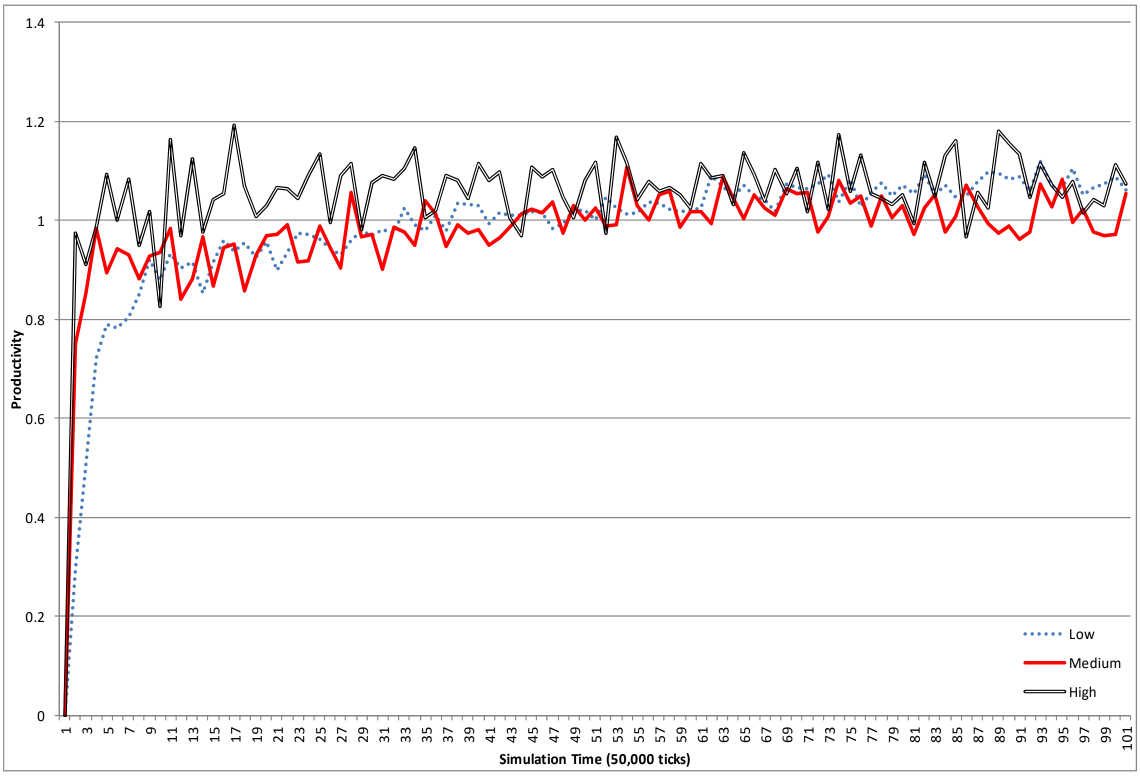

Figure 8: The performance of Linear rule with different learning parameter levels

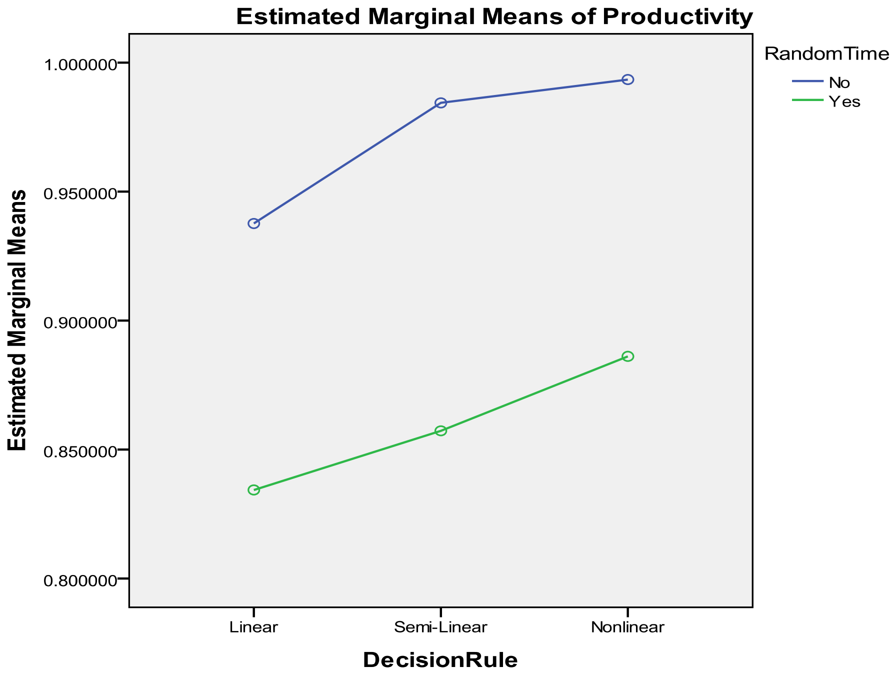

Figure 9: Performance of different factors

Figure 9 reveals a profound effect of time complexity on productivity. It seems that time complexity, unlike the environmental complexity, impinges on performance. By having deterministic times, activities A and B are more standardized, causing the cognitive map of PM to be formed more quickly than random times. The natural outcome of this quick convergence is reflected in the productivity gain. The dynamics of change for different decison rules depicted in Figure 10, Figure 11, Figure 12, and Figure 13 suggest that determinstic time scenarios always outperforms random scenarios with no exception. This implies that decreasing internal complexity of an organization by standardizing business processes bears fruit and ameliorates performance.

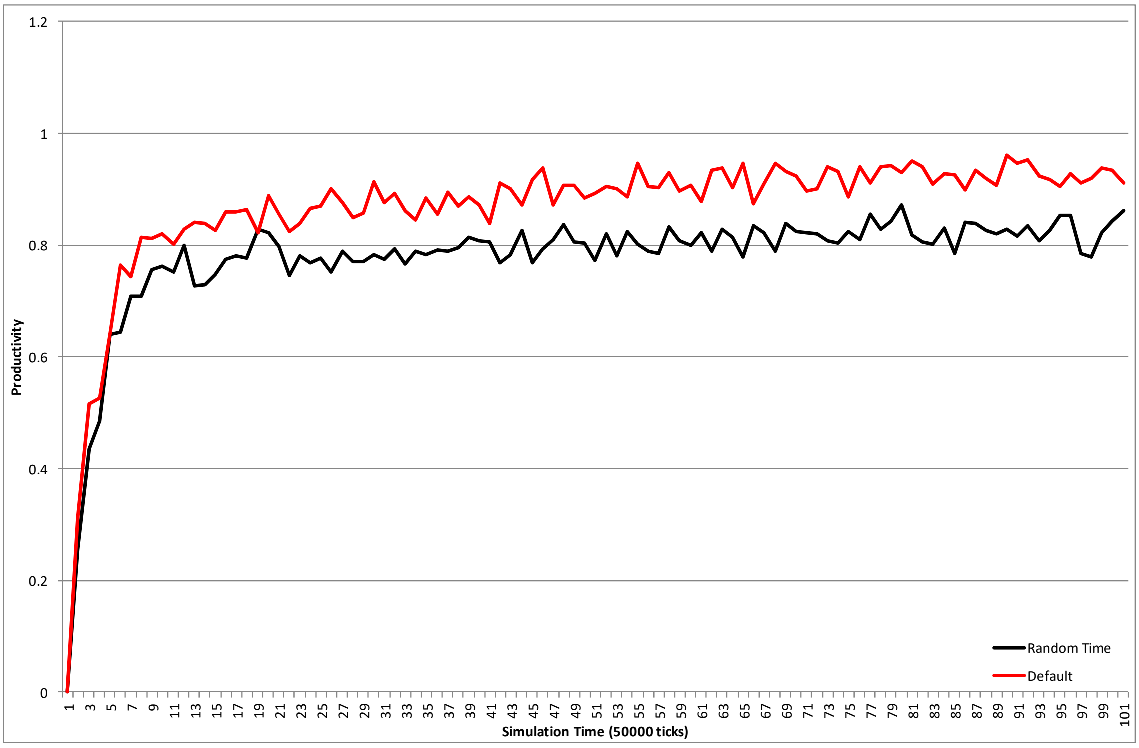

Figure 10: The Performance of Linear rule with different time complexities

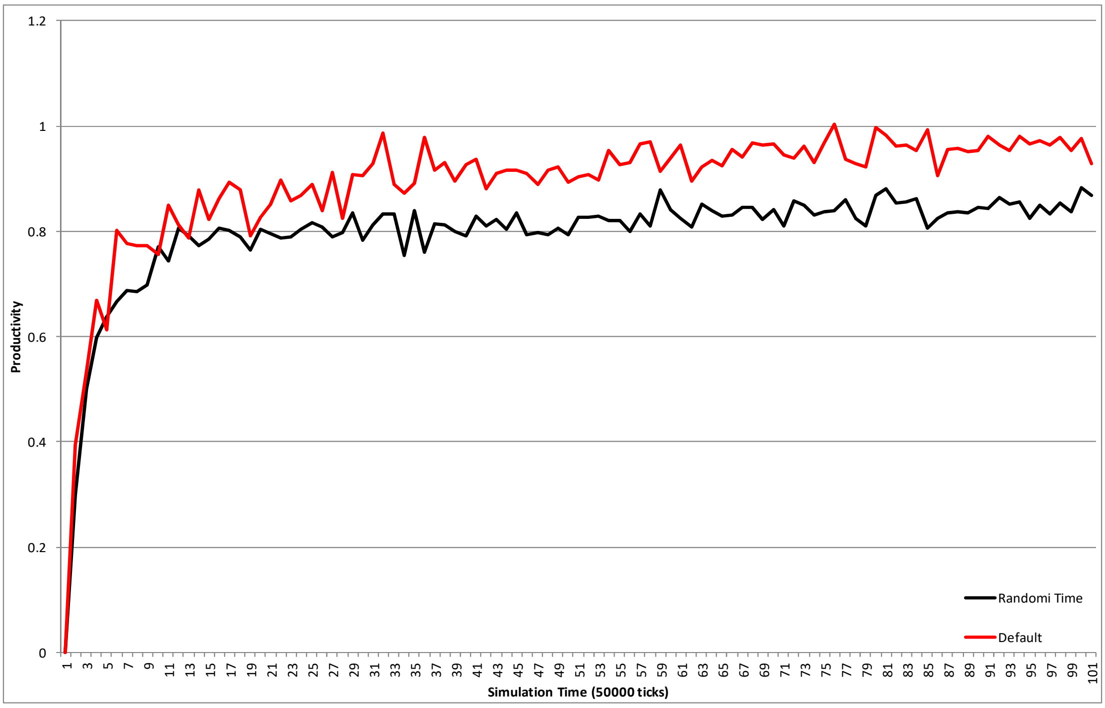

Figure 11: The Performance of Semi-Linear rule with different time complexities

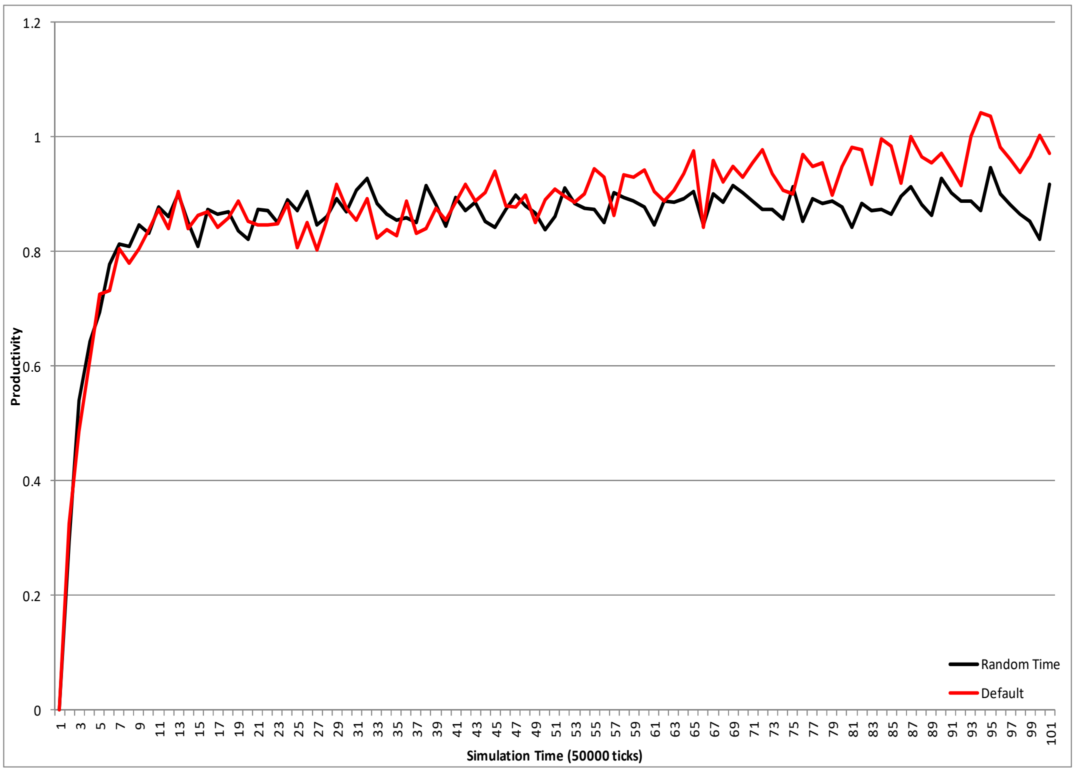

Figure 12: The Performance of Nonlinear rule with different time complexities

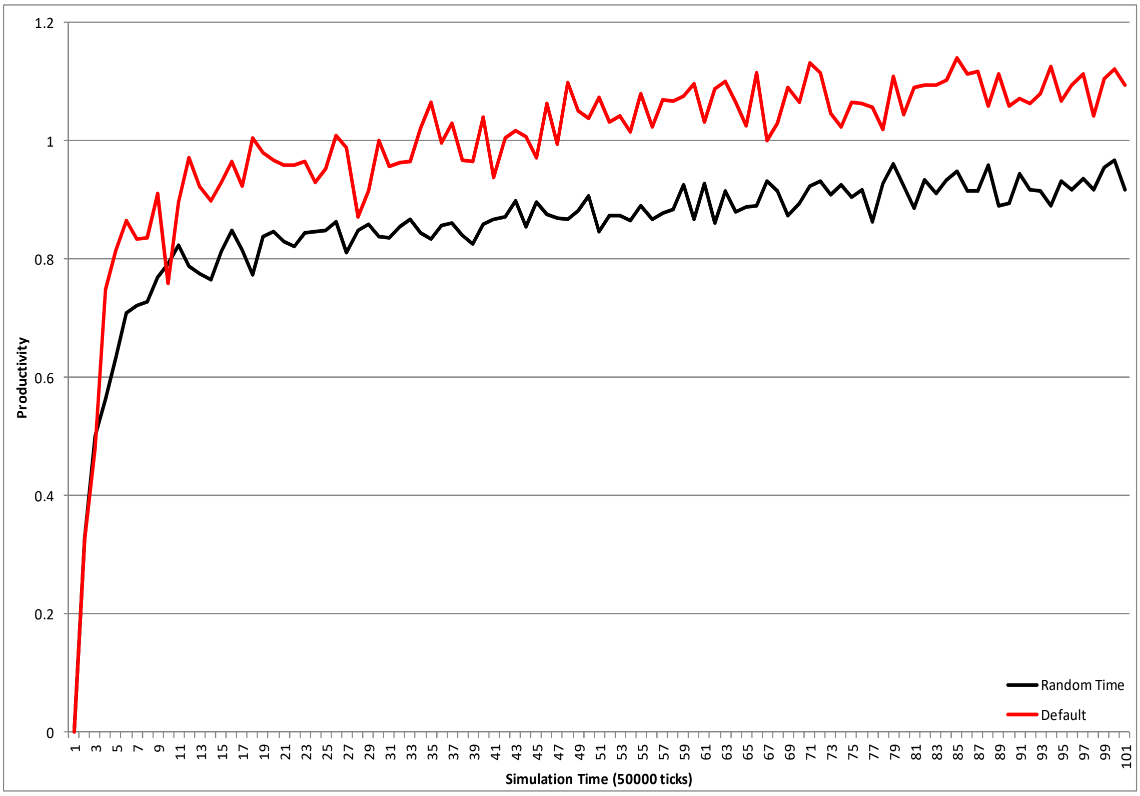

Figure 13: The Performance of Weighted Linear rule with different time complexities

5. Validation

Validation is the process of substantiating that a simulation model is an accurate representation of its referent and depends on objectives of modelling and the subject (Balci, 1994; Casti, 1997). When the subject of simulation is abstract (i.e. a concept), defining any quantitative measure seems to be impossible. Rather, this requires validation based on expert judgment, which is called face validation (Balci, 1994; Zacharias , MacMillan , & Van Hemel 2008). Zacharias et al (2008: 318) suggest that "in evaluating the usefulness of a broad conceptual model, the yardstick is often not how well supported the model is, but how much interesting research it inspires". Any specific project hasn't been simulated in this research; rather the developed model represents theoretically how projects could interact with their environment to deal with complexity. To validate the results, we have used the complexity framework presented in Table 1 by which 18 project have been studied. The complexity scores of these projects are presented in Table 7. Complexity dimensions is aggregated at the project level based on the number of complex dimensions. If less than two dimensions are complex (i.e. with scores more than 75) the project is deemed to have low complexity; projects with three complex dimensions have average complexity and project four or more complex dimensions are highly complex.

Table 7: Case project names and complexity scores (Transportation Research, National Academies of Sciences, & Medicine, 2014)

Project Name	Country	Complexity Dimension					Remarks
		Cost	Schedule	Technical	Context	Financing	
Capital Beltway	USA	10	25	85	40	95	Low complexity
Detroit River International Crossing	Canada-USA	75	85	70	95	100	High complexity
Doyle Drive	USA	80	75	80	75	95	High complexity
Green Street Road Rehabilitation	CANADA	85	70	100	40	25	Low complexity
Heathrow T5	UK	45	55	80	95	85	Average complexity
Hudson-Bergen Light Rail	USA	45	55	85	50	50	Low complexity
I-40 Crosstown	USA	55	70	35	100	60	Low complexity
I-95 New Haven Harbor Crossing	USA	25	85	40	75	70	Low complexity
I-595 Corridor	USA	10	70	85	60	100	Low complexity
Intercounty Connector	USA	70	85	55	85	85	Average Complexity

James River Bridge/ I-95 Richmond	USA	60	95	90	90	50	Average Complexity
Lewis and Clark Bridge	USA	25	55	85	100	10	Low complexity
Louisville Southern Indiana Ohio	USA	100	55	85	90	95	High complexity
New Mississippi River Bridge	USA	75	90	75	95	60	High complexity
North Carolina Tollway	USA	75	90	85	75	95	High complexity
Northern Gateway Toll Road	NZ	55	60	70	75	90	Low complexity
T-REX SE I-25/I-225	USA	100	85	90	95	95	High complexity
TX SH161	USA	70	75	60	90	95	Average Complexity

As seen in Table 8, there are highly complex projects which were very successful. This demonstrates the importance of adaptability. The adaptation has been modelled as a reinforcement learning algorithm but in real projects it is manifest in different project management practices. Some of the best practices for adaptation that have been worked in the case projects are summarized in Table 9.

Table 8: Case projects’ performance names and complexity scores (Transportation Research et al., 2014)

Project Name	Complexity Level	Project outcome/benefits	Project Successful?
Capital Beltway	Low complexity	• 14 miles of two new lanes in each direction • First time introduction of High Occupancy Vehicles (HOV) lanes to the Capital Beltway and reliable transit options to the Beltway and Tysons Corner, Virginia • Congestion-free network for carpools, vanpools, transit, and toll-paying motorists • Replacement of more than $260 million of aging infrastructure, including more than 50 bridges and overpasses • Construction of carpool ramps connecting I-95 with the Capital Beltway to create a seamless HOV network Source: ("Capital Beltway High Occupancy Toll (HOT) Lanes," 2019)	Yes
Detroit River International Crossing	High complexity	In progress	-
Doyle Drive	High complexity	• Sustainable design • Greenroads® Certification • Safer Roadway • Presidio Access • Enhanced Views • Context Sensitive Design	Except sustainability in which the project was partially successful, the project achieved its project objectives in other aspects ("Presidio Parkway Re-envisioning Doyle Drive," 2019).
Green Street Road Rehabilitation	Low complexity	• Superior structural performance	Yes, all objectives exceeded; approximately 55% cost saving

		• Improved road structural systems • More-sustainable infrastructure solutions • An improved life-cycle performance of the road structure • Reduction in construction time, energy requirements, construction-generated emissions, and climate risk during construction • Significant cost saving • Freeing more landfill space	
Heathrow T5	Average complexity	• Set new standards in delighting the traveller • Develop and deliver T5 to new industry standards of health, safety, and security • Earn the proactive support and trust of key stakeholders • Achieve exceptional performance to ensure value for money, on time delivery and an efficient and productive T5 • Leave behind a legacy of quality (Basu, Little, & Millard, 2009)	Yes. Design and construction performance targets were achieved (Transportation Research et al., 2014). The project won multiple awards however in the operation phase luggage-processing system failed (Transportation Research et al., 2014)
Hudson-Bergen Light Rail	Low complexity	• Regeneration of Hoboken waterfront area bordering the Hudson River • encouraging housing development over a previously run-down industrial land ("Hudson-Bergen - Railway Technology,")	No. Cost overrun as much as $ 67 million
I-40 Crosstown	Low complexity	• combined road and bridge improvement • careful planning to minimize disruption • on-time delivery (Shane, Gransberg, & Busch, 2011)	No. Little cost overrun but there was schedule delay (Transportation Research et al., 2014).

I-95 New Haven Harbor Crossing	Low complexity	• Replacement the existing bridge with a new signature structure • Improving traffic congestion and preventing it from continuing during the off-peak hours • Remedying the structural deficiencies of the existing I-95 bridge (Q-Bridge) over New Haven Harbor (Transportation Research et al., 2014). • Operational and safety improvements on I-95 to reduce abnormally high accident rates. • Capacity improvements along this section of I-95 to ease traffic congestion ("I-95 New Haven Harbour Crossing Improvement Program," 2019)	No. Estimated finish date was 2016 but the project was finished in third quarter of 2018.
I-595 Corridor	Low complexity	• reconstruction and widening of the I-595 mainline and all associated improvements ("I-595 Corridor Roadway Improvements- US Department of Transportation," 2019) • deliver responsive, cost effective, on-time and environmentally safe transportation solution ("I-595 Express," 2019)	Yes. The project was scheduled to finish in March 2014 and it was finished on time and within the budget; the project won a number of awards ("What a successful P3 looks like: Florida I-595 Corridor," 2019).
Intercounty Connector	Average Complexity	• providing a limited access, multimodal facility between existing and proposed development areas in Montgomery and Prince George's counties. • to increase community mobility and safety. • To facilitate the movement between economic centres of people and goods • To provide cost-effective transportation infrastructure to serve existing and future development that reflects local land use objectives;	The project was planned to finish in late 2011 (excluding last two sections) and finished on time. Sections 4 and 5 completed in 2014.

		• To help restore the natural, human, and cultural environments changed by past development impacts • To enhance homeland security (Transportation Research et al., 2014)	
James River Bridge/ I-95 Richmond	Average Complexity	• Restore bridge's condition to maintain long-term safety • Increase bridge capacity (Kozel, 2003)	Yes. The project was completed on time and with a minimum cost overrun due to unexpected work and early finish bonus (Transportation Research et al., 2014)
Lewis and Clark Bridge	Low complexity	• To build a new bridge on Ohio river • to stimulate the economy of the entire region ("Lewis and Clark Bridge Spans Ohio River between Kentucky and Indiana," 2017)	Yes. The delivery was on time and within budget (Junyong Ahn, 2011).
Louisville-Southern Indiana Ohio	High complexity	• to increase cross-river mobility by improving safety • to alleviate traffic congestion and connecting highways	Yes. The project was finished in 2016.
New Mississippi River Bridge	High complexity	• to reduce high crash rate on the existing bridge • To reduce congestion on the existing bridge (Transportation Research et al., 2014)	The project was completed in 2014.
North Carolina Tollway	High complexity	• to provide commuters with improved accessibility and connectivity to the Research Triangle Park • To relieve the heavy congestion on the existing north-south routes between Raleigh and Durham ("Triangle Expressway Project, North Carolina," 2019).	Yes; the project was finished in late 2012 ("Triangle Expressway Project, North Carolina," 2019).
Northern Gateway Toll Road	Low complexity	• To bypass usual congestion spots.	Yes; the road was opened in January 2009

		• More direct route between Auckland and Northland; straighter and 4km shorter. • Safer passing opportunities. • Easy payment options with electronic toll collection ("SH1 Northern Gateway Toll Road (NGTR)," 2019).	(Transportation Research et al., 2014).
T-REX SE I-25/I-225	High complexity	• Minimize inconvenience to the public • Meet or stay under the total T-REX Project budget of $1.67 billion • Provide a quality project • Meet or beat the scheduled fully operational target date of June 30, 2008.	Yes; the project was finished in September 2006 on schedule and within budget (Administration, 2007; Transportation Research et al., 2014)
TX SH161	Average Complexity	• to improve the transportation network in the region • to serve as a major link within the Dallas-Fort Worth regional transportation network • to reduce congestion along adjacent corridors ("FHWA - Center for Innovative Finance Support - Project Profiles," 2019)	The project was completed on schedule and on budget in late 2012 ("State Highway 161 Design-Build Texas," 2019).

Table 9: Best practices for adaptation (Transportation Research et al., 2014)

Complexity Dimension	**Best practices**
Cost	Flexibility in contracts, choosing the right contract type, considering risks involved in the low-bid process, thorough and in-depth risk analysis, partnering, existence of a dispute resolution process, value engineering
Schedule	Disciplined project management, including incentives and disincentives in contracts, Resource-loaded scheduling with Primavera, existence of a dispute resolution process, planning for risk management, detailed reporting
Technical	Taking proactive actions like hiring a consultant for contract formation and risk analyses and forming dispute resolution board, selection of right people and right contractors, decentralized QA/QC, minimize inspection and testing entities, procuring a consultant coordinator, embracing innovation, Learning from previous experiences,
Context	Reducing inconvenience to the Public, developing an aggressive marketing campaign, creating a culture of quality and trust, Proper

	collaboration, cooperation, and coordination with multiple entities, existence of a dispute resolution process
Financing	Considering different revenue-generating options, Analysing funding options in early stages, updating project costs frequently, reducing number of funding companies, using cash flow software

6. Conclusions

In this paper, an agent-based model is presented by which the effects of the environmental complexity on project performance is investigated. The developed model can reveal the dynamics of environmental complexity on project performance, something missing in the prevalent empirical studies in this area. It has been found that projects can take advantage of complexity to improve their own performance. It seems that more complex environments as defined in this research offer possibilities to projects to learn more appropriately in that the search space is bigger and predictive accuracy of learning is less critical. The learning memory of *project* plays a key role in adaptation in that by taking into account the performance for a short time (i.e. high α and β), *project* can adapt more efficiently with *environment*. Concerning the internal complexity modeled as random process times, the results demonstrate that internal complexity within the framework of this research seems to exacerbate *project* performance. Put another way, the performance of an project comprised of standardized business processes seems to be more satisfactory. The results of this research have been validated by data gathered from 18 projects. The empirical data show that project complexity is not always detrimental to performance and there are cases of highly complex project which have been executed well by means of different best practices like flexibility in contracts or highly coordinated stakeholders.

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