Modeling and Simulating Vicious Circles Problems

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Abstract: Time and cost overruns in new product development processes are often attributed to low quality information communication in early stages of the process when key decisions are made by individuals who have limited understanding of how micro-level decision-making can significantly affect macro-level system performance, that eventually leads to the phenomenon of "vicious circles" in new product development processes. Agent-based simulation is a promising approach that can be applied to understand complex systems, such as new product development processes. This paper reports an application of agent-based simulation to time-related aspects of vicious circles in a new product development process case study from a large UK-based manufacturing company. A simulation model was developed following an experimental method established in the research. In the model, work teams and their activities and contributions to the process are represented by autonomous agents. Initial simulation results showed agent-based simulation is an effective and efficient approach for understanding and studying vicious circles in new product development processes.

Keywords: New Product Development Processes, Vicious Circles Problems, Modeling and Simulation, Agent-Based Simulation

1. INTRODUCTION

Time and cost overruns in the development and delivery of large complex engineering projects are often attributed to low quality information communication early in the development process when key decisions are made and relatively little is known about their importance to a final output. The problem is exacerbated by so-called "vicious circles" that are typical of industrial product development processes. This paper reports research with data from a large UK-based manufacturing company that is building understanding of the "vicious circles" phenomenon. The research concerns a product development process with four key stages (teams): preliminary design, detail design, manufacturing and service. Engineers working early in this process often request information from colleagues working at later stages. However, limited resources and high workloads of engineers mean that some requests do not receive responses. As a result, engineers working early in the process are compelled to produce work based on incomplete information. A consequence of this is that designs are often returned from later stages for rework. The rework consumes time that could be otherwise spent responding to new requests which, in turn, leads to the need for more rework in the future. Vicious circles and their consequences have a significant influence on product design and development performance.

Agent-based simulation is a relatively new but fast developing research method to study complex industrial systems and scientific systems [1, 2, 3, 4, 5, 6]. By modeling individual agents in a simulation environment, macro-level system performance that is determined by multiple agents' attributes and behaviors can be reflected by micro-level interactions and influence between the agents [1]. Modeling and simulation techniques are becoming an important problem-solving method for many existing and conceptual systems [6, 7].

This paper reports an application of agent-based simulation to time-related aspects of a new product development process. In this paper, an industrial-based new product development process case study is introduced with the focus on business performance measurement, especially time-related aspects. According to an established experimental method, the new product development process is modeled and simulated using the agent-based simulation (ABS) method in a computer simulation platform. By operating autonomous and interactive agents, the behavior of the overall new product development process is demonstrated in a simulation world. This paper reports an initial experiment and model verification.

The paper begins with an introduction to the research background (section 2). This is followed by details of the experimental method (section 3), and case study (section 4) that were used, and a summary of key findings and future work (section 5).

2. RESEARCH BACKGROUND

This section introduces two important cornerstones of the research: new product development processes and modeling and simulation techniques.

2.1. New Product Development Processes

The processes used to design and develop products and then support them through their lives are referred to in a number of ways in the literature: for example, product design and development process [9], new product development process [8, 10], new product introduction process [11], Stage-Gate process [12], and many others. Key characteristics of these processes are that they comprise a series of steps, delivered by functional teams, through which design and development information is communicated and transformed. Fig. 1 shows the skeleton of a new product development process in a large UK-based manufacturing company. It comprises four functional teams: preliminary design, detail design, manufacturing and service.

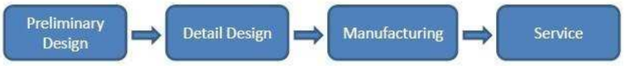


Fig. 1 New product development process

When the new product development process system runs, many information loops (in the form of requests for information and responses to these requests) occur between the work teams. These interactions result in product design and management information which influences whole new product development process performance.

2.2. Modeling and Simulation Techniques

Widely accepted definitions of the term 'simulation' are (1) , "the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behavior of the system and/or evaluating various strategies for the operation of the system" [13, 14]. and (2), "building a model of a real system (or a system-to-be), conducting experiments with this model, and creating some kind of output result for decision-making and implementation support" [15].

Modeling and simulation was originally used in application fields such as computer systems, manufacturing, business, government, ecology and environment, social and behavioral issues, biosciences [13]. Nowadays, simulation technology has also been applied in interdisciplinary research areas such as process decision-making [16] and product design and development systems [17]. To some extent, simulation technology can be considered as a third scientific research methodology, in addition to traditional deductive and inductive reasoning [3, 18, 19].

Within operational research communities, two popular simulation tools are discrete-event simulation and agent-based simulation (ABS) [20]. Discrete-event simulation has been the mainstay in the operational research simulation community for over 40 years [20]. Discrete-event simulation is one way of building up models to observe the time-based behavior of a system. Formal methods and procedures for building such simulation models have been established that ensure simulation models are credible [20]. Comparatively, agent-based simulation is a relatively new but fast developing approach [1, 2, 19]. The agent-based simulation method builds up simulation model as a bottom-up infrastructure [1], which means that system macro-level performance is influenced and determined by massive micro-level decisions amongst individual agents' and their activities. This makes ABS particularly well-suited to vicious circles in product development processes.

3. EXPERIMENTAL METHOD

The specific method used to carry out simulation experiments may vary for a range of reasons including differences in the problem being addressed, the purpose of the simulation, experimenters' preferences and limitations of simulation technologies. Along with exploring simulation techniques, some researchers have analyzed experimental methods [7, 14]. For example, Shannon [14] proposes the following 10 stage process: system definition, model formulation, data preparation, model translation, validation, strategic planning, tactical planning, experimentation, interpretation, implementation and documentation.

Fig. 2 shows the experimental method used in this research. The method accommodates Shannon's steps and the demands of the case study which, at the beginning of the research, was formulated as a real-world problem rather than a simulation problem. The experimental process included following 11 steps.

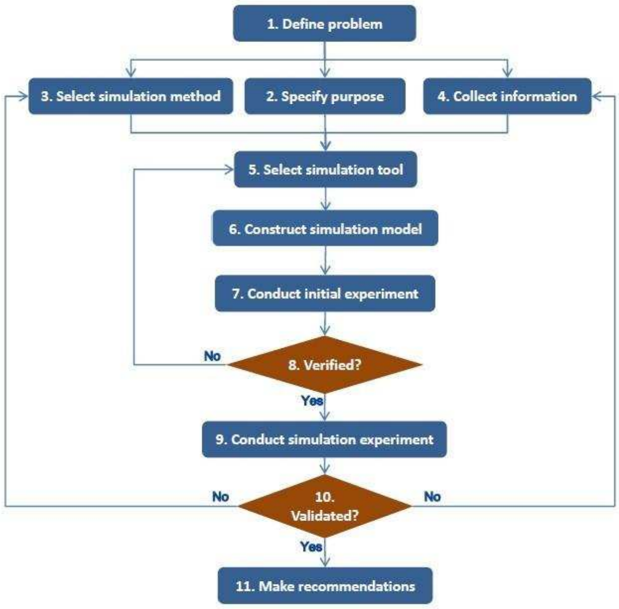


Fig. 2 Experimental method

1. **Define problem:** the real-world problem is analyzed, observations are recorded, and a goal for the simulation experiments is defined.
2. **Specify purpose:** the aim and objectives for simulation experiments are specified.
3. **Select simulation method:** a simulation method is selected with respect to research problem statement, research purpose.
4. **Collect information:** data and information needed to inform the simulation model definition and as input to the simulation experiments is identified and collected.
5. **Select simulation tool:** the simulation tool with which experiments will be carried out is selected.
6. **Construct simulation model:** the simulation model is built.
7. **Conduct initial experiment:** an initial experiment is carried out , using case study operation scenarios, to confirm the suitability of the selected simulation tool and the model architecture.
8. **Model verification:** the simulation model and initial experiment results are reviewed and discussed by a team including both simulation specialists and case study owners.

9. **Conduct simulation experiment:** simulation experiments are conducted using input data and information collected from the real-world problem domain and case study owners.
10. **Model validation:** the simulation model and experimental results are reviewed and discussed by a team including both simulation specialists and case study owners.
11. **Make recommendations:** the simulation results are used to inform management interventions in the real-world system. In the longer run, real world outcomes of these interventions can be compared with simulation results and used to further improve the efficacy of the simulation model.

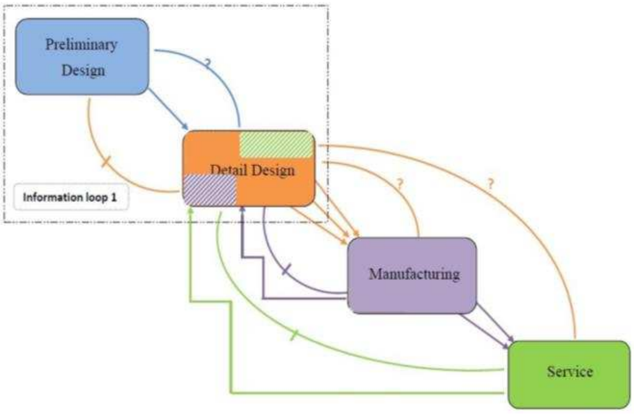
4. SIMULATION CASE STUDY

The case study arose from work with engineering teams in a large UK-based manufacturing company where both researchers and practitioners had observed social and organizational characteristics of so-called "vicious circles" in the new product development process. As a result, they identified an opportunity to gain insights that could improve the management of the process from an application of modeling and simulation techniques.

The application of the first eight steps of the experimental method outlined in Section 3 to time-related aspects of the new product development process case study is reported in this section.

4.1. Define Problem

The new product development process case study used in this research included four stages (and so teams): preliminary design, detail design, manufacturing and service. Fig. 3 illustrates the vicious circles problems in the case study process.



Keys:

- The straight arrows represent the passing of output from one stage to another;
- The curved line with a question mark stands for the information request, from up-stream team to down-stream team;
- The broken curved line means the request does not receive responses;
- The folded lines are rework request of the design from down-stream teams;
- The shaded areas are time taken to complete the necessary rework.

Fig. 3 Vicious circles in new product development process

At the beginning of the design process, the preliminary design team requests information from the detail design team. However, the detail design team is often so busy focusing on its own part of the process that it cannot provide a response quickly enough. For this reason, the preliminary design team continues work without the requested information and passes its output to the detail design team by a deadline that is defined in an overarching project plan. However, because the detail design team has not given their input at the start of the process, they find errors in the design that need to be rectified. They therefore return aspects of the design to the preliminary design team for additional work (rework). This forms Information Loop 1 in Fig. 3. Similar patterns of interactions occurs at other stages. For example, between detail design and manufacturing, the manufacturing team does not provide sufficient input at first, but later finds that the design is lacking with respect to manufacturability. This results more rework, often involving multiple functional teams, which again has a detrimental impact on product development performance.

4.2. Specify Purpose

The aim of the research was to simulate vicious circles observed in a large UK-based manufacturing enterprise's new product development process with a view to highlighting sources of waste by determining the impact of rework on the time taken to produce the final product. To this end, the purpose of the simulation experiment was to provide answers to the following questions.

- What are the time costs of rework caused by not spending time in responding to requests for information?
- What are the potential time savings to be gained from spending more time in responding to requests for information and therefore reducing the amount of future rework needed?
- If all requests for information received responses, what would be the time savings by rework reduction?
- If all rework due to lack of responses was eliminated, what would be the lead time reduction across the entire design process?
- What proportion of the detail design team's time should be spent on old versus new design packages?

4.3. Select Simulation Method

Each simulation method has its own advantages and shortcomings for the modeling and simulation specific real-world systems [17, 20, 21, 22]. The issue of which one will dominate the next generation simulation field is in discussion, but it is not easy to reach an agreement [20], especially when different problem domains are best suited to different kinds of simulation approach. Table 1 outlines primary advantages of two common simulation methods: agent-based simulation (ABS) and discrete-event simulation (DES).

The agent-based simulation method was selected for this research. Key reasons behind this choice lay in the fact that the real-world situation is regarded by problem owners as one where each team (at a micro-level) operates as an autonomous entity. Any queues are within the team entities and so would not be visible in the simulation. Key decisions made by the teams influence the performance of the whole design process (at the macro-level). For example, a given team can decide how much time and effort to devote to responding to information requests from other teams. This influences the frequency with which responses to requests from other teams are received and so the quality of the information available for the team that issued the request to work with.

Table 1 Simulation method selection

Advantages of Discrete-Event Simulation	Advantages of Agent-Based Simulation
process oriented; focus is on modeling the system in details, not the entities	individual based; focus is on modeling the entities and interactions between them
top-down modeling approach	bottom-up modeling approach
one control thread (centralized)	each agent has its own control thread (decentralized)
passive entities, that is something is done to the entities while they move through the system; intelligence is modeled as part in the system	active entities, that is the entities themselves can take on the initiatives to do something; intelligence is represented within each individual agent
queues are a key element	no concept of queues
flow of entities through a system; macro behavior is modeled	no concept of flows; macro behavior emerges from micro decisions of individual agents
input distributions are often based on objective data	input distributions are often based on theories or subjective data

Benefits of applying agent-based simulation to improve understanding of vicious circles in new product development processes can be explained from three perspectives. Firstly, a bottom-up modeling approach is appropriate because overall performance of the real-world system is actually influenced by independent decision-making of each work team. Secondly, in an ABS model, each agent has its own time-based control thread which enables the different teams, each represented as a separate agent, to make independent decisions. For example, agents can be used to represent each work team within multiple product development projects where each project is using a common development process. Thirdly, each active agents can make judgments and decisions which provides opportunities for the future integration of artificial intelligence (AI) technologies into the management of vicious circles in product development processes.

4.4. Collect Information

The experiment reported in this paper focused only on time dimensions of the case study process. The final ultimate goal of this research is to investigate full scale vicious circles problems and build up a comprehensive understanding of information management strategies to reduce risk levels in product development processes. Given the focus is on time, data related to the variables listed in Table 2 was collected.

Table 2 Variables definition

Variable	Definition	Example
Independent variables (inputs to the simulation experiments)		
t_S, Time (system ticks)	This is the amount of time for which the simulation will be run. It is automatically calculated by simulation system.	If t_S = 50 then, the simulation has been running for 50 ticks.
i, Frequency-of-requests-%	Frequency with which requests for information are generated	If i = 50, then, on average, requests are generated for 50% of the ticks that pass.
r, Frequency-of-responses-%	Frequency with which responses to requests for information are issued	If r = 50, then, on average, responses are issued for 50% of the requests that are received.
t_R, Time-units-used-by-response (ticks)	Number of time units needed to provide a response	If t_R = 3, then, it takes 3 ticks of system time to make a response.
Dependent variables (outputs of the simulation experiments)		
number-of-requests	The number of requests generated	
number-of-responses	The number of responses issued	
number-of-assumptions	The number of requests for which no response is made	
time-taken	The amount of time units used for providing responses	
time-taken / Time	The proportion of simulation system time used to provide responses	

4.5. Select Simulation Tool

NetLogo [23] was selected as the simulation tool in this research because it has friendly interactive interface, online user manual, useful examples, and a mature user community forum. In addition, NetLogo uses Java that is relatively straight forward for beginners to learn [4].

4.6. Construct Simulation Model

Fig. 4 provides a NetLogo screenshot of the simulation model. The model includes three sections: simulation input (Region A in Fig. 4), simulation output (Regions B&C), Information Loop 1 (Region D) in a simulation world (gray area). Clearer images of the four regions are provided in Fig. 5-8.

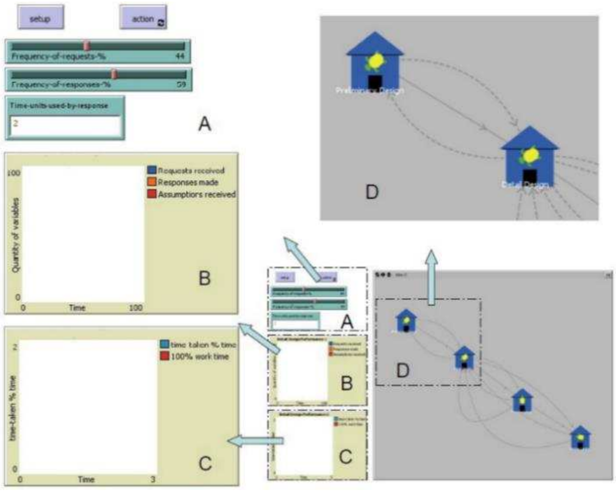


Fig. 4 NetLogo simulation model interface

The model includes four input variables: Time, Frequency-of-requests, Frequency-of-responses and Time-units-used-by-response. These are shown in Fig. 5. With respect to variables defined in Table 2, simulation rules were expressed using six equations.

number-of-requests = Time * Frequency-of-requests (1)

number-of-responses =number-of-requests * Frequency-of-responses (2)
number-of-assumptions = number-of-requests - number-of-responses (3)
number-of-requests = number-of-responses + number-of-assumptions (3')
time-taken = number-of-responses * Time-units-used-by-response (4)
time-taken / Time = number-of-responses * Time-units-used-by-response / Time (5)
time-taken / Time = Frequency-of-requests * Frequency-of-responses * Time-units-used-by-response (6)

The simulation rules, implemented as NetLogo procedures, govern the way in which individual agents behave and interact with each other when the model runs. Simulation results are displayed in the output sections shown in Regions B and C. The overall system performance, with respect to the number of requests generated, responses issued and assumptions made, is illustrated in the simulation output section in Region B. The amount of time used for making such responses, both as the amount of time volume (ticks) and as a proportion to total simulation time, are shown in the simulation output section in Region C.

4.7. Conduct Initial Experiment

An initial experiment used the data values given in Table 3.

Table 3 Initial experiment input data

Variable	Value	Comments
t_S, Time (system ticks)	571	system ticks
i, Frequency-of-requests-%	20	for preliminary design team
r, Frequency-of-responses-%	70	for detail design team
t_R, Time-units-used-by-response (ticks)	2	for detail design team

Inputs for the initial experiment are given in Table 3, the simulation results are shown in Fig. 5, and the simulation world (Information Loop 1) is shown in Fig. 6.

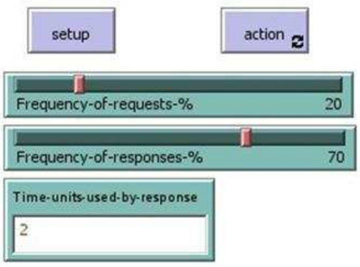


Fig. 5 Simulation input

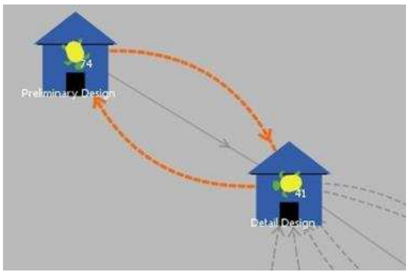


Fig. 6 Information loop 1

Fig. 7 and Fig. 8 show the initial experiment results after the model has run for a time (t_S) of 571 ticks. In Fig. 7, the blue line represents the number of requests generated by the preliminary design team, the orange line the number of responses issued by the detail design team, and the red line the number of assumptions the preliminary design team had to make. At any given point in time, the value of the blue line should equal the sum of the values of the orange and red lines, as expressed in Equation (3'). The greater the value of the Frequency-of-requests, the greater the slope of the blue line. Both green and red lines have the same characteristics.

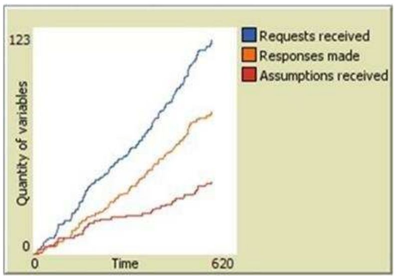


Fig. 7 Initial experiment results-1

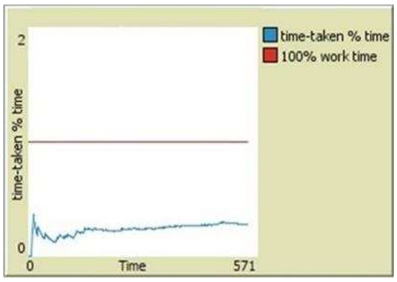


Fig. 8 Initial experiment results-2

4.8. Model Verification

The aim of model verification is to confirm two points: (1) whether the agents' actions and performance, as specified in the simulation rules expressed in the Section 4.6, are realistic; and (2) whether the NetLogo model has sufficient potential to enable further investigation of vicious circles. To this end, a verification experiment was carried out for a longer time of 68500 system ticks (tS), and other independent variables were kept to the same values as for the initial experiment (see Table 3). The results from the verification experiment are displayed in Fig. 9 and Fig. 10.

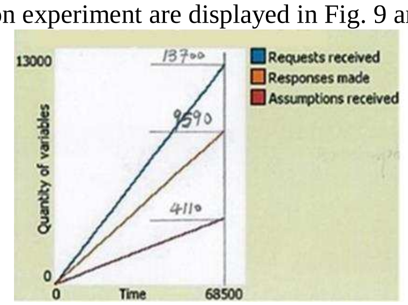


Fig. 9 Verification experiment results-1

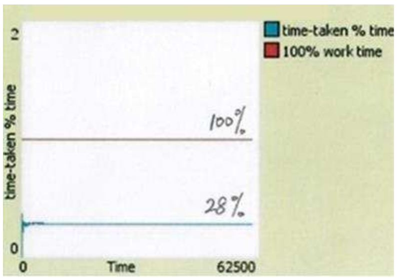


Fig. 10 Verification experiment results-2

System performance data measured in the simulation results are shown as annotations in Fig. 9 and Fig. 10; these values (shown in Table 4) were calculated using the simulation rules (Section 4.6).

Table 4 Model verification result

Dependent Variables	Simulation Result	Values Calculated by Simulation Rules
number-of-requests	13700	Time * Frequency-of-requests = 68500 * 20% = 13700
number-of-responses	9590	number-of-requests * Frequency-of-responses = 13700 * 70% = 9590
number-of-assumptions	4110	number-of-requests - number-of-responses = 13700 – 9590 = 4110
time-taken / Time	28%	Frequency-of-requests * Frequency-of-responses * Time-units-used-by-response = 20% * 70% * 2 = 28%

In Table 4, four dependent variables have the same quantity, either measured in the simulation output graphs or calculated by simulation rules. The agents' behaviors accurately reflect the simulation rules and variables aligned with expectations of the case study owners. For these reasons, we concluded that the agent-based simulation tool NetLogo is an effective means to further investigate new product development process performance and vicious circles.

5. CONCLUSIONS AND FUTURE WORK

An application of agent-based simulation to vicious circles in a new product development process case study is introduced in this paper. The focus of the simulation was on time-related aspects of the process performance. To this end, an eleven-step experimental method procedure was developed to guide model development and experiments conduction. Using the simulation tool NetLogo, the authors developed a simulation model upon which both initial and verification experiments were conducted. Experimental results confirmed that agent-based simulation is an effective and efficient approach to investigate new product development process performance and potentially further explore factors that influence it. Research work reported in this paper relates to Information Loop 1, which covers the preliminary design and detail design teams. Current work is focusing on the development of a full-scale simulation model including the manufacturing and service process steps and teams, in order to build a wider understanding and explore factors that influence the formation of vicious circles. The ultimate goal of the research is to create an artificial intelligence management tool for the operation management in new product introduction systems, in order to organize resources, such as time, budgets and human resources, as effectively and efficiently as possible.

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