Dynamics of Interventions –

Relationship between Scale of Change and Performance

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Abstract

Research, as well as three decades of working with managers across diverse cultures, nationalities, and industries, revealed consistent patterns of counter-productive decision-making in their organisations. Managers appear to exhibit an unmistakable tendency to "over-intervene" in the systems (companies, organisations, communities, etc) they are responsible for. This indicates an inadequate level of understanding and appreciation of the complex dynamics, hence generating unnecessary fluctuations and instability in their organisations. Maani et al. (2004), Sterman (1989), and Sweeny (2000) have studied these phenomena in experimental and simulated environments respectively. Anecdotal evidence, as well as research results, highlight a number of mental models and assumptions commonly held by managers. One of the most apparent assumptions observed is the notion of "the harder you push, the faster it goes", and thus, larger-scaled interventions should result in better performance. This research uses empirical evidence elicited from realistic simulation models of organisations (Microworlds) to shed light upon the relationship between scale of interventions and performance. The results showed that even though large-scaled interventions are effective in the start-up phase of systems, they are generally counter-productive for mature systems operating in steady states. Such results confirm findings from recent research, including the multi-year longitudinal studies of organisations by Collins (2001).

Key Words: Complex decision-making, dynamic behaviour, change management, mental models.

Introduction

Dynamic processes of decision-making are an integral part of life. closed-loop, decision feedback processes are everywhere, from the management of governments and multinational supply chains, right down to the day-to-day lives of individuals (driving a car, cooking a meal, and even while washing their hands). Decision-makers are often required to make a sequence of decisions where each decision affects the circumstances or state in which later decisions are made (Mackinnon & Wearing, 1985). For example, a government makes policy decisions based on the current or future state of the country. Then corresponding interventions are devised and implemented, which lead to changes in the state of the country. Based on those outcomes, further decisions and interventions are carried out, thus forming a continuous dynamic decision-making (DDM) process, as shown in Figure 1.

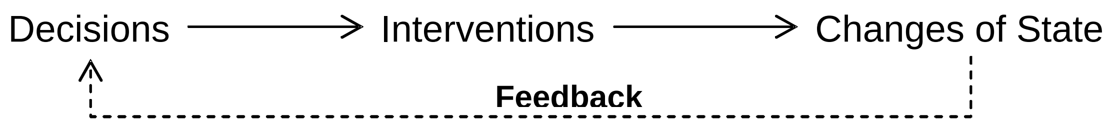


Figure 1 A Dynamic Decision-making Process

Being such a vital part of life, notions of dynamic decision-making embedded in decision-makers' mental models are, however, rather primitive and inadequate. The limitations of mental models in complex systems and DDM, in relation to bounded rationality and misperceptions of feedback were illustrated in studies including Simon (1957, 1979, 1987), Morecroft (1983, 1985), Senge (1991), Sterman (1989), Maani et al. (2004) and Li et al. (2007). One of such common assumptions in DDM is the linear argument that dramatic changes result in dramatic outcomes, or "the harder you push, the faster it goes". When a driver wants to arrive earlier at his destination, his solution is to drive faster – "the faster you drive, the earlier you'll arrive". On a hot day, when a resident wants to cool down her room to make it feel more comfortable, her solution is to turn the fan of the air conditioning system to the max – "the faster the fan, the sooner it cools". Based on such mental models, this linear relationship between the scale of interventions and outcomes are often by decision-makers in complex systems. For example, the faster the developments are, the bigger the economic growth (Meadows et al. 1972), the bigger the orders, the faster the backlog gets filled (Sterman 1989), the higher the production target and the longer hours worked, the more output produced (Keating et al. 1999), the lower the price, the faster the inventory is cleared (Kanter, 2001).

According to such linear assumption, the scale of the "solutions" implemented can often be augmented by the scale of the "problem" perceived by the decision-maker. For example, in the case of a large sales backlog (the "problem"), the manager decides to place bigger orders (the "solution") in order to make up lost sales (Sterman, 1989). The linear assumption of "the harder you push, the faster it goes" reinforces the tendency of managers to carry out large scale interventions when they find themselves in grave peril of survival. Moreover, when coupled with the feedback nature of dynamic decision-making, the large-scaled interventions are further reinforced, whether or not improvements of the systems happen (if the results are positive, let's push harder to make it even better. If we can't see good results, may be we didn't push hard enough, so let's push harder!). Studies of such large-scale approaches mentioned above, however, showed a generally counter-productive pattern of "better-before-worse" performance in the long run, resulting from radical interventions, as illustrated in Figure 2.

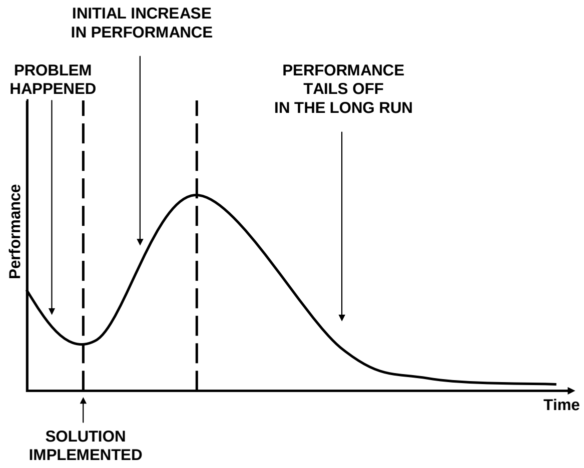


Figure 2 The "better-before-worse" Phenomenon.

Meadows et al. (1972) outlined the continuous exploitation of resources leads to exponential growth and development. In the long-run, however, such pattern of exploitation accumulates negative impacts such as pollution, which in-turn limits growth of the system. Sterman (1989) in the study of the misperception of feedback illustrated how the apparent solution of excessive orders cannot solve the problem of sales backlog. Instead, it can bring down the well-being of a whole supply chain. Keating et al. (1999) showed how the obvious solution of extended work hours, even though can increase throughput immediately, failed to deliver the intended result in a sustainable manner. It seems that larger-scale interventions do result in better performance under certain circumstances. However, the sustainability of such improvements is questionable. Serious questions are therefore raised about the relationship between the scale of interventions and the corresponding performance. First of all, do such relationship exist? If so, how does the scale of interventions impact performance?

Research Objectives

The aim of this study is to investigate the relationship between the scale of interventions in a DDM environment and the corresponding performance. Such relationship is illustrated in Figure 3 in a simple DDM situation.

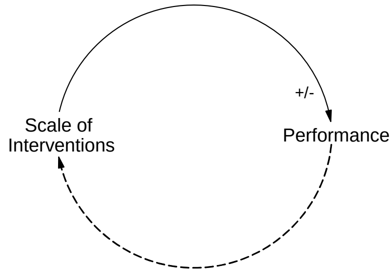


Figure 3 A Simple Dynamic Decision-making Situation

Figure 3 outlines a simple closed-loop DDM process based only upon the Scale of Interventions and the corresponding Performance. The Scale of Interventions is proposed to affect Performance, which will in turn impact the Scale of Interventions that follow. For example, a large scale intervention may result in positive performance. Based on such positive outcome (feedback), the decision-maker decides upon the scale of the next intervention. In a "goal-seeking" scenario, the positive performance may result in a reduction in the scale of the next intervention, thus balancing the dynamics of the system. In a "greedy" scenario, however, the positive performance may result in a further increase in the scale of the next intervention, in attempt to reinforce the positive dynamics.

This study aims to address the following questions:

1. Is there a relationship between the scale of interventions and the corresponding performance? (The solid arc in Figure 3)
2. If so, what is the nature of this relationship?

Note that the impact of performance upon scale of interventions (the feedback represented by the dotted arc in Figure 3) is beyond the scope of this study.

The Research Approach

This study bases the data collection and analysis methodologies on the Individual Differences Approach (Brehmer, 1992), which is commonly used for studies of decision-makers' behavioural issues; for example, Dörner et al. (1983), Brehmer (1992) and Maani & Maharaj (2004). Such approach studies the differences among participants in complex tasks, by observing their actions and performance in a complex problem (usually a simulated environment). Responses from these experiments are then divided into two or more groups, or ranked according to their performance. These groups (or ranked individuals) are then compared with respect to their behaviour during the simulation period, in order to find possible explanations for the differences in performance. The use of the Individual Differences Approach in this study is outlined in Figure 4.

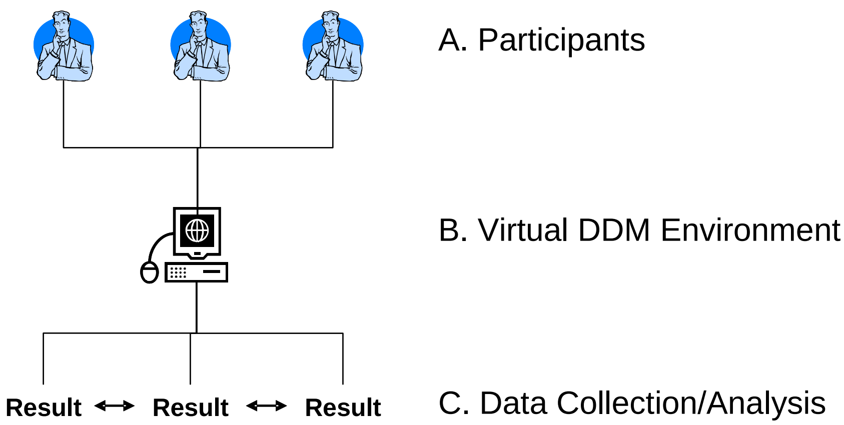


Figure 4 The Individual Differences Approach

The experiments carried out in this study involve individual participants managing the simulated environments to maximise cumulated profits. The average duration of the experiment sessions is two hours, where data regarding the participant's decisions, interventions, and performance are collected. Details of the experiments are discussed below, with references to Figure 4.

A. The Research Participants

224 responses were collected from 129 participants in this study over a 3 year period. Participants, aged between 14-54, include business students and practitioners at various levels, from highschool to postgraduates, and from managers to CEOs.

This group of participants from a diverse background was chosen in order to achieve a reasonable level of generalisability of the findings. Besides their backgrounds, participants also have varying levels of understanding in systems thinking theory and experience in simulation game-play.

B. Virtual DDM Environment

Similar to previous studies based on the Individual Differences Approach, this study observes the behaviour of participants in decision tasks with computer simulation models (Microworlds). Two Microworlds were used for data collection in this study. They were the Service Quality Microworld (SQM) developed by the MIT Systems Dynamics Group, and the Brand Management Microworld (BMW) developed by Strategy Dynamics Ltd. Both Microworlds are well-developed and tested for simulating real-world dynamics. The simulated environments facilitate a DDM scenario for the participants, with a reasonable level of flexibility allowed in decision-making.

Two Microworlds were chosen for this study to ensure a variety of business circumstances being modelled and tested. These models have similar interfaces for game-play, which reduces the issues of adaptiveness and incompatibility for the participants, yet the natures of the businesses being modelled are significantly different. Details about the two Microworlds are discussed below.

The Service Quality Microworld (SQM)

The SQM simulates the operations of a generic service company. The simulation starts at a "steady state" where "output variables" such as incoming orders, orders completed, work backlog, rework, hiring, personnel turnover, time pressure (employee), monthly profit, and monthly expenses are held at a constant rate.

During the experiments, participants can manipulate the values of three "decision variables" (along the course of 60 months) in order to achieve certain goals, such as maximising cumulative profits, minimising rework, or maximising production. The decision variables are monthly "Net Hiring", "Production Goal", and "Quality Goal". By intervening with any/all of these three input variables, various output variables will be affected through complex dynamics. The simulator generates the behaviour over time of a number of KPIs as graphs and reports.

Brand Management Microworld (BMW)

The BMW simulates a business organization at its start-up, introducing a new brand of drinks in an established market. The participants are given a “launch budget” (£20 million by default) at the beginning which they may utilise throughout the course of the product’s launch (12 years). Output variables include consumer awareness of the brand, sales, stores stocking the brand, advertising campaign reach, monthly profits. Since the model represents an organisation at start-up, unlike SQM, the model does not begin at a steady state.

During the simulation, participants can manipulate the values of three “decision variables” (along the course of 12 years, ie. 144 months) in order to achieve certain goals, such as maximising profits, maximising sales, maximising the number of stores stocking the brand. These decision variables are “Wholesale Price”, “Advertising per Month”, and “Size of Sales Force”. By changing any/all of these three input variables, various output variables will be affected through the complex dynamics. A large selection of KPIs is also available as graphs, tables, and reports.

C. Data Collection/Analysis

In the experiment sessions, the participants were required to manage the simulated environment in order to maximise cumulated profits. A total of 224 responses were collected (118 from SQM sessions and 106 from BMW sessions). Participants worked individually during the sessions with no breaks so no information exchange and “interaction effects” were expected to occur. Detailed information of the participants’ decisions and interventions carried out, and the resulting performance in the simulation model were collected. An extract of the data collected from participant 06 is presented in table 1. The full record of interventions is presented in Appendix A.

Table 1 Interventions of Participant 06SQM Recorded

Month	Prod Goal
0	31250
1	30000
2	30000
3	30000
4	28000
5	28000
6	28000
7	29000
8	29000
9	29000
10	29000
11	29000
12	30000
13	30000
14	31000
15	31000

As shown in table 1, participant 06 intervened by lowering the initial production goal from 31250 units/month to 30000 units/month in the first month, then a further reduction happened in month 4, from 30000 units/month to 28000 units/month, and so on. The participant’s interventions resulted in a loss of $7751501 at the end of the 60 month simulated period. The performance (cumulated profit at the end of the simulation) of each individual participant in the same simulator group (SQM or BMW) were then ranked, with the scale of their corresponding interventions compared to identify any relationships. Details about data analysis variables and the analysis process are discussed in the following section.

Data Analysis

The objective of data analysis in this study is to identify the relationship between the scale of interventions and the corresponding cumulated profits. This is carried out by using correlation tests. Due to the unique circumstances in the two Microworlds, data analysis is carried out separately according to the Microworld used in the experiment.

Defining Interventions in the two Microworlds

Participants were asked, during the experiment sessions, to maximise profits by making decisions and carrying out interventions, using the decision variables offered in the Microworlds. These decision variables are:

Table 2 Decision Variables in Microworlds

SQM:	**Initial Value**
Net Hiring (Monthly)	13
Production Goal (Monthly)	31250
Quality Goal (1 is the normal quality level. The bigger the number, the higher the quality level expected)	1
BMW:	**Initial Value**
Wholesale Price	£8.50
Advertising Spending (Monthly)	£200,000
Size of Sales Force	20

Interventions in the Microworlds are defined as changes in the values of these decision variables. By changing these values, the state of the system modelled will be modified, thus creating an impact upon the goal, cumulated profits. Examples of such impacts are listed below. Note that this information was not explicitly given to participants before game-play.

Table 3 Primary Dynamics in Microworlds

SQM:	**Direct Impact**
Increase in Net Hiring	Increase in Total Personnel Increase in Total Spending
Increase in Production Goal	Increase in Production Increase in Time Pressure
Increase in Quality Goal	Increase in Quality Increase in Time Pressure
BMW:	**Direct Impact**
Reduction in Wholesale Price	Reduction in Retail Price Reduction in Profit Contribution
Increase in Advertising Spending	Increase in New Aware Consumers Reduction in Profit Contribution
Increase in Size of Sales Force	Increase in New Stores Reduction in Lost Stores Reduction in Profit Contributions

Changes in the values of decision variables constitute an intervention, which can happen at different "scales" or "magnitude". For example, participant A may decide to increase Net Hiring (SQM) from the initial value of 13 to 15 per month, while participant B may increase the value to 18. In this case, participant B is making a bigger-scaled intervention than participant A. Note that the scales of interventions are considered on an absolute basis. That is, a change of Net Hiring from 13 to 18 (+5) is of the same magnitude as a change from 13 to 8 (-5).

This simple definition of scale works well when participants are intervening with only one decision variable. When more than one decision variables are involved, the different values of the variables have to be normalised. For example, a +5 intervention in Net Hiring (from 13 to 18) is different from a +5 intervention in Production Goal (from 31250 to 31255) or a +5 intervention in Quality Goal (from 1 to 6) (That's six-times the initial quality level!!). The normalisation of decision variables converts all their values into an index with a base of 1 at their initial value, as presented in Table 4.

Table 4 Initial Indices of Decision Variables

SQM:	**Initial Value**	**Index**
Net Hiring	13	1
Production Goal	31250	1
Quality Goal	1	1
BMW:	**Initial Value**	**Index**
Wholesale Price	£8.50	1
Advertising Spending	£200,000	1
Size of Sales Force	20	1

Any changes made in the values of these decision variables will result in a change in the values of the corresponding indices. This is shown in Table 5 based on the extract of response 06.

Table 5 Normalised Interventions

Month	**Prod Goal (V)**	**Index (I)**	**Indexed Change (C)**
0	31250	1	
1	30000	0.96	0.04
2	30000	0.96	
3	30000	0.96	
4	28000	0.896	0.064
5	28000	0.896	
6	28000	0.896	
7	29000	0.928	0.032
8	29000	0.928	
9	29000	0.928	
10	29000	0.928	
11	29000	0.928	
12	30000	0.96	0.032
13	30000	0.96	
14	31000	0.992	0.032
15	31000	0.992	

The monthly values (V_t) entered by the participants throughout the simulation period were converted into indices (I_t). These are shown in the above table in the columns headed "Prod Goal" and "Index" respectively. The index (with a base value of 1) for each month is based upon the decision variable's initial value (V_0) using the following formula:

$$I_t = \frac{V_t}{V_0} \times 1$$

In month 1, a change in Production Goal was made by the participant from 31250 units/month to 30000 units/month. These values were indexed as 1 and 0.96 respectively. A change of 0.04 is recorded (in the column headed "Indexed Change". This value of change (Ct) is the absolute value of the difference between the current period (t) and the previous period's (t-1) index, calculated using the formula:

$$C_t = \left| I_t - I_{t-1} \right|$$

Normalisation of data with indices allows a unified measure of the scale of interventions among the three decision variables in both Microworlds. The overall scale of the participant's interventions is defined as the average magnitude of changes applied (MAG) to all decision variables involved. This is represented by the following formula (n = number of interventions during the simulated period):

$$MAG = \frac{\sum C_t}{n}$$

This "average magnitude" variable from each response in the same Microworld group is correlated against the "performance" variable represented by the cumulated profits at the end of the simulation. The analysis process is described in the next section.

Data Analysis

The correlation between the MAG variable (average magnitude of changes) and the performance is tested for both Microworlds, with the following null hypothesis[1].

H_0: The average magnitude of interventions does not have an effect on cumulative profits.

The outputs of the correlation tests for the two Microworlds are summarised in Tables 6 and 7[2]:

[1] Note that due to the nature of the Brand Management Microworld, most participants have used up their start up budget of £20m before the completion of the simulated period (144 months), and therefore, have resulted in a premature termination of the simulation session. In order to maintain consistency across all responses, the simulation output used for analysis is restricted to 63 months (unsuccessful runs are usually terminated after this period). All proceedings after that period were truncated. That means, the magnitude variable captures the average change between month 0-63, and the task performance is represented by the cumulative profits figure in month 63.

[2] The input data of the correlation models conforms to the statistical assumptions of Normality, Linearity, and Homoscedacity.

Table 6 Output of the SQM Correlation Model

Service Quality Microworld

		MAG	Cumulative Profits
MAG	Pearson Correlation	1	-.241(**)
	Sig. (2-tailed)		.008
	N	118	118
Cumulative Profits	Pearson Correlation	-.241(**)	1
	Sig. (2-tailed)	.008	
	N	118	118

** Correlation is significant at the 0.01 level (2-tailed).

Table 7 Output of the BMW Correlation Model

Brand Management Microworld

		MAG	Cumulated Profits
MAG	Pearson Correlation	1	.402(**)
	Sig. (2-tailed)		.000
	N	106	106
Cumulated Profits	Pearson Correlation	.402(**)	1
	Sig. (2-tailed)	.000	
	N	106	106

** Correlation is significant at the 0.01 level (2-tailed).

As seen in the tables, the correlation coefficients from both models show significant evidence against H_0 (SQM: -0.241, sig 0.008, BMW: 0.402, sig 0.000), which both imply a relationship between the average magnitude of interventions and the performance. Based on such results, conclusions can be drawn upon the research questions as follows:

1. Is there a relationship between the scale of interventions and the corresponding performance?
2. If so, what is the nature of this relationship?

The correlation output (Tables 6 and 7) showed significant correlation between the average magnitude of interventions and the cumulated profits of individual participants for both Microworlds (SQM: sig. 0.008, BMW: sig. 0.000). Both values showed a significant correlation between the two variables, which implies that the scale of interventions is related to performance in both Microworlds, thus shedding light upon the first research question.

In order to answer the second question, whether the relationship is positive or negative, it is necessary to note also the signs of the coefficients for both models. In Tables 6 and 7, it is seen that the correlation coefficients are -0.241 (SQM) and 0.402 (BMW). These values suggest a negative relationship under the SQM environment, and a positive relationship under the BMW environment. These implications are shown in the simple DDM diagrams in Figure 5.

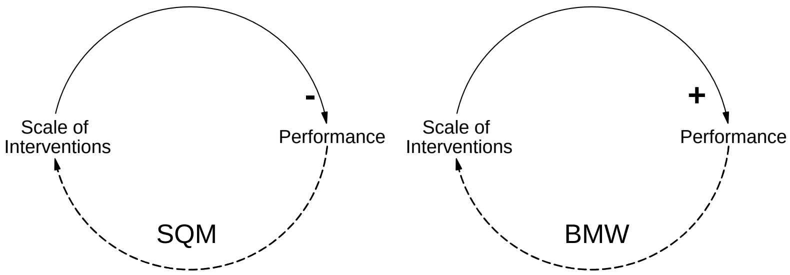


Figure 5 Findings Illustrated by Simple DDM Dynamics

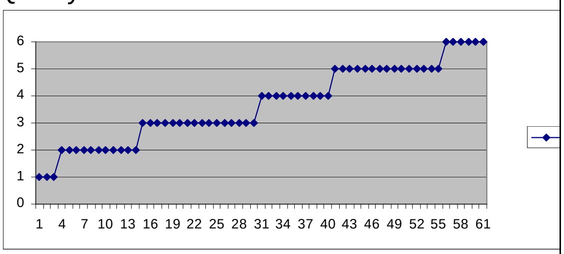
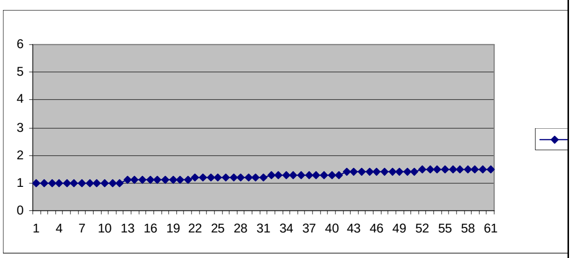
These results imply that under the SQM environment, larger-scale interventions lead to worse performance in general; whereas in the BMW environment, larger-scale interventions tend to result in better performance. This leads to serious concern about other implications from the models that may impact such a relationship, and thus, a careful study of the business environments in both models needs to be carried out.

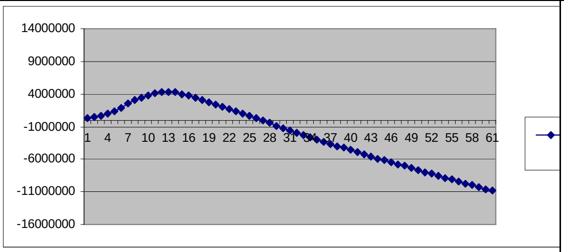
The two Microworlds simulate significantly different business environments. The SQM model simulates a well established, profit-making business running in a steady state, whereas the BMW model simulates a business at start-up, with zero consumer awareness. The results from this study supported the argument that performance is impacted by the scale of interventions in both of these models, but in different "directions". For instance, at a "start-up" state as in BMW, larger-scaled interventions tend to give better results, whereas at a "steady-state" as in SQM, smaller-scaled interventions tend to perform better.

In order to further substantiate this argument, a closer observation of the experiment responses is carried out. This is achieved by comparing and contrasting responses from both Microworlds, with interventions of similar approaches at different magnitudes. The simulated behaviour over time of different performance indicators are investigated with respect to the findings of this study.

Comparison of SQM Responses (09 & 37)

Two sample responses (09 and 37) from the SQM experiment are chosen for comparison. Both participants chose to manage the Microworld using "Quality Goal", in order to maximise profits. As seen in Figure 6, both participants took a similar strategy of increasing Quality Goal approximately once every year, but at different rates. Participant 09 increased quality goal by 1 every time an intervention happens, while participant 37 increased quality goal by 0.1 each time.

SQM 09	SQM 37
Quality Goal	
	
Cumulated Profits	



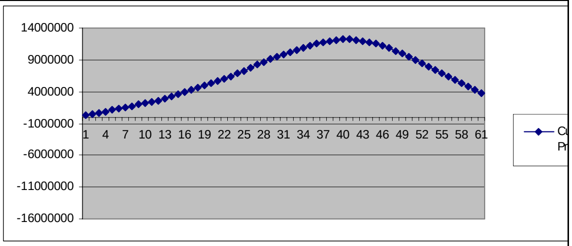
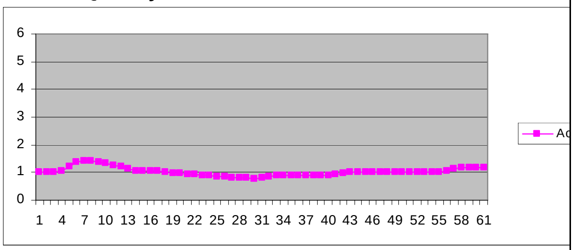


Figure 6

Participant 09's scale of interventions is much larger than participant 37's. The performance of participant 09 showed a cumulative loss of $11m (approx.), whereas participant 37 achieved a cumulated profit of $4m (approx.). It is apparent that the response with the larger-scaled interventions in this case performed much worse than the other. A closer observation of the dynamics can further explain the phenomenon.

SQM 09	SQM 37
Actual Quality	



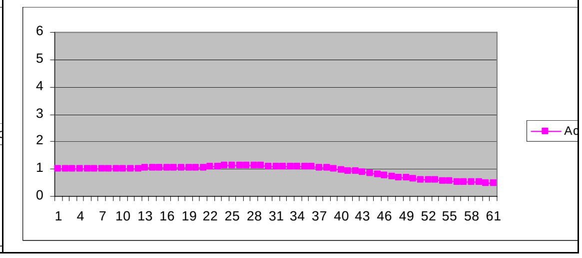
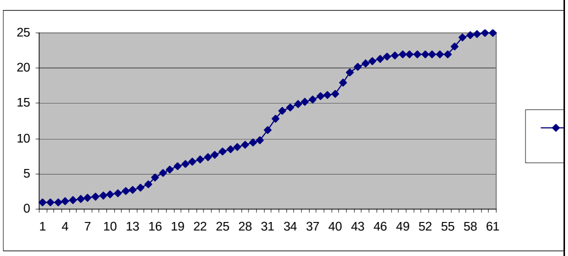
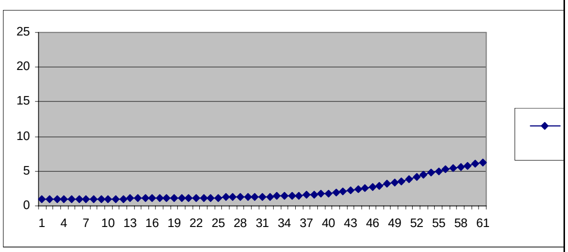


Figure 7

As seen in Figure 7, the actual quality levels achieved in both responses over time are similar. Even though participant 09 "pushed" the quality goal much harder than participant 37, the actual quality level over time did not show a proportional improvement. This can be explained by the time pressure of workers over time and the resulting personnel turnover, as shown in Figure 8 below.

SQM 09	SQM 37
Time Pressure	





Personnel Turnover & Total Personnel	

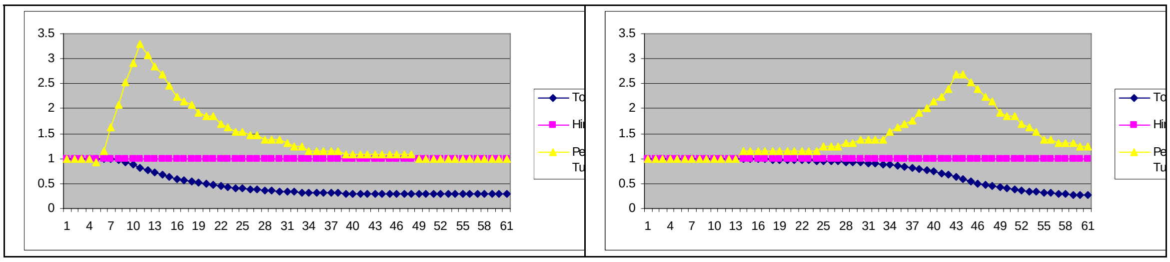


Figure 8

Participant 09's large-scaled increases in Quality Goal resulted in a rapid build up of time pressure for workers. As a result, workers became stressed and the personnel turnover rate increased. With fewer people working (the hiring rate was held constant), the time pressure reinforces itself to a much higher level. On the other hand, participant 37's increases in Quality Goal was much smaller, thus maintained a stable time pressure level over time. However, the continual increase in Quality Goal still resulted in high personnel turnover rates, which happened at a much later time.

As a result of the build-up in time pressure and the lowered capacity in response 09, the actual production level (orders completed) went down, and therefore, a build-up of work backlog occurred, which further reinforced time pressure (Figure 9). Even though the quality level was maintained with the extraordinarily high quality goal, the production performance is poor, which contributed to the huge cumulative loss towards the end. Response 37, on the other hand, had a decline of orders completed at a much slower rate and at a much later time, and therefore, a much slower build-up of work backlog. The high quality goal level imposed by participant 37 towards the end ultimately resulted in a decline in cumulative profits, but at a much slower rate than what was seen in response 09.

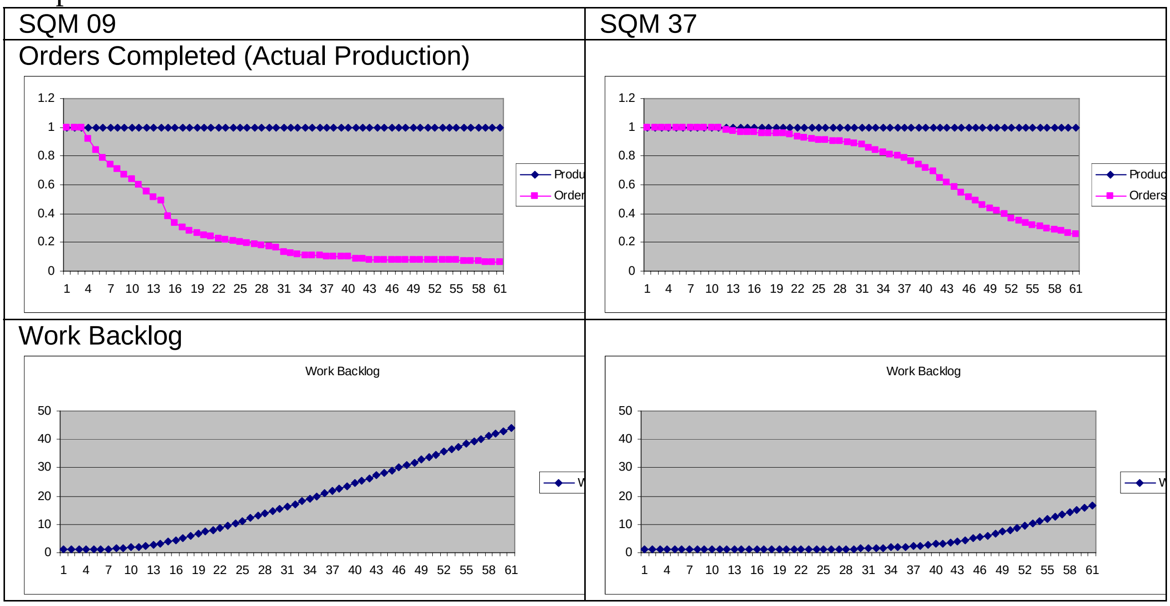


Figure 9

The above comparison showed dynamics consistent with this studies findings, by illustrating how larger-scaled interventions in a system at "steady-state" result in bigger "ripples" or feedback that can ultimately be counter-productive. As seen in Figure 8, even though the initial large-scaled increase in Quality Goal did result in an increase in profits, a rapid build-up in time pressure and drainage in capacity was also happening. Very soon, the negative impacts took over, and the expected improvements could no longer be achieved.

<u>Comparison of BMW Responses (06 & 49)</u>
Two sample responses (06 and 49) from the BMW experiment are chosen for comparison. Both participants chose to manage the Microworld using "Advertising Spending", in order to maximise profits. As seen in Figure 10, both participants took a similar strategy of increasing Advertising Spending, while participant 06's interventions showed a more consistent pattern of change with bigger increments (the average scales of interventions of participants 06 and 49 are 1.21 and 0.82 respectively).

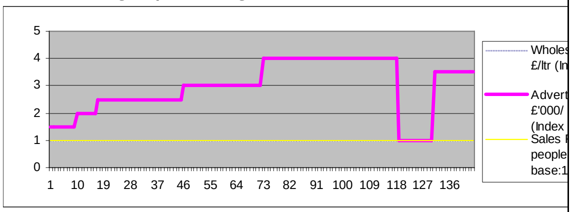
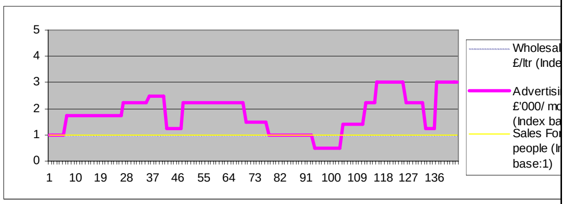
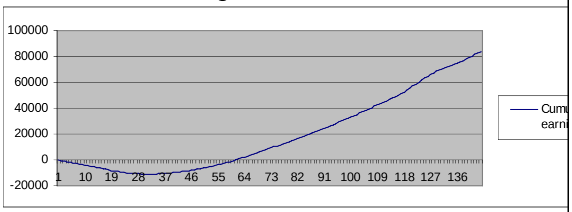
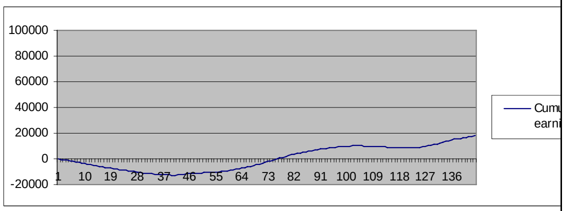
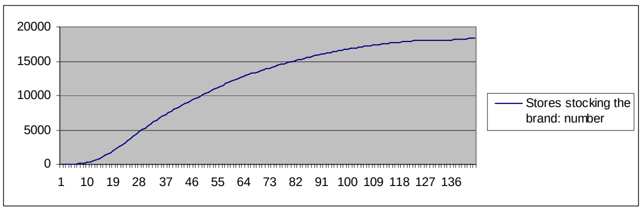
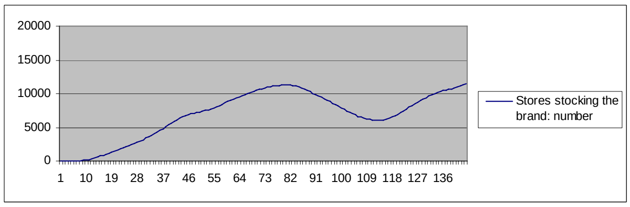
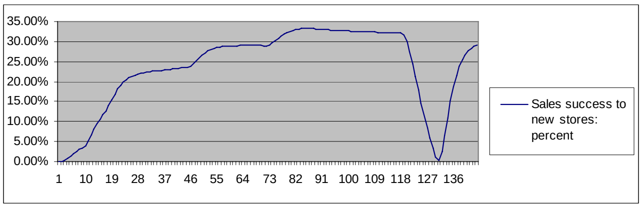
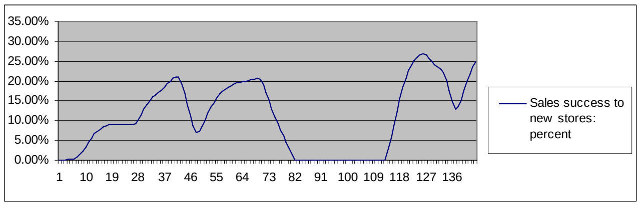
<table>
<tr><td>BMW 06</td><td>BMW 49</td></tr>
<tr><td>Advertising Spending
</td><td></td></tr>
<tr><td>Cumulative Earnings
</td><td></td></tr>
</table>

Figure 10

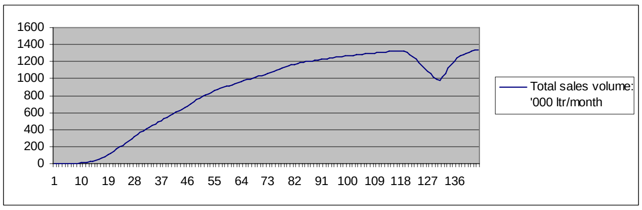
Participant 06, with larger-scaled interventions, achieved a cumulative profit of $84m (approx.), while participant 49 achieved a cumulative profit of $18m. In both cases, the behaviour over time of cumulative profits showed a pattern of "worse before better", where the initial investment in advertisement resulted in losses. Breakeven did not happen until the fifth year (for participant 06) and the sixth year (for participant 49). The comments from the participants showed that participant 49 was in doubt about the initial losses, and therefore showed an inconsistent intervention pattern in Advertising Spending. The resulting outcomes besides cumulated profits is shown in Figure 11 below.

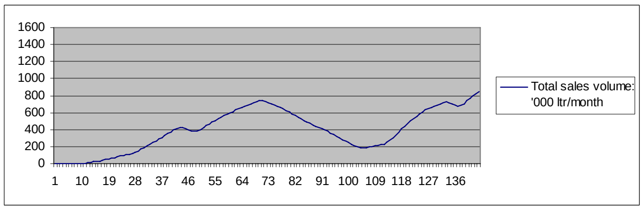
<table>
<tr><td>BMW 06</td><td>BMW 49</td></tr>
<tr><td>Stocking Stores
</td><td></td></tr>
<tr><td>Sales Success to New Stores</td><td></td></tr>
</table>



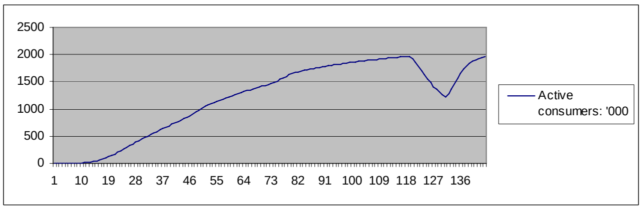


Total Sales Volume





Active Consumers



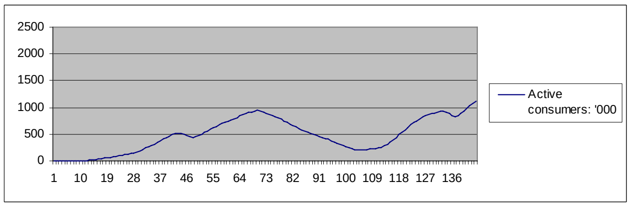


Figure 11

The resulting effects under participant 06's management showed a much more consistent pattern of improvement than participant 49's, in areas including the number of stores stocking the brand, sale success to new stores, sales volume, and attracting new customers. All such improvements contribute to the improvements in profits.

As seen in these two cases, pushing harder did make it go faster because under BMW's scenario, which a the start-up phase of the simulated business, the positive impact of increased Advertising Spending far outweighs its negative impacts. That is, the business and publicity gained is worth the money invested, and therefore, as seen in Figure 10, the initial losses were recovered by the increased sales. It is, however, safe to assume that, as the drinks market matures (there are 5,000 potential customers in the market), diminishing returns from Advertising Spending kicks in and therefore, the sales and publicity gained will no longer be worth the money invested, and thus, negative effects from the investment will take over, thus supporting the findings of this study that even though large-scaled interventions are effective at start-up of systems, they may become counter-productive once the systems mature. Such ideas are further discussed in the following section.

Discussion

The findings of this study portrayed a significant relationship between the scale of interventions and performance in complex systems. A positive relationship is seen in complex systems at their start-up phases, while for mature systems at steady-states, a negative relationship is seen. Such findings shed light upon effective management of complex systems in terms of scales of interventions, and the limited mental model of "the harder you push, the faster it goes".

Dierickx et al. (1989) illustrated similar phenomena using the concept of asset stock accumulation, which argues that, in the initial phase of a stock's accumulation, significant inflows are often beneficial, due to the higher rate of success towards achieving the goal of stock fulfilment. However, as the accumulated stock approaches its limit (for example, capacity, market saturation), finer adjustments of inflows are preferred, due to the potential risk of stock overflow. Such occurrences are also noted in the study of Boom & Bust (Paich et al., 1993), and The Limits to Growth (Meadows et al., 1972), that large-scale interventions at the start-up phase of systems could be effective in achieving goals such as growth and development. However, as the system approaches its limits, large-scale interventions (as yesterday's solution) became detrimental to the overall well-being of systems.

Observations of such dynamics was also suggested in the Flywheel/Doom Loop analogy by Collins (2001). When a heavy flywheel is in an idle state, a tremendous amount of effort in a consistent manner is required for it to start turning. This state of the flywheel corresponds to the environment which BMW simulates, a new business at its start-up. Our results show that at this stage, larger-scale interventions are favoured. However, one must bear in mind that the direction of the interventions must be correct, and the consistency of the interventions must be maintained, as suggested by Collins, in order to achieve positive results.

Once the flywheel reaches the breakthrough state (when the momentum of the spinning flywheel reinforces its own motion), its rotations became self-propelling, and therefore, minimal additional effort is required to maintain its motion. Note that at this stage, any form of major effort exerted onto the flywheel in an inconsistent manner (such as, in a different direction) will result in serious break down in the form of damages to the flywheel and injury to the operator. This state resembles the simulated environment of the SQM, where the business organisation is running in a steady state. In this state, only minimal interventions are required in order to maintain its well-being. Any form of large-scale interventions may interrupt the company's proper function, and therefore puts the company at risk. Our results showed also, that smaller-scale interventions are favoured in this model.

While the findings of this study shed strong light on the impact of different-scaled interventions towards performance in DDM environments, such findings are not to be perceived as a part of a "framework" for optimal decision-making strategies. That is, to interpret the findings from this research as saying that making bigger interventions at the start-up phase of businesses will guarantee outstanding performance is perhaps premature. Dynamics of organisations are idiosyncratic and, therefore, effective interventions for different organisations would be organisation specific, and may not be totally generalisable. The findings of this study are instead lending empirical support for the notion that the linear mental model of "the harder you push, the faster it goes" is not a one-size-fits-all solution, yet it is not entirely false. Even though such mentality is seen as counter-productive in previous studies (for example, Meadows 1972, Sterman 1989, Keating et al. 1999, Kanter, 2001), this study shows that larger-scale interventions do result in positive performance under certain circumstances (for example, during the start-up phase of systems). The key to support sustainable long-term performance is therefore to better understand the state of the system, and thus, the timing of different scaled interventions. For instance, when a system is starting up (for example, the opening of a new business venture), larger-scaled interventions may be favourable to kick-start the dynamics, as inferred by the findings of this study. The critical factor in the DDM process, however, is to understand when the transition from “start-up” to “mature” happens. In other words, when would large-scale interventions become counter-productive? Does it happen at a specific point in time or is it a gradual transformation process? How can it be identified? Future studies along these lines may be carried out with experiments involving adjustments and alterations to the structures of Microworlds, in order to simulate different scenarios under the same model, so that more can be learnt about such transitions, and thus, adds to the understanding about how different scaled interventions impact performance in DDM tasks.

References

Brehmer, B. (1992). "Dynamic Decision Making: Human Control of Complex Systems." Acta Psychologica **81**: 211-241.

Collins (2001). Good to Great. N.Y., Harper Business.

Dierickx, I. and K. Cool (1989). "Asset Stock Accumulation and Sustainability of Competitive Advantage." Management Science **35**(12).

Dörner, D., R. Kreuzig, et al. (1983). Lohhausen: Vom Umgang mit Unbestimmtheit und Komplexitat. Bern, Huber.

Kanter, R. (2003). "Leadership and the Psychology of Turnarounds." Harvard Business Review **81**(6): 58.

Keating, E., R. Oliva, et al. (1999). "Overcoming the Improvement Paradox." European Management Journal **17**(2): 120-134.

Li, A. and K. Maani (2007). Pitfalls in Decision-Making in Complex Systems. International System Dynamics Conference, Boston.

Maani, K. and V. Maharaj (2004). "Links Between Systems Thinking and Complex Decision Making." System Dynamics Review **20**(1): 21-48.

Mackinnon, A. and A. Wearing (1985). "Systems Analysis and Dynamic Decision Making." Acta Psychologica **58**: 159-172.

Meadows, D. (1972). The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind. London, Potomac Associates.

Meadows, D. (1992). Beyond the Limits - Global Collapse or a Sustainable Future. England, Earthscan.

Morecroft, J. (1983). "System Dynamics: Portraying Bounded Rationality." OMEGA **11**(2): 131-142.

Morecroft, J. (1985). "Rationality in the Analysis of Behavioral Simulation Models." Management Science **31**(7): 900-916.

Paich, M. and J. Sterman (1993). "Boom, Bust, and Failures to Learn in Experimental Markets." Management Science **39**(12).

Senge, P. (1991). The Fifth Discipline - The Art & Practice of The Learning Organization. Adelaide, Random House.

Simon, H. (1957). Models of Man - Social and Rational. New York, John Wiley & Sons, Inc.

Simon, H. (1979). "Rational Decision Making in Business Organizations." The American Economic Review **69**(4): 493.

Simon, H. (1987). "Decision Making and Problem Solving." Interfaces **17**(5): 11-31.

Sterman, J. (1989). "Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment." Management Science **35**(3): 321-339.

Sweeney, L. and J. Sterman (2000). "Bathtub Dynamics: Initial Results of a Systems Thinking Inventory." System Dynamics Review **16**(4): 249-286.

Appendix A

Record of interventions by participant 06 in SQM experiment.

Month	Prod Goal	Month	Prod Goal	Month	Prod Goal	Month	Prod Goal
0	31250						
1	30000	**16**	32000	**31**	35530	**46**	16000
2	30000	**17**	33000	**32**	33530	**47**	15000
3	30000	**18**	34000	**33**	32530	**48**	15000
4	28000	**19**	33000	**34**	42530	**49**	14000
5	28000	**20**	23000	**35**	25530	**50**	14800
6	28000	**21**	23000	**36**	20530	**51**	15800
7	29000	**22**	23000	**37**	20000	**52**	16000
8	29000	**23**	23000	**38**	20000	**53**	16000
9	29000	**24**	24000	**39**	19000	**54**	15000
10	29000	**25**	24000	**40**	17000	**55**	16500
11	29000	**26**	24000	**41**	17000	**56**	16800
12	30000	**27**	45530	**42**	18000	**57**	16500
13	30000	**28**	35530	**43**	17000	**58**	16600
14	31000	**29**	35530	**44**	15000	**59**	16200
15	31000	**30**	35530	**45**	16000	**60**	16000
C. Profits	-7751501						