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Measuring learning under uncertainty

Svein Erlend Martinussen

Norwegian Defence Research Establishment (FFI)

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Halvor Ajer	Project Manager
Johnny Bardal	Director

English summary

This report describes a method for measuring learning outcome in cases where no learning objective is defined. This is typically a challenge for open ended, interactive experiments with prototype systems. A participant’s tendency over time to provide increasingly similar pre- and post-experiment evaluations of system utility, is interpreted as learning. The method makes it possible to monitor learning for complex systems, without prior knowledge about concepts of operation and procedures. The method has been applied to data from an interactive simulation experiment. Analysis of variance show significant learning during the experiment. A model is proposed that describe how simulation time, experience, and closeness to the system during the experiment influence learning.

Sammendrag

Denne rapporten beskriver en metode for å måle læring i tilfeller der læringsmål ikke er definert. Dette er typisk en utfordring for frie interaktive eksperimenter med prototypsystemer. En deltagers tendens, over tid, til å levere stadig mer like pre- og post-eksperiment evalueringer av nytte av systemet tolkes som læring. Metoden gjør det mulig å monitorere læring for komplekse systemer, uten forhåndskunnskaper om operasjonskonsept og prosedyrer. Metoden er blitt brukt på data fra et interaktivt simuleringseksperiment. Variansanalyse viser signifikant læring i løpet av eksperimentet. Det foreslås en modell som beskriver hvordan simuleringstid, erfaring, og nærhet til systemet under eksperimentet påvirker læring.

Contents

1 Introduction

After having worked with virtual prototypes for several years, we have, on a number of occasions, encountered the problem of identifying when a learning process levels off. The problem is not easily addressed since preconceived answers about how to use new technology may be wrong or not known at all. To mitigate this uncertainty we have resorted to measuring the change in the perceived utility of the system as testing proceeds. The measuring has been done by means of questionnaires containing Likert scales that describe the utility of the system [1], and the analysis has been done by means of item-response theory [2].

The ”apprentice’s toolbox” would be a good metaphor for conveying the content of our model for measuring learning. An apprentice of any trade would initially in the learning process have a hard time predicting which tools to use for a certain assignment. If asked before carrying out her assignment her preferences for selection of tools would differ from the preferences for selection of tools after the assignment has been carried out. This difference in the assessment of utility of tools, before and after the asignment, would decrease as she gains experience in her trade.

In a traditional craft, with well established practices, a lot of the learning would take place during the instruction the apprentice is likely to get before the assignment. When experimenting with virtual prototypes though, few instructions may be available before the assignment. The toolbox and the assignment may be completely new. Thus, learning would take place during a process of trial and error as the apprentice tries to solve the assignment. What is learnt would depend on the assigned task, what role the apprentice is given and what the general conditions are. A learning process would encompass sharp changes to perceived utility, due to sudden insights about the system, in between gradual changes due to gathering of experience. Given some time, the process should converge towards the apprentice true assessment of the utility of the system.

We propose the following definition of learning, for use in cases where no knowledge exist before the commencement of the experiment:

> Learning under uncertainty can be measured by monitoring over time the amount of change for pre- and post-experiment evaluations to item responses that belong to a Likert scale that describes the utility of the system.

The definition has been shown to produce indications of learning for interactive simulation experiments with 8 and 16 participants doing experiments for one week, for systems at an organizational level equivalent to platoon size in military terms. As will be shown in the next chapter, the definition provides a measure that identifies significant learning for a multiple week experiment on a brigade size system of systems (structure).

First of all we shall outline our model for measuring learning and contrast it with models from traditional item response theory. Secondly, we will have a look at the data obtained for the experiments, and the conclusions that may be drawn from the analysis.

2 Measuring change in percieved utility

The assessment of preferences for system properties differs from the assessment of performance or psychological traits, which are usually measured by item response theory [2]. For assessment of performance and traits, accepted measures exist, and the problem is limited to identifying variables that provide good correlation and discrimination. For measurement of preferences accepted measures do exist, but what constitutes a good combination of scores may not be known. Preferences are measured by pitching system traits against each other, and may wary from person to person, for instance due to differences in perception of risk. By measuring the amount of changes to scores for variables that describe the percieved functionality or the composition of the system, we avoid the problem of deciding beforehand what a good score is. The amount of changes to preferential scores is expected to be reduced as the understanding of the system increases. We expect this process to converge towards a true generic appreciation of the utility of the system.

According to true score theory [2], a score X is comprised of a true value T_X and an error E_X. The pretest score is then given by:

$$X = T_X + E_X \tag{2.1}$$

You may have experienced the need to change your mind about the usefulness of a piece of equipment or a system, for instance after having brought a pair trainers for a mountain hike. The same tendency to reassess the utility of a system may be observed when playing with simulated systems. The main reason for this kind of reassessment of utility is lack of experience. We shall assume that the participant's posttest preference represents a perfect understanding of the scenario and her own role in it. Misconceptions about the utility of a system are therefore only represented by the pretest-error contribution. We make no attempt to describe a model for the generic utility of the system. The generic utility would require an error contribution to the posttest score that include terms due to lack of experience. Our model is therefore only valid for the scenario being played. The measure provided is expected to converge towards a generic value for the utility of the system for each new scenario and repetition in the experiment.

For assessment of preferences after an interactive simulation experiment we assume that the participant knows her preferences (with regard to the specific scenario and the role having been played) properly. We shall therefore assume that no uncertainty or error exists for the post-test measurement, and that the posttest score (Y) is represented exactly by the true score (T_Y).

$$Y = T_Y \tag{2.2}$$

The difference between the pre and the posttest scores is:

$$D = Y - X \tag{2.3}$$

Measuring change by carrying out pre- and post-tests usually reduces the ability to draw conclusions [3]. We shall show that, with the assumption of perfect representation of preferences after an interactive simulation experiment, the ability to conclude using differences will increase. This is not a requirement for using the method, since the measurement of change of preferences apparently is the only feasible measure, but it is a result of the fact that we measure preferences.

With these assumptions, the variances for the true and measured differences are:

$$\sigma_{TD}^2 = \sigma_{TY-TX}^2 = \sigma_{TY}^2 + \sigma_{TX}^2 - 2\rho_{TYTX} = \sigma_Y^2 + \sigma_X^2\rho_{XX'} - 2\sigma_Y\sigma_X\rho_{YX} \tag{2.4}$$

$$\sigma_D^2 = \sigma_Y^2 + \sigma_X^2 - 2\sigma_Y\sigma_X\rho_{YX} \tag{2.5}$$

So the reliability (ρ) of the difference is:

$$\rho_{DD'} = \frac{\sigma_{TD}^2}{\sigma_D^2} = \frac{\sigma_Y^2 + \sigma_X^2\rho_{XX'} - 2\sigma_Y\sigma_X\rho_{YX}}{\sigma_Y^2 + \sigma_X^2 - 2\sigma_Y\sigma_X\rho_{YX}} \tag{2.6}$$

For item responses based on no relevant previous experience we may assume that the correlation between the pre and post responses is zero ($\rho_{XY} = 0$). We may also assume that the reliability of the pretest score is zero ($\rho_{XX'} = 0$). This leads to the following relation:

$$\rho_{DD'} = \frac{\sigma_Y^2}{\sigma_Y^2 + \sigma_X^2} \tag{2.7}$$

For responses based on perfect understanding of the system, and of own preferences, it may be assumed that the correlation between pre and post tests is perfect. It may also be assumed that the reliability of the pretest scores is identical to one. This leads to the obvious conclusion that the reliability of the measured differences is perfect. So for conditions ranging from a perfect understanding of own preferences to a limited understanding of own preferences for the last played scenario, the reliability of the difference score is always positive.

A closer investigation of the quality of the score difference, starting from equation 2.6 and assuming $\sigma_X = \sigma_Y$ reveals the following relation:

$$\rho_{DD'} = \frac{\frac{1}{2}(1 + \rho_{XX'}) - \rho_{YX}}{1 - \rho_{YX}} \tag{2.8}$$

Analyzing this expression we can see that the reliability of the difference score is positive when:

$$\rho_{XX'} > 2\rho_{YX} - 1 \tag{2.9}$$

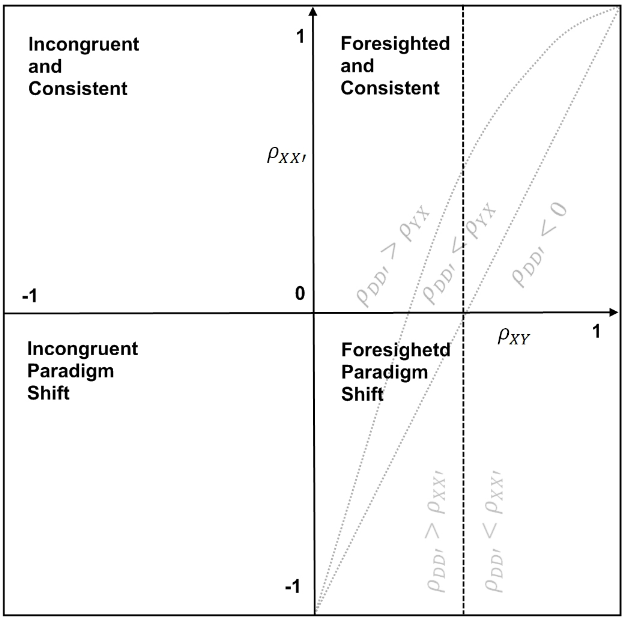

Figure 2.1 Reliability of item-response differences for system preferences as related to learning.

This corresponds to $\frac{3}{4}$ of the positive combination of reliabilities. The area where the difference score is negative is associated with participants that provide similar assessments of the system before and after the experiment, but wich change their pre-experiment assessment between identical experiments. Making fundamental changes to ones assumption about a system is a natural part of learning. With the method for measuring learning that we propose, paradigm shifts would reduce the reliability of the proposed measure of learning. Over time though, one would expect to see fewer paradigm shifts. Paradigm shifts would probably be associated with inexperienced participants reaching breakthrough insights about system performance. Paradigm shifts could also be associated with entirely new systems that even experienced participants cannot assess correctly before experimenting.

By analyzing the expression for reliability we also see that the difference score is better than the cross-test reliability for all pre- and post-test reliabilities less than $\frac{1}{2}$. At the same time the difference reliability ($\rho_{DD'}$) is better than the pre-test versus post-test reliability (ρ_{YX}) for the following condition:

$$\rho_{YX}^2 - 2\rho_{YX} > \frac{\rho_{XX'} + 1}{2} \tag{2.10}$$

The different regions of reliability have been entered into figure 2.1. The reliability of our difference score is best suited for participants that produce consistent evaluations, and that have something to learn from the scenario being played.

The correlations and reliabilities for the different measures of change have specific interpretations when true score theory is used for preference measurements. The reliability of the pretest score

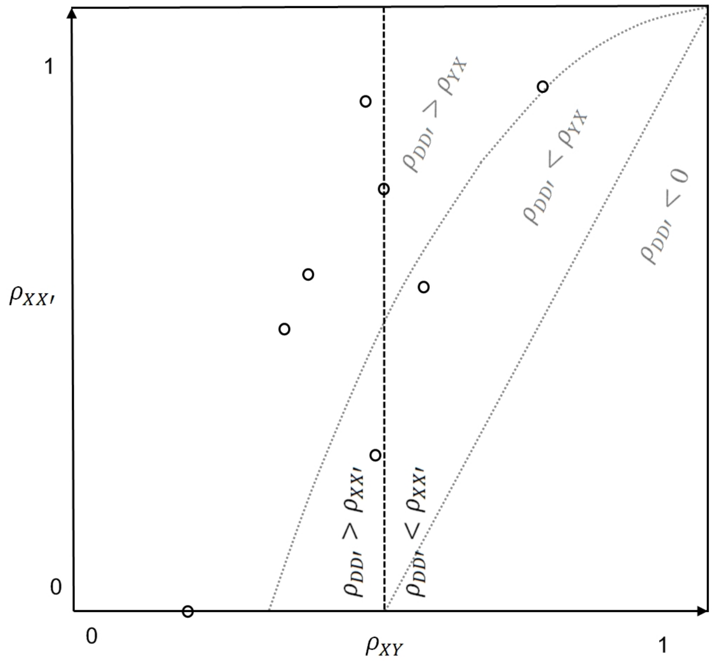

Figure 2.2 Participants that took part in two parallel experiments with identical systems and scenarios, one at the beginning and one at the end of the series of experiments.

($\rho_{XX'}$) represents the participant's propensity to deliver similar assessments of utility for similar scenarios. This says something about how consistent the participants preferences is when carrying out pretest assessments. The reliability of the pre- and post-difference score (ρ_{YX}) represents the participants propensity to deliver similar assessments of utility before and after an experiment. This says something about how foreseeing the participant is about her own preferences. Finally the reliability of the experiment to experiment difference ($\rho_{DD'}$) represents the participants propensity to suffer the same changes to system preferences when exposed to new experiments.

The rationale for introducing the difference score when measuring preferences is that it eliminates the error contribution from uncertainty about the utility of the system traits. The co-variation of the pre- and post-test scores is expected to increase with increasing knowledge of the system. As new tactics and procedures are discovered, the participant is expected to reevaluate her preferences for similar scenarios, but as long as this does not pull the overall reliability into the paradigm shift region the quality of the measure of learning still would be good.

The regions of the diagram in figure 2.1 with negative correlations would accommodate participants of a curious sort. The incongruent region would be associated with participants being unable to learn. The incongruent and consistent participant would keep repeating her misconceptions about the system and never learn, whereas the incongruent paradigm shift participant would keeps trying out new misconceptions and never achieves new insight.

All the data of our experiment place participants in the foresighted and consistent region, se figure 2.1. This is to be expected for experienced subject-matter experts. A moderate amount of paradigm shifts would pull the reliabilities towards the foresighted paradigm shift region. This would cause problems for measuring learning in the way that has been proposed. Only one of the participants can be found on the border-line between the consistent and paradigm shifting region. This is the youngest and most inexperienced participant in the experiment.

From figure 2.2 it can also be seen that most observations are located in the region where the difference measure produces the best reliabilities. None of the observations can be found in the region where the reliability of the difference measure is negative.

3 Changes in percieved utility interpreted as learning

Having established that the difference measure described above produces reliable measurements, we shall proceed to investigate what the measure means, and how it relates to learning. The post and pre-test difference for a certain item on a Likert scale measuring preferences for system traits is:

$$D_i = Y_i - X_i \tag{3.1}$$

For a given participant and a given scenario the normalized amount of change in preferences between post-test and pre-test evaluations is given by:

$$\varDelta K_p = \sum_{i=1}^{N_p} \frac{|D_i|}{\alpha N_p} \tag{3.2}$$

The formula index p is the participant number, i is the Likert-item number, N is the total number of Likert items that has been answered, and α is the scale length used for evaluating preferences. It is natural to interpret K_p as knowledge, and ΔK_p as knowledge gained by the participant while playing the scenario. Accumulation of knowledge is then measured by computing the average amount of changes to preferences for system traits, one experiment or scenario at a time. Learning is measured by differentiating knowledge over the time having been spent playing.

$$L_p(t) = \frac{\varDelta K_p}{\varDelta t} = \sum_{i=1}^{N_p} \frac{|D_i|}{\alpha N_p \varDelta t} \tag{3.3}$$

The system traits measured must represent all traits that any participant may consider to be relevant. A value of one for ΔK_p would represent a complete reversal of assessment of all system traits. In this case all knowledge about the system would have been obtained during the last experiment. Assuming uniformly distributed random answers the amount of change for each experiment would be

$\frac{8}{25}$ for a five point Likert scale. As can be seen from the data in the appendix, very few assessments exhibit that high values.

We can now proceed to test the method on the results from our simulation experiment.

4 Learning measured for people playing military force-structures in three different scenarios

The following empirical study did not emerge out of thin air. It was designed based on the circumstantial data obtained in previous small scale experiments [4]. The small scale experiments did not provide enough data to measure significant effects, but they enabled us to formulate hypotheses about the observations having been made. The experiment being reported here was expected to provide enough data for testing [5].

Scenario studies and system alternatives had been produced as part of the overarching work [6] and [7]. An interactive simulation representing the system and its surroundings was rapidly produced on the basis of readily available simulators [8]. The experimental scheme included 16 one day experiments with between 10 and 20 participants each time. The participants were selected among professionals with varying degrees of experience and analysts with knowledge of the domain. Each one-day event started out with a short briefing of the scenario and the structures to be played. Two designated leaders were then allowed some time for planning and giving of orders, before the commencement of the simulation. The questionnaires was distributed just before the simulation started, and retrieved just after the simulation had ended, se appendix A.

Plotting accumulated knowledge for each experiment as a function of time reveals learning as a slope to the accumulated knowledge. Measurement of accumulation of knowledge took place only during gameplay. The part of the learning that took place between play sessions was not measured. As can be seen from figure 2.2 a lot of learning took place between the first and the last repetition of that specific scenario and system. In this case a lot of the learning probably took place by associating experiences from other scenarios with this specific system and scenario. It could also be that some of the learning took place during the introduction before playing, or during debriefing after playing. In that case learning probably took place by knowledge being transferred between participants. By using knowledge accumulated only during sustained periods of play, as a measure of learning, we probably avoid some of the fits and bouts incurred by paradigm shifts or changes of opinion.

Plotting learning for each experiment as a function of time displays the instantaneous rate of change of knowledge having been obtained for an experiment. Our experiments were set up with one main learning objective. The objective was to identify if a given task could be finished with the given system, for a certain scenario. The experiment would be terminated, once the objective had been met. One of the scenarios was considered to be especially challenging. Most of the play-sessions were terminated due to complete failure in the effort to reach the objective. It may be assumed that this important knowledge about the system was obtained relatively fast. As can be seen from table

	N (questionaires)	Mean	Std. Deviation	Skewness	Kurtosis
$\Delta K[0,1][-]$	214	0.14	0.07	0.7	0.7
$L[0,\infty)[\frac{1}{hour}]$	214	0.04	0.03	2.3	9.0

Table 4.1 Statistical properties of accumulated knowledge and learning.

4.1 using learning as a measure increases scatter in the data. This is probably because the experiment was planned with a specific, time-independent and recurring learning objective. Introducing a time-dependent measure of learning would therefore be expected to increase the scatter in the data.

Using learning as a measure of the process of understanding the system, in cases where scenario-specific objectives and termination criteria have been established, seems not to be appropriate. Accumulated knowledge is a better measure when experiments are conducted with specific objectives and termination criteria. For open ended experimentation without specific objectives and termination criteria, it is likely that learning would be the best measure. In such cases the length of each experimental session could vary, and the knowledge obtained would be dependent on the time spent experimenting. Differentiation with regard to time would reduce variation introduced by possible variations in experiment duration.

Our experiment was planned with a specific end state for each playing session. We shall therefore use accumulated knowledge as a measure of the process of understanding the system. Our hypotheses from previous experiments where that either learning decreases over time, or boredom increases for each questionnaire being completed. Using the definitions provided above, we can formulate this more precisely.

> H1: Learning, as defined above, can be observed when participants conduct interactive simulation (that is to say $\frac{\Delta K}{\Delta t} < 0$, where t is the time spent experimenting with the system)
>
> H2: The observed reduced tendency to make changes to posttest evaluations is a result of participants increased boredom with questionnaires (that is to say $\frac{\Delta K}{\Delta n} < 0$, where n is the number of questionaries).
>
> H0: No reduction in the difference between pre- and post tests (that is to say $\frac{\Delta K}{\Delta t} \geq 0$ or $\frac{\Delta K}{\Delta n} \geq 0$).

To test H1 we carry out a linear regression analysis of variance. We find that it is very unlikely that the slope of the accumulated knowledge is not negative when plotted as a function of time.

$P(\frac{\Delta K}{\Delta t} \geq 0) = 0.01$

In other words there is a 1% probability of falsely rejecting H0. We used the participants system-related simulation time as the independent variable. It would be expected that you have less to learn for each repetition of the experiment. So it is highly likely that the time spent playing reduces the accumulated knowledge for the next experiment, and H1 is supported.

To test H2 we again carry out a linear regression analysis of variance using the number of questionnaires the participants has encountered. We find that we the probability that the slope of the accumulated knowledge is positive, when plotted as a function of number of questionnaires having been filled out for each participant, is not negligible.

$P(\frac{\Delta K}{\Delta n} \geq 0) = 0.31$

In other words there is a 31% probability of falsely rejecting H0. So we can't exclude the possibility that the amount of changes to the questionnaire increases with the number of questionnaires. This would be contrary to the hypothesis that the participants are bored by questionnaires, and H2 is not supported.

5 Effects that may influence learning

Other data indicate that the learning measured by this method is strongly dependent on the complexity of the system [9]. For other systems the scatter plot between the amount of changes to preferences and the time spent experimenting with the system would exhibit other learning curves. Our early experiments with less complex systems clearly show steeper learning curves. We do not have enough data to analyze this phenomenon.

Upon inspection of the data, there are several other interesting features that was not anticipated when the experiment was planned. First of all there seems to be a dependency between relevant experience and ability to learn (as defined above). A scatter plot of the dependent and independent variable clearly shows this (se figure 5.1 and 5.2)

Since the experiment was not designed to obtain this relation, we lack data in the region between 30 and 40 years experience. Even though we only have one participant with 40 years of experience, the results correspond to the expectations of the modified true score theory above. It is expected that experienced participants have less to learn from interactive simulations than others.

Upon inspection of the data we also discovered another interesting relation. The ability to learn seems to be strongly correlated to the closeness to the system during the simulation exercise. During the experiment the role of the participants was divided into "players", "opposing force" and "umpires". The umpires never took part in the simulation and only observed what happened. The opposing force never directly played the structure, but observed the consequences of its usage. Finally the actual players of the structure experienced the utility of the structure first hand. We have quantified the closeness to the system during simulation by dividing the participants into two groups. One group consists of players, and the other group of opposing force and umpires. There are no significant differences for the average learning for the two categories that did not actually play the structure. A scatter plot of S for those playing and those not playing clearly shows a difference (se figure 5.3). The difference is significant to a level less than 0.0005. Again it should be noted that the experiment was not designed to reveal this relationship, so the data for the independent variable is scarce for the umpires participating in the experiment.

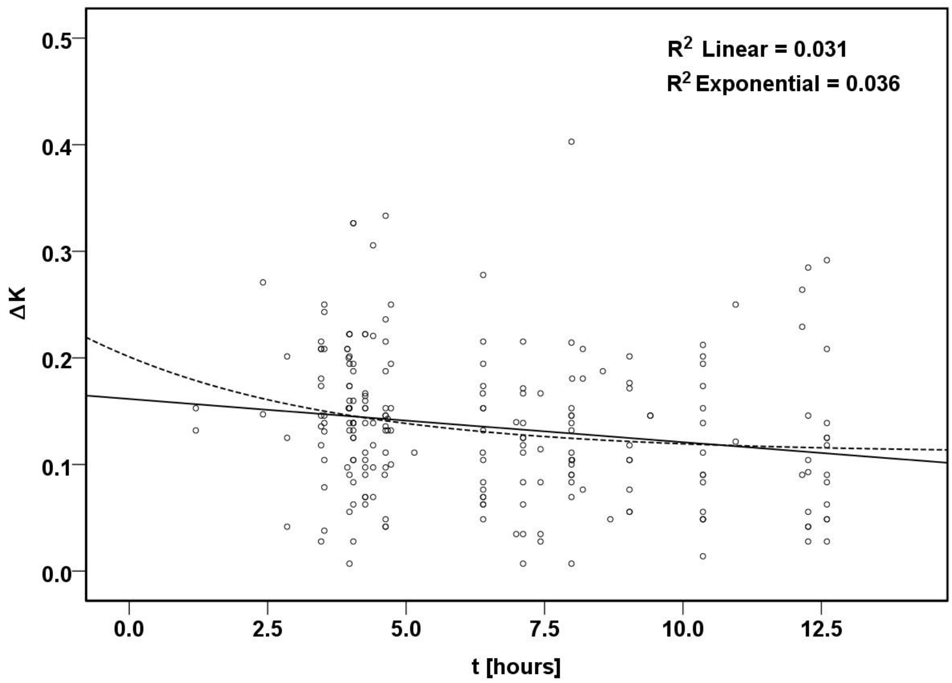

Figure 5.1 *Scatter plot with the measure of learning ΔK, as a function of simulation-time.*

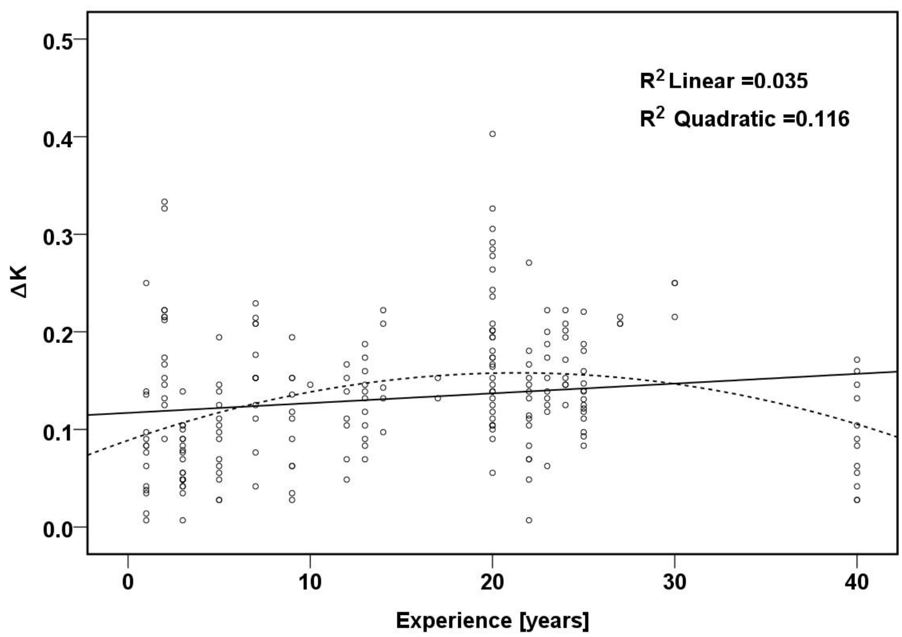

Figure 5.2 *Scatter plot with the measure of learning ΔK, as a function of experience.*

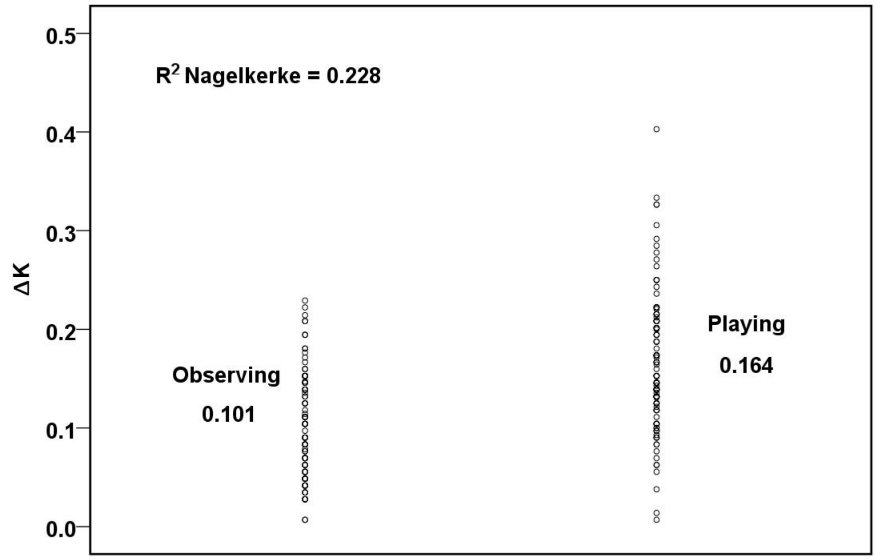

Figure 5.3   Scatter plot with the measure of learning ΔK, for players and observers.

Both in the case of the dependency on experience and the dependency of closeness to the system during simulation the effects are worth mentioning (R^2= 0.12 and 0.17) even though the experiment was not planned to investigate these effects. It would be beneficial for further experiments to cover the gaps in the data for long experience, and for learning among umpires.

The experimental data obtained contains 214 complete pre- and post-evaluations of one-day simulation exercises. With this many data points it should be possible to support a three parameter regression model for the prediction of learning during interactive simulation exercises. A simple linear simultaneous regression carried out using SPSS [10] results in a model with R^2=0.20 without accounting for the apparent nonlinearity in the dependency of the experience. All the independent variables have a significant influence on the model, and are included as part of a statistical linear regression. With the introduction of a quadratic dependency of experience and a moderate improvement in the modeling of the simulation time dependency, by adopting an exponential mode, nonlinear regression yields the model shown in equation 5.1.

$$\Delta K_p = -8.6 \cdot 10^{-5} E^2 + 4.0 \cdot 10^{-3} E + 6.4 \cdot 10^{-2} \exp(-1.4 \cdot 10^{-1} t) + \left\{ \begin{array}{ll} 0.10 & Player \\ 0.05 & Observer \end{array} \right. \tag{5.1}$$

The model parameters are as follows: E is the participant's relevant experience in years, t is the participant's time spent experimenting, and a constant is added with values depending on the closeness of the participant to the system during the experiment. The model explains 27% of the variation in the data. No improvements were obtained by attempting to introduce interactions between the variables.

6 Conclusion

A method has been proposed for measuring learning. The method is based on true-score theory and measurements of differences in participants assessment of utility of the system being studied. The reliability of pre- and post-assessments can be shown to be positive given that the participant in the learning process does not dramatically change her conception about the system being studied. It can also be shown that the reliability of the measure suggested for assessing learning, in most cases, is better than that of a simple pre- and post-assessments of utility. Thus the measurement of differences in perceived utility of a system can be considered to produce good assessments of learning under uncertainty.

Using the suggested measure of learning, significant learning-effects have been shown for a large interactive simulation experiment. Statistical regression shows that perceived utility differences are best predicted by a nonlinear model including participants experience, experiment-duration and closeness to the system during experimentation. The model explains 27% of the variance in the data.

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Appendix A Data from questionaires

Explanation to table headdings:

S Structure number

P Player number

R_s Repetition number for this structure

N_{sp} Number of structures currently having been experienced for the player

N_{gp} Number of games attended by the player

T_{sim} Duration of the game [h]

T_{sp} Time currently spent experiencing this structure for the player [h]

T_s Time currently spent for this structure [h]

T_{gp} Time currently spent gaming for the player [h]

C Closeness to the structure during play [1 = played, 2 = played opposition, 3 = observed]

M Military expert [0 = False, 1 = True]

E Experience (both military and relevant civilian) [years]

X Average pretest score

Y Average posttest score

ΔK Amount of knowledge accumulated during the game (as defined previously)

L Learning experienced on average during the game (as defined previously)

Table A.1 Accumulated data from questionaires

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
1	1	1	1	1	3.5	3.5	3.5	3.5	1	1	10	-0.14	0.06	0.146	0.041
1	2	1	1	1	3.5	3.5	3.5	3.5	2	0	3	0.64	0.66	0.079	0.022
1	3	3	1	1	3.5	3.5	8.2	3.5	3	1	22	0.31	0.42	0.181	0.052
1	3	4	1	2	4.0	7.4	12.2	51.7	3	1	22	-0.17	0	0.114	0.029
1	4	3	1	1	3.5	3.5	8.2	3.5	3	0	5	0.5	0.69	0.146	0.042
1	4	4	1	2	4.0	7.4	12.2	51.7	3	0	5	-0.17	-0.28	0.028	0.007
1	5	1	1	1	3.5	3.5	3.5	3.5	1	1	20	-0.26	0.19	0.139	0.039
1	5	2	1	2	1.2	4.7	4.7	4.7	1	1	20	0.19	0.11	0.132	0.110
1	5	3	1	3	3.5	8.2	8.2	8.2	1	1	20	0.22	0.5	0.181	0.052
1	5	4	1	4	4.0	12.2	12.2	60.4	1	1	20	0.06	-0.25	0.090	0.023
1	6	3	1	1	3.5	3.5	8.2	7.0	1	0	13	0.03	0.11	0.118	0.034
1	6	4	1	2	4.0	7.4	12.2	55.2	1	0	13	-0.39	-0.39	0.083	0.021
1	7	1	1	1	3.5	3.5	3.5	3.5	1	1	30	0.58	0.03	0.250	0.071
1	7	2	1	2	1.2	4.7	4.7	4.7	1	1	30	0.08	-0.24	0.250	0.208
1	9	1	1	1	3.5	3.5	3.5	3.5	2	0	7	0.78	0.61	0.208	0.059
1	9	2	1	2	1.2	4.7	4.7	4.7	2	0	7	0.56	0.5	0.153	0.127
1	9	3	1	3	3.5	8.2	8.2	8.2	2	0	7	0.19	0.17	0.076	0.022
1	9	4	1	4	4.0	12.2	12.2	44.1	2	0	7	0.31	0.33	0.229	0.058
1	10	3	1	1	3.5	3.5	8.2	3.5	3	0	9	0.69	1.2	0.136	0.039
1	10	4	1	2	4.0	7.4	12.2	51.7	3	0	9	1.14	1.28	0.035	0.009
1	11	3	1	1	3.5	3.5	8.2	3.5	1	1	27	0.23	0.06	0.208	0.060
1	12	4	1	1	4.0	4.0	12.2	43.6	1	0	23	0.39	0	0.200	0.050
1	13	1	1	1	3.5	3.5	3.5	3.5	1	1	20	0.25	-0.06	0.243	0.069
1	13	2	1	2	1.2	4.7	4.7	4.7	1	1	20	0.33	-0.06	0.194	0.162
1	13	3	1	3	3.5	8.2	8.2	8.2	1	1	20	-0.06	0.28	0.208	0.060
1	13	4	1	4	4.0	12.2	12.2	51.8	1	1	20	0.78	0	0.264	0.067
1	15	2	1	1	1.2	1.2	4.7	1.2	1	0	14	0.58	0.44	0.132	0.110
1	15	3	1	2	3.5	4.7	8.2	4.7	1	0	14	0.22	0.69	0.143	0.041
1	16	4	1	1	4.0	4.0	12.2	8.6	2	0	2	0.22	0.39	0.153	0.039
1	17	3	1	1	3.5	3.5	8.2	3.5	1	0	2	0.53	0.11	0.174	0.050
1	17	4	1	2	4.0	7.4	12.2	47.3	1	0	2	-0.06	-0.33	0.167	0.042
1	18	3	1	1	3.5	3.5	8.2	3.5	1	1	24	-0.32	0.31	0.208	0.060
1	19	3	1	1	3.5	3.5	8.2	8.2	2	1	40	0.72	0.83	0.028	0.008
1	20	1	1	1	3.5	3.5	3.5	3.5	1	0	3	0.36	0.17	0.104	0.030
1	20	2	1	2	1.2	4.7	4.7	4.7	1	0	3	0.19	0	0.100	0.083

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
1	20	4	1	3	4.0	8.7	12.2	51.3	2	0	3	0.5	0.31	0.049	0.012
1	22	3	1	1	3.5	3.5	8.2	3.5	1	1	30	0.26	0.53	0.215	0.062
1	25	1	1	1	3.5	3.5	3.5	3.5	1	0	25	0.52	0.33	0.131	0.037
1	25	3	1	2	3.5	7.0	8.2	8.2	1	0	25	0.2	0.35	0.140	0.040
1	25	4	1	3	4.0	11.0	12.2	41.3	1	0	25	0.31	0.71	0.121	0.031
1	26	2	1	1	1.2	1.2	4.7	1.2	1	1	17	-0.06	-0.06	0.153	0.127
1	26	3	1	2	3.5	4.7	8.2	4.7	1	1	17	0.19	0.28	0.132	0.038
1	27	1	1	1	3.5	3.5	3.5	3.5	1	0	1	0	0.03	0.038	0.011
1	27	3	1	2	3.5	7.0	8.2	7.0	2	0	1	-0.03	-0.11	0.035	0.010
1	27	4	1	3	4.0	11.0	12.2	55.2	1	0	1	0.14	1	0.250	0.063
2	2	1	2	2	4.0	4.0	4.0	24.4	2	0	3	0.58	0.58	0.056	0.014
2	2	2	2	3	2.4	6.4	6.4	26.8	2	0	3	0.58	0.56	0.049	0.020
2	2	3	2	4	4.0	10.4	10.4	30.8	2	0	3	0.53	0.56	0.049	0.012
2	3	1	2	3	4.0	4.0	4.0	19.7	3	1	22	0.61	1.08	0.132	0.033
2	3	2	2	4	2.4	6.4	6.4	22.1	3	1	22	0.97	0.92	0.069	0.029
2	3	3	2	5	4.0	10.4	10.4	26.1	3	1	22	0.69	0.92	0.083	0.021
2	4	1	2	3	4.0	4.0	4.0	19.7	3	0	5	0.47	0.47	0.139	0.035
2	4	2	2	4	2.4	6.4	6.4	22.1	3	0	5	0.58	0.83	0.063	0.026
2	4	3	2	5	4.0	10.4	10.4	26.1	3	0	5	0.64	0.86	0.056	0.014
2	5	1	2	5	4.0	4.0	4.0	24.4	1	1	20	0.22	-0.03	0.174	0.044
2	5	2	2	6	2.4	6.4	6.4	26.8	1	1	20	0	0.03	0.104	0.043
2	5	3	2	7	4.0	10.4	10.4	30.8	1	1	20	0.03	0.44	0.174	0.044
2	6	1	2	3	4.0	4.0	4.0	23.2	1	0	13	0.25	0.44	0.174	0.044
2	6	2	2	4	2.4	6.4	6.4	25.6	1	0	13	0.25	0.61	0.132	0.055
2	6	3	2	5	4.0	10.4	10.4	29.6	1	0	13	0.39	0.89	0.139	0.035
2	9	1	2	5	4.0	4.0	4.0	12.2	2	0	7	0.86	0.81	0.153	0.038
2	9	2	2	6	2.4	6.4	6.4	14.6	2	0	7	0.86	1.36	0.153	0.063
2	9	3	2	7	4.0	10.4	10.4	18.6	2	0	7	0.94	1.17	0.111	0.028
2	10	1	2	3	4.0	4.0	4.0	19.7	3	0	9	0.75	0.97	0.194	0.049
2	10	2	2	4	2.4	6.4	6.4	22.1	3	0	9	1.19	0.92	0.153	0.063
2	10	3	2	5	4.0	10.4	10.4	26.1	3	0	9	1.39	1.31	0.090	0.023
2	12	1	2	2	4.0	4.0	4.0	16.2	1	0	23	0.56	0.5	0.222	0.056
2	12	2	2	3	2.4	6.4	6.4	18.7	1	0	23	0.78	0.81	0.174	0.072
2	12	3	2	4	4.0	10.4	10.4	22.6	1	0	23	0.89	0.89	0.153	0.038
2	13	1	2	5	4.0	4.0	4.0	24.4	1	1	20	0.22	-0.03	0.201	0.051
2	13	2	2	6	2.4	6.4	6.4	26.8	1	1	20	0.28	0.17	0.278	0.115

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
2	13	3	2	7	4.0	10.4	10.4	30.8	1	1	20	0.56	0.78	0.194	0.049
2	17	1	2	3	4.0	4.0	4.0	19.7	1	0	2	0.31	0.19	0.222	0.056
2	17	2	2	4	2.4	6.4	6.4	22.1	1	0	2	0.47	0.17	0.215	0.089
2	17	3	2	5	4.0	10.4	10.4	26.1	1	0	2	0.31	1.12	0.212	0.053
2	18	1	2	2	4.0	4.0	4.0	16.9	1	1	24	0.08	0.08	0.222	0.056
2	18	2	2	3	2.4	6.4	6.4	19.3	1	1	24	0.25	0.42	0.194	0.081
2	18	3	2	4	4.0	10.4	10.4	23.2	1	1	24	0.42	0.94	0.201	0.051
2	19	1	2	2	4.0	4.0	4.0	24.4	2	1	40	0.69	0.86	0.160	0.040
2	19	2	2	3	2.4	6.4	6.4	26.8	2	1	40	1.2	1.14	0.063	0.026
2	19	3	2	4	4.0	10.4	10.4	30.8	2	1	40	1.19	1.22	0.090	0.023
2	20	1	2	4	4.0	4.0	4.0	19.3	2	0	3	0.42	0.56	0.090	0.023
2	20	2	2	5	2.4	6.4	6.4	21.7	2	0	3	0.69	0.67	0.076	0.032
2	20	3	2	6	4.0	10.4	10.4	25.7	2	0	3	0.69	0.83	0.049	0.012
2	23	2	1	1	2.4	2.4	6.4	6.4	1	1	22	0.19	0.44	0.271	0.112
2	23	3	1	2	4.0	6.4	10.4	10.4	1	1	22	0.31	0.42	0.167	0.042
2	24	2	1	1	2.4	2.4	6.4	10.4	2	1	25	1.03	0.88	0.147	0.061
2	24	3	1	2	4.0	6.4	10.4	14.4	2	1	25	0.86	1.22	0.111	0.028
2	27	1	2	4	4.0	4.0	4.0	23.2	1	0	1	0.94	0.92	0.007	0.002
2	27	2	2	5	2.4	6.4	6.4	25.6	1	0	1	0.94	0.94	0.083	0.035
2	27	3	2	6	4.0	10.4	10.4	29.6	1	0	1	0.83	0.89	0.014	0.004
2	28	1	1	1	4.0	4.0	4.0	21.0	2	0	12	1.06	1.56	0.153	0.038
2	28	2	1	2	2.4	6.4	6.4	23.4	2	0	12	1.5	1.28	0.069	0.029
2	28	3	1	3	4.0	10.4	10.4	27.3	2	0	12	1.39	1.31	0.049	0.012
3	2	2	3	5	2.9	2.9	7.1	15.3	2	0	3	0.53	0.58	0.042	0.015
3	3	1	3	6	4.3	4.3	4.3	7.7	3	1	22	1.22	1.44	0.069	0.016
3	3	2	3	7	2.9	7.1	7.1	10.6	3	1	22	1.39	1.42	0.007	0.002
3	4	1	3	6	4.3	4.3	4.3	7.7	3	0	5	0.83	1.03	0.090	0.021
3	4	2	3	7	2.9	7.1	7.1	10.6	3	0	5	1.06	1.44	0.125	0.044
3	4	3	3	8	5.1	12.3	12.3	15.7	3	0	5	1.22	1.11	0.028	0.005
3	5	1	3	8	4.3	4.3	4.3	12.5	1	1	20	1.31	1.09	0.164	0.039
3	5	2	3	9	2.9	7.1	7.1	15.3	1	1	20	1.2	1.11	0.111	0.039
3	5	3	3	10	5.1	12.3	12.3	20.5	1	1	20	1.39	1.33	0.056	0.011
3	6	1	3	6	4.3	4.3	4.3	11.3	1	0	13	0.61	0.47	0.160	0.037
3	6	3	3	7	5.1	9.4	12.3	19.2	1	0	13	0.77	1.08	0.146	0.028
3	10	1	3	6	4.3	4.3	4.3	7.7	3	0	9	1.47	1.86	0.111	0.026
3	10	2	3	7	2.9	7.1	7.1	10.6	3	0	9	1.61	1.58	0.063	0.022

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
3	12	1	3	5	4.3	4.3	4.3	4.3	1	0	23	1.42	1.44	0.063	0.015
3	12	2	3	6	2.9	7.1	7.1	7.1	1	0	23	1.53	1.08	0.125	0.044
3	13	1	3	8	4.3	4.3	4.3	12.5	1	1	20	1.08	1.36	0.153	0.036
3	13	2	3	9	2.9	7.1	7.1	15.3	1	1	20	1.03	0.97	0.167	0.058
3	13	3	3	10	5.1	12.3	12.3	20.5	1	1	20	0.81	1.56	0.285	0.055
3	15	1	2	3	4.3	4.3	4.3	8.9	2	0	14	0.92	1.31	0.222	0.052
3	17	1	3	6	4.3	4.3	4.3	7.7	1	0	2	0.33	0.72	0.222	0.052
3	17	2	3	7	2.9	7.1	7.1	10.6	1	0	2	0.78	0.64	0.215	0.076
3	17	3	3	8	5.1	12.3	12.3	15.7	1	0	2	0.28	0.58	0.146	0.028
3	18	1	3	5	4.3	4.3	4.3	7.7	1	1	24	0.89	0.44	0.153	0.036
3	18	3	3	6	5.1	9.4	12.3	12.9	1	1	24	0.75	0.5	0.146	0.028
3	19	1	3	5	4.3	4.3	4.3	12.5	2	1	40	1.42	1.28	0.104	0.024
3	19	2	3	6	2.9	7.1	7.1	15.3	2	1	40	1.19	1.46	0.171	0.060
3	19	3	3	7	5.1	12.3	12.3	20.5	2	1	40	1.67	1.67	0.042	0.008
3	20	1	3	7	4.3	4.3	4.3	12.5	2	0	3	0.72	0.78	0.069	0.016
3	20	2	3	8	2.9	7.1	7.1	15.3	2	0	3	0.83	0.86	0.035	0.012
3	21	2	1	1	2.9	2.9	7.1	2.9	1	1	20	1.06	1.53	0.201	0.071
3	21	3	1	2	5.1	8.0	12.3	8.0	1	1	20	1.5	1.64	0.104	0.020
3	24	2	2	3	2.9	2.9	7.1	2.9	2	1	25	0.86	0.81	0.125	0.044
3	24	3	2	4	5.1	8.0	12.3	8.0	2	1	25	0.75	1.31	0.181	0.035
3	25	1	2	4	4.3	4.3	4.3	12.5	1	0	25	1.28	1.17	0.139	0.033
3	25	2	2	5	2.9	7.1	7.1	15.3	1	0	25	0.94	0.83	0.118	0.041
3	25	3	2	6	5.1	12.3	12.3	20.5	1	0	25	0.93	1.14	0.093	0.018
3	27	1	3	7	4.3	4.3	4.3	11.3	1	0	1	0.94	0.94	0.097	0.023
3	27	2	3	8	2.9	7.1	7.1	14.1	2	0	1	0.94	1	0.083	0.029
3	27	3	3	9	5.1	12.3	12.3	19.2	2	0	1	1.03	1.03	0.042	0.008
3	28	1	2	4	4.3	4.3	4.3	9.0	2	0	12	0.97	1.19	0.167	0.039
3	28	2	2	5	2.9	7.1	7.1	11.8	2	0	12	1.42	1.03	0.139	0.049
3	28	3	2	6	5.1	12.3	12.3	17.0	2	0	12	1.11	1.25	0.104	0.020
3	29	3	1	1	5.1	5.1	12.3	5.1	2	1	5	0.83	0.83	0.111	0.022
4	2	1	4	6	4.6	4.6	4.6	35.4	2	0	3	0.72	0.58	0.049	0.011
4	3	1	4	8	4.6	4.6	4.6	30.7	3	1	22	1.11	0.86	0.146	0.032
4	3	3	4	9	4.4	9.0	13.1	35.1	3	1	22	0.69	0.67	0.104	0.024
4	4	1	4	9	4.6	4.6	4.6	30.7	3	0	5	1.17	0.89	0.097	0.021
4	4	3	4	10	4.4	9.0	13.1	35.1	3	0	5	0.56	0.53	0.104	0.024
4	5	1	4	11	4.6	4.6	4.6	35.4	1	1	20	0.69	0.36	0.236	0.051

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
4	5	3	4	12	4.4	9.0	13.1	43.9	1	1	20	0.86	0.22	0.201	0.046
4	6	3	4	8	4.4	4.4	13.1	38.6	1	0	13	0.28	0.33	0.069	0.016
4	9	1	3	8	4.6	4.6	4.6	23.2	2	0	7	1.33	0.94	0.042	0.009
4	9	3	3	9	4.4	9.0	13.1	27.6	2	0	7	0.56	0.79	0.176	0.040
4	10	3	4	8	4.4	4.4	13.1	35.1	3	0	9	1.42	1.67	0.118	0.027
4	11	1	2	2	4.6	4.6	4.6	8.1	1	1	27	0.44	0.25	0.215	0.047
4	12	1	4	7	4.6	4.6	4.6	27.3	1	0	23	1.25	1.06	0.188	0.041
4	12	3	4	8	4.4	9.0	13.1	31.7	1	0	23	0.58	0.39	0.118	0.027
4	13	3	4	11	4.4	4.4	13.1	35.2	1	1	20	0.81	0.97	0.139	0.032
4	14	3	1	1	4.4	4.4	13.1	4.4	1	1	20	0.53	0.42	0.306	0.069
4	15	3	3	4	4.4	4.4	13.1	13.3	1	0	14	1.14	0.86	0.097	0.022
4	17	1	4	9	4.6	4.6	4.6	30.7	1	0	2	0.5	-0.5	0.333	0.072
4	18	1	4	7	4.6	4.6	4.6	27.9	1	1	24	0.83	0.64	0.146	0.032
4	18	3	4	8	4.4	9.0	13.1	32.3	1	1	24	0.69	0.17	0.171	0.039
4	19	1	4	8	4.6	4.6	4.6	35.4	2	1	40	1.5	1.58	0.132	0.029
4	19	3	4	9	4.4	9.0	13.1	43.9	2	1	40	1.81	1.92	0.056	0.013
4	20	1	4	9	4.6	4.6	4.6	30.3	2	0	3	0.72	0.89	0.042	0.009
4	20	3	4	10	4.4	9.0	13.1	34.7	2	0	3	0.78	0.78	0.056	0.013
4	23	1	2	3	4.6	4.6	4.6	15.0	1	1	22	0.36	0.75	0.153	0.033
4	25	3	3	7	4.4	4.4	13.1	28.8	1	0	25	1.28	0.44	0.221	0.050
4	27	1	4	10	4.6	4.6	4.6	34.2	1	0	1	0.83	0.57	0.136	0.029
4	27	3	4	11	4.4	9.0	13.1	38.6	1	0	1	0.75	0.61	0.076	0.017
4	28	1	3	7	4.6	4.6	4.6	32.0	2	0	12	1.53	1.14	0.111	0.024
5	2	1	5	7	4.0	4.0	4.0	43.9	2	0	3	0.58	1.03	0.139	0.034
5	2	2	5	8	3.9	8.0	8.0	47.8	2	0	3	1.03	1.06	0.007	0.002
5	3	1	5	10	4.0	4.0	4.0	39.2	3	1	22	0.44	0.33	0.139	0.034
5	3	2	5	11	3.9	8.0	8.0	43.1	3	1	22	0.36	0.58	0.111	0.028
5	3	3	5	12	4.6	12.6	12.6	47.7	3	1	22	0.31	0.39	0.049	0.011
5	4	1	5	11	4.0	4.0	4.0	39.2	3	0	5	0.47	-0.14	0.194	0.048
5	4	2	5	12	3.9	8.0	8.0	43.1	3	0	5	0.33	0.17	0.069	0.018
5	4	3	5	13	4.6	12.6	12.6	47.7	3	0	5	0.25	0.06	0.049	0.011
5	5	1	5	13	4.0	4.0	4.0	47.9	1	1	20	0.47	0.22	0.104	0.026
5	5	2	5	14	3.9	8.0	8.0	51.9	1	1	20	0.33	-0.03	0.146	0.037
5	5	3	5	15	4.6	12.6	12.6	56.5	1	1	20	0.19	0.22	0.118	0.026
5	6	1	5	9	4.0	4.0	4.0	42.7	1	0	13	0.56	0.25	0.188	0.046
5	6	2	5	10	3.9	8.0	8.0	46.6	1	0	13	0.44	0.14	0.104	0.026

S	P	R_s	N_{sp}	N_{gp}	T_{sim}	T_{sp}	T_s	T_{gp}	C	M	E	X	Y	ΔK	L
5	6	3	5	11	4.6	12.6	12.6	51.2	1	0	13	0.03	0	0.090	0.020
5	9	1	4	10	4.0	4.0	4.0	31.6	2	0	7	0.39	0.17	0.125	0.031
5	9	2	4	11	3.9	8.0	8.0	35.6	2	0	7	0.42	0.31	0.214	0.054
5	9	3	4	12	4.6	12.6	12.6	40.2	2	0	7	0.75	0.53	0.208	0.045
5	10	1	5	9	4.0	4.0	4.0	39.2	3	0	9	1.53	1.42	0.028	0.007
5	10	2	5	10	3.9	8.0	8.0	43.1	3	0	9	1.64	1.19	0.153	0.039
5	10	3	5	11	4.6	12.6	12.6	47.7	3	0	9	1.25	1.33	0.063	0.014
5	11	2	3	3	3.9	3.9	8.0	12.0	1	1	27	0.58	-0.03	0.208	0.053
5	12	1	5	9	4.0	4.0	4.0	35.7	1	0	23	0.78	0.64	0.132	0.033
5	12	2	5	10	3.9	8.0	8.0	39.6	1	0	23	0.69	0.14	0.139	0.035
5	13	1	5	12	4.0	4.0	4.0	39.3	1	1	20	1	-0.19	0.326	0.081
5	13	2	5	13	3.9	8.0	8.0	43.2	1	1	20	1.42	-0.08	0.403	0.102
5	13	3	5	14	4.6	12.6	12.6	47.8	1	1	20	1.22	0.44	0.292	0.063
5	14	1	2	2	4.0	4.0	4.0	8.5	1	1	20	1.22	0.72	0.139	0.034
5	14	2	2	3	3.9	8.0	8.0	12.4	1	1	20	0.72	0.71	0.100	0.025
5	14	3	2	4	4.6	12.6	12.6	17.0	1	1	20	0.69	0.81	0.125	0.027
5	15	2	4	5	3.9	3.9	8.0	17.3	1	0	14	1	1.19	0.208	0.053
5	16	3	2	2	4.6	4.6	12.6	4.6	2	0	2	0.39	0.47	0.090	0.020
5	17	1	5	10	4.0	4.0	4.0	34.8	1	0	2	0.44	0.03	0.326	0.081
5	17	2	5	11	3.9	8.0	8.0	38.7	1	0	2	-0.44	0.06	0.132	0.034
5	17	3	5	12	4.6	12.6	12.6	43.3	1	0	2	0.36	0.08	0.125	0.027
5	18	1	5	9	4.0	4.0	4.0	36.3	1	1	24	0.69	0.86	0.125	0.031
5	19	1	5	10	4.0	4.0	4.0	47.9	2	1	40	1.61	1.28	0.083	0.021
5	19	2	5	11	3.9	8.0	8.0	51.9	2	1	40	2	1.42	0.146	0.037
5	19	3	5	12	4.6	12.6	12.6	56.5	2	1	40	1.89	1.78	0.028	0.006
5	20	1	5	11	4.0	4.0	4.0	38.7	2	0	3	0.75	0.72	0.104	0.026
5	20	2	5	12	3.9	8.0	8.0	42.7	2	0	3	0.83	0.47	0.090	0.023
5	20	3	5	13	4.6	12.6	12.6	47.3	2	0	3	0.67	0.72	0.083	0.018
5	24	1	3	5	4.0	4.0	4.0	22.8	2	1	25	0.81	0.78	0.160	0.039
5	24	2	3	6	3.9	8.0	8.0	26.8	2	1	25	1.03	0.81	0.083	0.021
5	25	2	4	8	3.9	3.9	8.0	32.8	1	0	25	0.62	0.25	0.097	0.025
5	25	3	4	9	4.6	8.6	12.6	37.4	1	0	25	0.31	0.29	0.188	0.041
5	27	1	5	12	4.0	4.0	4.0	42.7	1	0	1	1	0.86	0.063	0.015
5	27	2	5	13	3.9	8.0	8.0	46.6	1	0	1	0.89	0.92	0.090	0.023
5	27	3	5	14	4.6	12.6	12.6	51.2	1	0	1	1.03	0.58	0.139	0.030