Int. J. Engng Ed. Vol. 25, No. 2, pp. 318–323, 2009
Printed in Great Britain.
0949-149X/91 $3.00+0.00

A Model for Assessing Web-Based Simulations in Engineering Education*

WEI-FAN CHEN
College of Information Sciences and Technology, The Pennsylvania State University, P.O. Box PSU, Lehman, PA 18627-0217, USA. E-mail: weifan@psu.edu

This study provided a statistical model to assess varied types of Web-based simulations in a digital-filter design course. Ninety-one undergraduate students participated in an experimental study. Two independent variables were studied: Web-based simulations (batch-based, comparison-based, and interval change-based simulations); and prior Internet familiarity (high and low). Two dependent variables were measured: a knowledge achievement test, and a problem-solving belief test. The experimental research design of the study was a 3 $\times$ 2 randomized post-test design. Multivariate Analysis of Variance (MANOVA) was used to analyze collected data. The main effects and the potential interaction of the two independent variables were examined. Results indicate that Web-based simulation with a simple batch-based design yielded a significantly better learning performance than two other complex simulation designs (comparison-based and interval change-based simulations) ($F[2,85] = 4.274$, $p < 0.05$).

Keywords: Digital-filter design, e-learning, Web-based simulation.

INTRODUCTION

IN ENGINEERING EDUCATION, the use of Web-based simulations as an instructional strategy is becoming a future trend for designing technical e-learning environments. Previous engineering education research indicated that Web-based simulations enhanced students' active learning experience [1–2], encouraged self-learning by providing hands-on exercises [3] and facilitated the traditional classroom teaching and learning processes [4–5]. The major learning factors identified as contributing to positive student learning experience in a simulation-based environment included the effectiveness of dynamic multiple representations and animations [6–7], student active involvement in generating and validating hypotheses [8] and interactive role-playing and gaming [9–10]. However, little research focused on assessing the effectiveness of Web-based simulations by implementing a truly experimental method.

The purpose of this study is to provide a statistical model for assessing Web-based simulations. One rigid experimental study was conducted to elaborate the purpose. The content area for conducting this experimental research is digital-filter design. This experimental study investigated the effect of various types of Web-based simulations on engineering undergraduate students' learning achievement and attitude. Based upon the purpose of the study, three research null hypotheses were drawn as follows:

1) no significant differences in student test achievement and their problem-solving belief when they learn in varied types of Web-based simulations;
2) no significant differences in student test achievement and their problem-solving belief when they have different prior internet familiarity;
3) no significant interaction in student test achievement and their problem-solving belief between the two studied independent variables: Web-based simulation and prior internet familiarity.

WEB-BASED SIMULATION IMPLEMENTATION

This study investigated various types of Web-based simulations in a digital-filter design course. The digital-filter design course is typically designed for undergraduates to understand the concepts of digital signal processing, sampling theorem, Fourier transformation, convolution, Z transformation, Infinite Impulse Response filter (IIR), and Finite Impulse Response filter (FIR). This course involves complicated mathematical equations and dynamic waveform variations.

The system architecture of this Web-based simulation comprises four different modules:

1) End-user module,
2) Universal Description Discovery and Integration (UDDI) server,
3) Applications (AP) server,
4) Database server.

The end-user module consists of users' computers and browsers. The UDDI server supports registra-

* Accepted 8 December 2008.

tion of Web services and service publishing via the internet. The AP server provides IIS service and three Web-based simulations, namely, batch-based, comparison-based and interval change-based simulations. The database server primarily stores and manages accounts created for users, keeps records of online discussions and publishes Web-based simulation materials for the digital-filter design course. The implementation of the Web services employs a MATLAB development tool and the .NET from Microsoft to develop Web service solutions.

EXPERIMENTAL RESEARCH DESIGN

Ninety-one undergraduate students in a digital-filter design course participated in the study from a university of technology in Taiwan. Two independent variables were investigated in the study:

1) Web-based simulations (batch-based, comparison-based and interval change-based simulations);
2) prior Internet familiarity (high and low).

The study measured two dependent variables:

1) a knowledge achievement test,
2) a problem-solving belief test.

These two tests were conducted after students completed their assigned experimental simulations. A seven-point Likert-type scale was designed to measure the results of the dependent measures. The Cronbach's alpha reliability coefficient is 0.764 for the 25-item test instrument. In order to guarantee the validity of the two dependent measures, all the test items were reviewed and validated by subject matter experts in the University.

The research design of the study was a 3×2 randomized post-test design, since there were three levels for the first independent variable and two levels for the second variable. Multivariate Analysis of Variance (MANOVA) was used to analyze collected data. The main effects and the potential interaction of the two independent variables were examined.

WEB-BASED SIMULATIONS

Simulation #1 (batch-based simulation)

The first type of simulation allows students to run simulations by changing dynamic-filter parameters. The resulting waveforms help them to better understand the variations of waveform under different parametric values by clicking an 'Execute' button. Figure 1 shows the input of four parameters (Wp, Ws, Rp and As) and the resulting waveform magnitude, magnitude in dB, and impulse. The Wp is the maximum frequency of passband namely cut-off frequency of passband. In

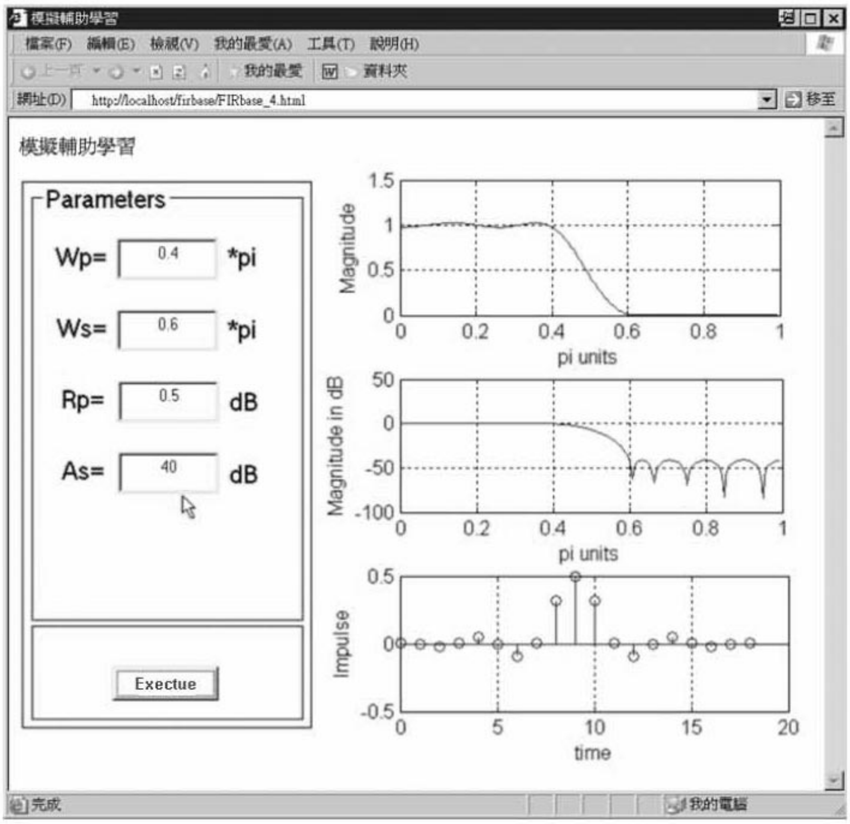

Fig. 1. Batch-based simulation.

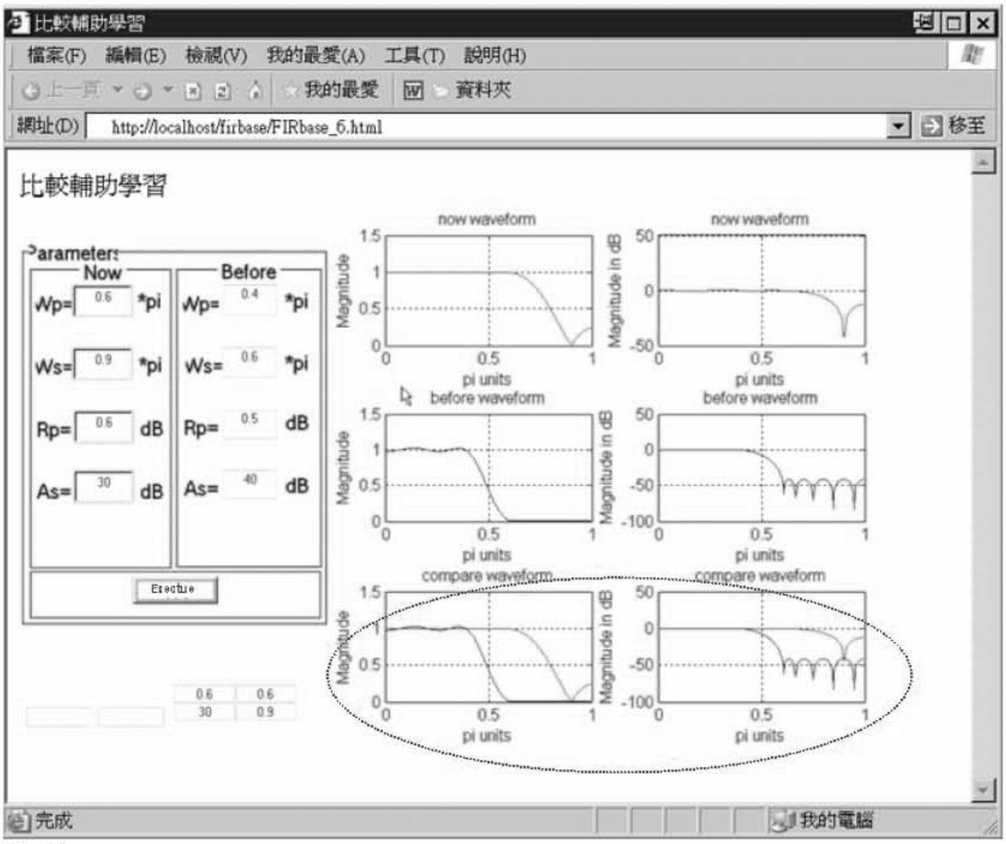

Fig. 2. Comparison-based simulation.

other words, Wp is the edge frequency of passband; the Ws is the minimum frequency of stopband namely cut-off frequency of stopband. In other words, Ws marks the beginning frequency of passband; Rp is the amplitude of the ripple in the passband, usually expressed in decibels; As is the minimum attenuation of amplitude in stopband, usually expressed in decibels.

Simulation #2 (comparison-based simulation)

The second type of simulation displays current parametric values, their previous inputs and three sets of waveforms in order to show the present state, previous state and their comparison. For example, Figure 2 compares the waveforms of Wp = 0.4, Ws = 0.6, Rp = 0.5, and As = 40 (before) and Wp = 0.6, Ws = 0.9, Rp = 0.6, and As = 30 (after).

Simulation #3 (interval change-based simulation)

The third type of simulation displays the process of changing amplitudes in a batch-based simulation (see Simulation #1). Users observe the relationship between change of parameters and amplitude variation during a batch-based simulation. For example, in Figure 3, Wp = 0.4, Ws = 0.6, Rp = 0.5, and As = 40 are input parameters in the Expectation area; interval values of Rp = 0.083 and As = 6.667 for each automatic change are input parameters in the Change area. Different waveform amplitudes are displayed after execution. This simulation allows the display of stepwise variation of waveforms through automatic interval change of parameters.

EXPERIMENTAL PROCEDURE

The student subjects answered a seven-point Likert-type question about their internet familiarity before they were randomly assigned to various types of Web-based simulation groups. Based on the result of the question, they were divided into two groups of high and low prior internet familiarity (45 and 46 students in each, respectively) according to a median cutting score. To avoid potential sampling bias, a stratified sampling method was used to assign students randomly into Web-based simulation groups.

After being randomly assigned, the students had 45 minutes to complete their Web-based simulations. After finishing their Web-based simulations, the subjects took their post-tests.

RESULTS

According to Cronk [11], a Wilks' Lambda in the multivariate analysis of variance would determine whether independent variables and their interaction had any effect on dependent variables. Table 1 below shows that the effect of interaction

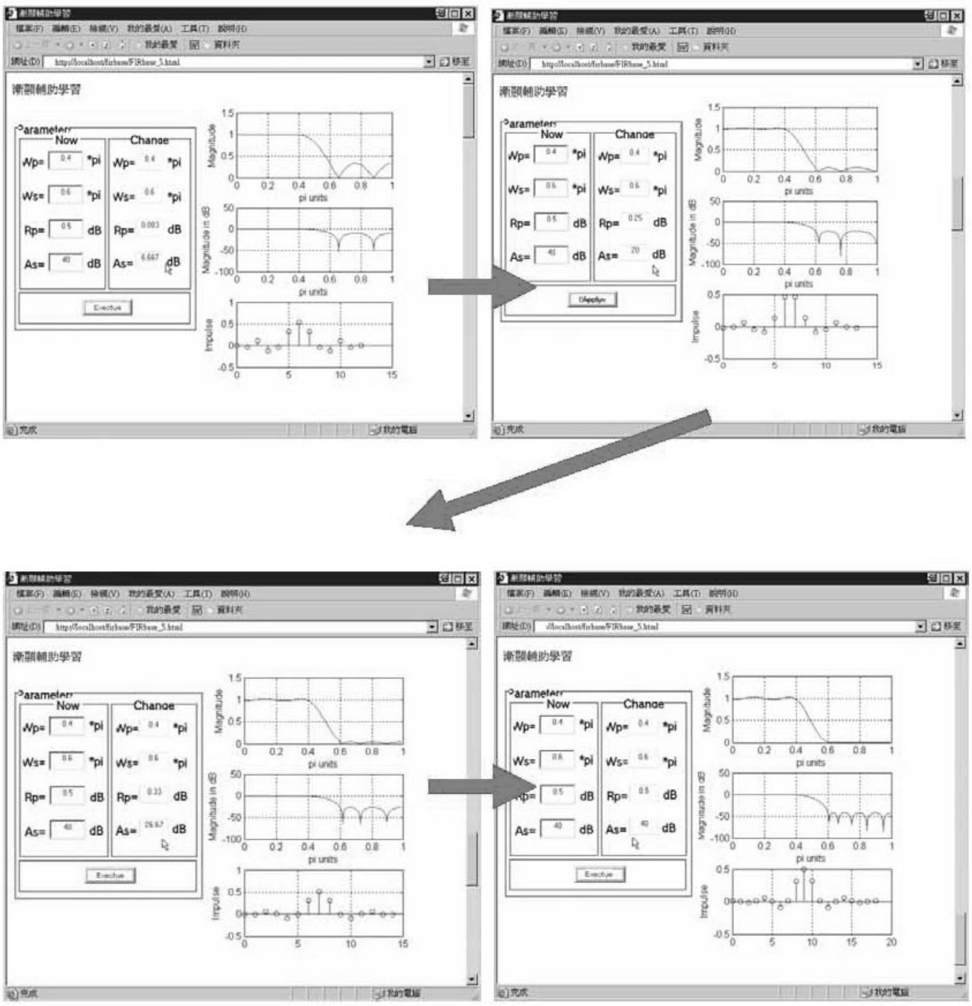

Fig. 3. Interval change-based simulation.

between Web-based simulations and prior Internet familiarity was not significant (Wilks' Lambda = 0.953; p = 0.394). This result retained the null hypothesis 3 in the study. Similarly, the effect of prior Internet familiarity on dependent measures did not show significant differences (p = 0.427). Therefore, the null hypothesis 2 should not be rejected. However, a significant effect of Web-based simulations was found (Wilks' Lambda (4,168) = 0.867, $p < 0.05$). Therefore, the null hypothesis 1 should be rejected. Further univariate analyses are needed to investigate.

For the null hypothesis 1, an analysis of variance was conducted for each of the two dependent measures. The results from these two dependent measures are reported as follows.

For the knowledge test measures, the analysis of variance showed that significant differences among simulation groups existed ($F[2,85] = 4.274$, $p < 0.05$). Since significant differences existed in the knowledge test, the follow-up Tukey's Honestly Significant Difference (HDS) was conducted to determine where the differences came from among the simulation groups [11]. Table 2 shows that significant differences were found between simulation 1 (batch-based simulation) and simulation 2 (comparison-based simulation), and between simulation 1 and simulation 3 (interval change-based simulation). However, no significant differences occurred between the simulation 2 and simulation 3.

For the problem-solving belief measures, the analysis of variance showed that significant differences among simulation groups existed ($F[2,85] = 3.308$, $p < 0.05$). The Tukey HDS indicated that significant differences existed between simulation 1 and simulation 3. However, no significant differences were found between simulation 1 and simu-

Table 1. Multivariate tests

Effects	Wilks Lambda	F	P
Prior Internet familiarity	0.980	0.859	0.427
Simulations	0.867	3.112	0.017*
Interaction	0.953	1.029	0.394

* Significant at 0.05 level F: F ratio; p: p value

Table 2. Tukey HDS for knowledge test

Source	Mean Diff.	Std. Err.	Sig.
Simulations 1 & 2	11.110	4.482	0.040*
Simulations 1 & 3	11.839	4.553	0.029*
Simulations 2 & 3	0.729	4.443	0.985

* Significant at 0.05 level

Table 3. Tukey HDS for problem-solving belief measure

Source	Mean Diff.	Std. Err.	Sig.
Simulations 1 & 2	0.247	0.116	0.089
Simulations 1 & 3	0.288	0.118	0.044*
Simulations 2 & 3	0.040	0.115	0.935

* Significant at 0.05 level

lation 2, and between simulation 2 and simulation 3 (Table 3).

In summary, statistical results showed significant differences in students' dependent measures among the three Web-based simulations. Specifically, regardless of levels of prior Internet familiarity, simulation 1 (batch-based simulation) was superior to simulation 3 (interval change-based simulation) for the two studied dependent measures (knowledge test and problem-solving belief measure). In addition, simulation 1 was significantly better than simulation 2 (comparison-based simulation) on the knowledge test. Table 4 shows a summary of the results of the statistical testing on hypothesis 1.

Table 4. Summary of hypothesis 1 test

Tests	Null Hypothesis 1
Knowledge test	Rejected (S1 > S2; S1 > S3)*
Problem-solving belief	Rejected (S1 > S3)*

* Significant at 0.05 level; S: Simulation

CONCLUSION

This study adopted a statistical model to assess systematically the effect of various types of Web-based simulations in engineering education aiming at improving Web-based pedagogical activities. The results indicated that the Web-based simulation with a simple batch-based design yielded a significantly better learning performance than the other two complex simulation designs (comparison-based and interval change-based simulations). Students in the simple batch-based simulation group expressed a significantly stronger belief in their problem-solving measure than the complex interval change-based simulation group. In other words, students may find difficulty when they learn in a complex Web-based simulation environment by themselves. The dynamic results produced by complex simulations may be too complicated for them to comprehend in an experimental environment. Those complex simulation results may need further clarification by using other associated instructional strategies and learning supports from classroom instructors and other resources as well. In addition, students' problem-solving belief influences their learning performance. The results of the study can be applied to other related engineering disciplines that focus on using Web-based simulation as an instructional strategy in the classroom.

This experimental study provided a framework for assessing Web-based simulations by involving human subjects. According to the findings of the study, future research should continue to investigate the impact of Web-based simulation environments on students' learning achievement, especially on their higher order cognitive abilities, such as comprehension, problem-solving and critical-thinking skills. Additionally, future studies should consider more human factors in a Web-based learning environment, such as learners' individual differences, learning styles, preferences in learning visual/audio materials, etc. Many of the independent variables associated with the study of human-computer interaction should be taken into account in the design of Web-based simulations.

REFERENCES

1. T. F. Wiesner and W. Lan, Comparison of student learning in physical and simulated unit operations experiments, *J. Eng. Educ.* **93**(3), 2004, pp. 195–204.
2. J. O. Campbell, J. R. Bourne, P. J. Mosterman and A. J. Brodersen, The effectiveness of learning simulations for electronic laboratories, *J. Eng. Educ.* **91**(1), 2002, pp. 81–87.
3. F. Stern, et al., Hands-on CFD educational interface for engineering courses and laboratories, *J. Eng. Educ.*, **95**(1), 2006, pp. 63–83.
4. J. G. Mackenzie, W. B. Earl, R. M. Alien and I. A. Gilmour, Amoco computer simulation in chemical engineering education, *J. Eng. Educ.* **90**(3), 2001, pp. 331–345.
5. A. Parush, H. Hamm and A. Shtub, Learning histories in simulation teaching: The effects on self-learning and transfer, *Comp. & Educ.* **39**, 2002, pp. 319–332.
6. J. van der Meij and T. de Jong, Supporting students' learning with multiple representations in a dynamic simulation-based learning environment, *Learning and Instruction*, **16**, 2006, pp. 199–212.
7. M. Esteves and A. J. Mendes, A simulation tool to help learning of object oriented programming basics, *Proceedings of the 34th ASEE/IEEE Frontiers in Education Conference*, F4C-7/12 (2004).
8. M. Puustinen, M. Baker and K. Lund, GESTALT: A framework for redesign of educational software, *J.Comp. Assisted Learning*, **22**, 2006, pp. 34–46.

9. N. Bos and N. S. Shami, Adapting a face-to-face role-playing simulation for online play, *Educ. Tech. Res. and Dev.* **54**(5), 2006, pp. 493–521.
10. A. Amory, K. Naicker, J. Vincent and C. Adams, The use of computer games as an educational tool: Identification of appropriate game types and game elements, *Brit. J. Educ. Tech.* **30**(4), 1999, pp. 311–321.
11. B. C. Cronk, *How to Use SPSS*. Los Angeles, CA: Pyrczak Publishing, (1999).

Wei-Fan Chen is an Assistant Professor of Information Sciences and Technology at The Pennsylvania State University. He received the B.S. degree in Information and Computer Engineering from Chung Yuan Christian University, Taiwan in 1993, and the M.Ed. and Ph.D. degrees in Instructional Systems from The Pennsylvania State University, University Park, in 1999 and 2002, respectively. His research and teaching interests include cognitive and information sciences and technology as related to learning. He studies human-computer interaction, especially for cognitive learning for undergraduate students.