

Hands-on experience of manual control in a human-machine systems engineering course

J.C.F. de Winter, D. Dodou, S. de Groot, D.A. Abbink, P.A. Wieringa

Department of BioMechanical Engineering, Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands (j.c.f.dewinter@tudelft.nl)

Abstract

This paper presents the results of integrating hands-on experience in an engineering MSc course on human-machine systems. Students could voluntarily complete a homework assignment in which they performed manual control tasks using dedicated software. The tasks were accompanied by questions that students had to answer using the theory taught in the lectures. The lecturer processed the students' recorded data and presented the results in class. One-and-a-half month after the completion of the assignment, students took a written exam on all topics of the course, including manual control theory. Students ($n = 32$) reported in a questionnaire that the assignment was valuable in improving their understanding of manual control (mean = 7.80, SD = 1.53 on a 10-point scale with anchors at 1 (*poor*) and 10 (*excellent*)). A correlation analysis of assignment participation, questionnaire responses, assignment grades, and exam scores is reported as well.

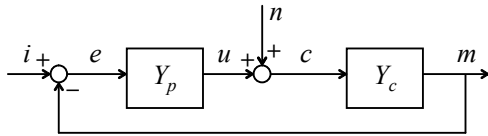
Keywords: manual control theory, human-machine systems, hands-on experience, active learning, McRuer Crossover Model

1. INTRODUCTION

There has been extensive effort to improve the effectiveness of instructional methods in engineering courses. Many have proposed the use of simulation software as a method of active learning, particularly in the field of control engineering [1]–[6]. Although the effectiveness of behavioural activity (e.g., hands-on activity, discussion, and free exploration) as an instructional method has been criticised [7], others have shown that active learning can positively influence students' attitudes and achievements compared to passive lectures [8]. A six-thousand-student survey by Hake [9] showed that courses in introductory physics which made substantial use of interactive-engagement methods scored two standard deviations higher on a test of problem solving than courses which made little or no use of such methods. A study of Thornton and Sokoloff [10] showed that active learning by means of computer-based tools significantly improved students' conceptual understanding of Newton's laws of motion. In a review on active learning, Prince [11] concluded that although the results vary in strength, broad support exists for all forms of active learning they examined, namely in-lecture student activity, student engagement, collaborative learning, cooperative learning, and problem-based learning.

Stappers et al. [12] developed an interface for teaching manual control theory. The interface combined a game-like simulation of a motorcycle with reflective theory-like linear gauge controls. The motorcycle could be steered for 0 up to 4th order of control. Initial testing of Stappers et al. indicated that the interface stimulated the students to "play around" and improved their understanding of manual control theory.

The present paper describes the results of integrating hands-on experience of manual control as part of an engineering course on human-machine systems. Focus is on the McRuer Crossover Model (MCM) [13], which is one of the most important models in the field of human-machine systems [14]. The MCM is a mathematical function that uses control-theoretic terms to describe how humans use feedback in a manual control task (figure 1). Human control is quantified in terms of a gain and a time delay, and can be judged in terms of control bandwidth and phase margin. The aim of assignment was to increase students' understanding of manual control theory.



Model of one-dimensional continuous control

The MCM can be described using a one-dimensional compensatory tracking task, as illustrated above. The human, modelled as a linear system Y_p , generates a control response c . This response is input to the controlled element Y_c , the position of which is represented by m . The human is continuously presented with an error signal (e), which is the difference between i and m . The system input, also referred to as the forcing function or the reference signal, is represented by i (It is possible to disturb Y_c as well). The remnant n represents the difference between the predicted control response u and the experimentally measured control response c . Types of displays other than compensatory can also be defined. During pursuit tracking, for example, both the actual (m) and desired path (i) are presented to the human.

Movie of 10-s compensatory tracking task with a first-order controlled element:

<http://www.anualmanual.org/MMSlab/Compensatory.zip>

The MCM (Equation 1) describes an invariant relationship at the aggregate open loop (human + controlled element) Y_{OL} [13]:

$$Y_{OL}(j\omega) = Y_p Y_c \doteq \frac{\omega_c e^{-j\omega\tau_e}}{j\omega}; \text{ near } \omega_c$$

Equation (1)

with j denoting complex number and ω the frequency (rad/s). Two model parameters describe the open-loop control behaviour, namely the crossover frequency ω_c and the effective time delay τ_e :

- 1) ω_c represents the open-loop gain. It provides a measure of the frequency band of the forcing function (or disturbances) that the human can follow (or suppress). For minimum error, the human should adopt an optimal ω_c . When ω_c is low, errors will not be diminished rapidly and the human-machine system will be sloppy and slow-to-respond. Increasing ω_c improves tracking accuracy but at the cost of a diminishing phase margin. Therefore, there is an upper limit to ω_c .
- 2) τ_e represents an aggregate approximation of all time delays in the open-loop. For minimum error, a low τ_e is beneficial. An increase of τ_e reduces the phase margin, which forces the human to reduce the gain ω_c . τ_e is determined by the human's perceptual and information processing delays, as well as high-frequency neuromuscular lags.

Movie of increasing ω_c while keeping τ_e at 0.3 s: <http://www.anualmanual.org/MMSlab/Crossovermodel1.zip>

Movie of increasing τ_e delay while keeping ω_c at 2 rad/s: <http://www.anualmanual.org/MMSlab/Crossovermodel2.zip>

The red line represents the closed-loop response; the black line represents the open-loop response.

The MCM predicts that the human acts as an optimal controller to satisfy the demands for minimizing error within stability constraints, that is, the open-loop has the characteristics of a “good servo”. The integral $1/j\omega$ in the open-loop ensures that the amplitude ratio is high for a large frequency band, implying that errors are followed accurately. Moreover, the integral property ensures that the amplitude ratio is less than 1 before the phase margin becomes negative, implying that stability requirements are satisfied. The describing function Y_p has the form of a gain, a time delay, a lead element reflecting anticipation, and a lag element reflecting smoothing. According to the MCM, humans adapt their controller behaviour in three ways:

- 1) The human can adapt his/her lead and lag terms to achieve the open-loop integrator characteristic according to Equation 1 (at least in the frequency region around the crossover frequency). This means that when the human needs to control a double integrator, for example, he/she will behave like a differentiator.
- 2) The human can actively change how strongly he/she responds to errors, thereby influencing the crossover frequency.
- 3) The human can change parts of his/her time delay in responding or can change the tightness of the grip on the controls, thereby influencing the τ_e .

The human controller is also affected by environmental, operator-centred, and procedural variables, but these are not explicitly modelled in the MCM. Operator-centred variables comprise, but are not limited to, motivation, fatigue, and training [13].

FIGURE 1. The McRuer Crossover Model explained, with examples.

2. HOMEWORK ASSIGNMENT

This section describes how the homework assignment was incorporated in the human-machine systems course.

2.1 Performing the homework assignment

MSc students engaged in two 2-hour lectures on manual control theory within a 13-lecture course on human-machine systems. Manual control theory was occasionally repeated during other lectures of the same course, as well as during a summarizing lecture. The course featured a homework assignment on manual control theory in which students could participate voluntarily. The homework was placed on the electronic blackboard of the course right after the first lecture on manual control. The students were asked to hand in the assignment up to two weeks after the second lecture on manual control. Students who successfully completed the assignment (more than 55% correct answers) gained one credit point for their final grade of the human-machine systems course.

In the homework assignment, students performed eight 40-s one-dimensional tracking tasks and two target-acquisition tasks (table 1). Tasks A, B, and C aimed to provide an understanding of how order of control affects tracking accuracy. Tasks C, D, and E aimed to show the effect of various displays, and tasks F, G, and H were included to teach how different characteristics of a control system affect human control when the order of control remains constant. Tasks I and J did not focus on MCM, but on Fitts' law [15] instead, and aimed to teach how Fitts' law applies for different dynamics of the controlled element.

The tasks were mouse-controlled and were performed using the dedicated software named MMSlab2. MMSlab2 includes a visual interface for tracking and target acquisition tasks (figure 2), replicating the early work of Duane McRuer and his co-workers in the 1960s. An error symbol was displayed as a green cross moving on a black background. The target was represented by a white square fixed in the middle of the screen. For each of the tracking tasks (A–H), the students were requested to obtain an as low root mean squared error (*RMS Error*) as possible, that is, to position the error symbol in the centre of the white box as accurately as possible. For the target-acquisition tasks (I, J), the students had to position the green vertical line on the white square as quickly as possible. Each target-acquisition task consisted of 25 step responses. The students were encouraged to perform multiple tries of each task to improve their scores.

Task	Display	Controlled element dynamics	
A	Compensatory	1/s	First-order control (velocity control)
B	Compensatory	1	Zero-order control (position control)
C	Compensatory	1/s ²	Second-order control (acceleration control)
D	Compensatory with first order quickening	1/s ²	Same as task C, but here a quickening display was used, which is a type of predictive display [16]
E	Pursuit	1/s ²	Same as task C, but here a pursuit display was used
F	Compensatory	1/s with 0.2-s delay	Same as task A, but here the velocity of the controlled element was determined by the mouse position delayed with 0.2 s
G	Compensatory	5/s	Same as task A, but here the system responded five times more sensitively
H	Compensatory	-0.5/(0.5 - s)	Inherently unstable system resembling the characteristics of an inverted pendulum
I	Target acquisition	1	Zero-order control (position control)
J	Target acquisition	1/s	First-order control (velocity control)

TABLE 1. Displays and dynamics of the controlled element of the eight tracking and the two target-acquisition tasks.

The interface of MMSlab2 contains menus with information and choices about the input (e.g., tracking mode, graphics resolution) and output (e.g., statistics and scores, frequency analysis, raw data) signals, the forcing function settings, and the system settings (e.g., order of control). At the end of each task, graphs with the time history of all signals (forcing function, error, and output) as well as Bode plots were provided, so that the student could reflect on his or her performance.

The forcing function (figure 3) consisted of the sum of 10 sine waves of different frequencies, amplitudes, and phase shifts. Generally, when more than five sine functions are used, the signal appears random, preventing that the human can predict the perturbation [16].

The tasks were accompanied by 16 questions which students had to answer using the theory taught during the lectures, the original article of McRuer and Jex about the MCM [13], and the experience that they had gained by executing the tasks. The questions aimed to make the students think about their control performance and behaviour, and to link it to the manual control theory. Questions were, for example, “After completing a task, MMSlab2 shows you plots of your performance. Provide the bode plots containing transfer functions of *pilot*, *system*, and *Open Loop* of tasks A, B, and C. Qualitatively describe the differences between the three bode plots using the McRuer Crossover model”, “What are the approximate Crossover frequencies and phase margins for tasks A, B, and C?”, and “Describe how the Crossover frequency relates to *RMS Error*.”

The students were asked to send their answers electronically to the lecturer, together with the recorded data of the trial of their best score (i.e., their lowest *RMS Error*) for each task.

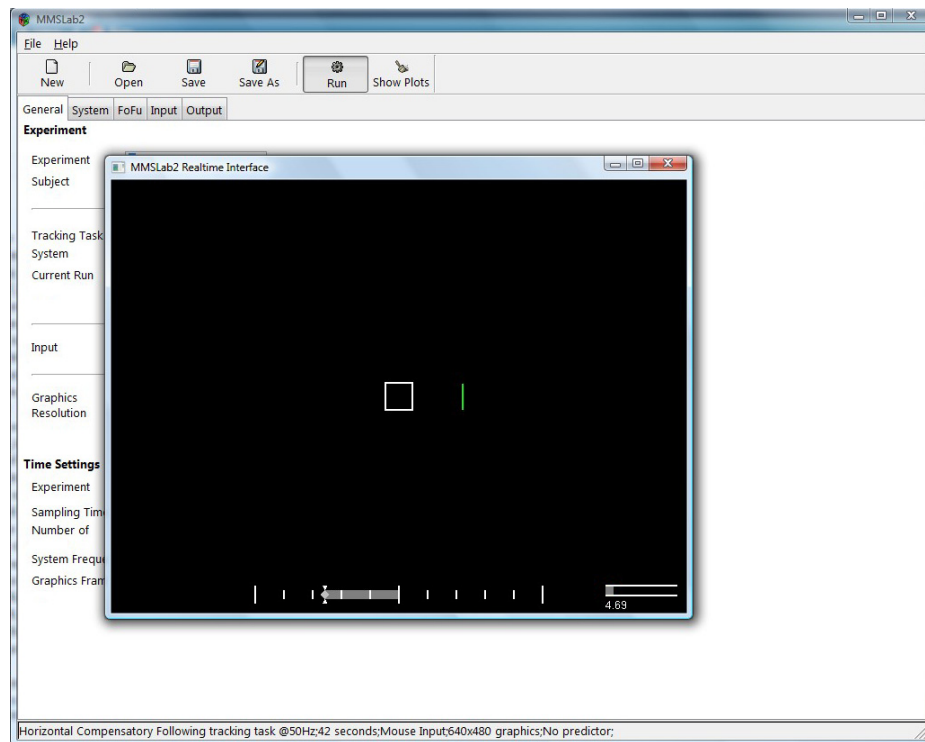


FIGURE 2. Screenshot of the MMSlab2 interface. The bottom bar represents the mouse position (on a scale from -1 to 1). With a compensatory display, the white box is centred of the screen. The green vertical line segment represents the error symbol; it can move horizontally from the left (-1.1) to the right (+1.1) of the screen.

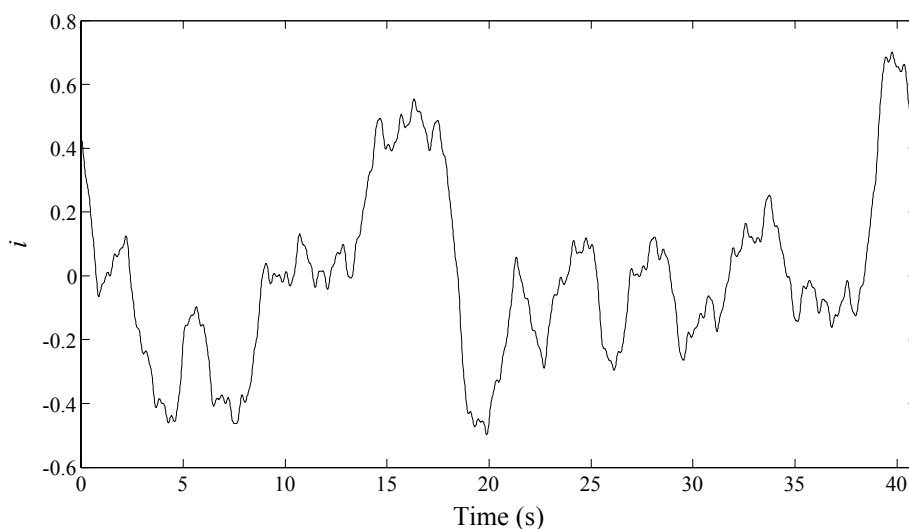


FIGURE 3. Forcing function (i) generated by adding 10 sine waves. This forcing function was used in all tracking tasks (tasks A–H).

2.2 Processing the data

For each of the tasks A–H and for each of the student datasets, the lecturer performed a discrete Fourier transform on the recorded mouse position (c) and the error signal (e). The ratio between these two provided an approximation of the human transfer function (Y_p). For each task and student, the following measures were calculated:

- *RMS Error*, the root mean squared error; a measure of tracking accuracy.
- *SD Input*, the standard deviation of the mouse position; a measure of control activity.
- ω_c , the crossover frequency approximated by fitting the MCM on the amplitude ratio of c/e .
- τ_e , the effective time delay approximated by fitting the MCM on the phase shift of c/e .

Because the MCM is valid only around the crossover frequency, fitting of the MCM was done on the nearest four frequency points around the point where the amplitude ratio crossed 1.

2.3 Presenting the results of the data analysis

The results of the data analysis were presented during a 30-min lecture given one week after the assignment deadline. The answers to all 16 questions were covered in that lecture. This section describes the results related to tasks A, B, and C as presented during the lecture.

The *RMS Error* for tasks A, B, and C was presented (figure 4). Students were able to see that, for everyone, *RMS Error* was lowest for zero-order-control (task B) and highest for second-order-control (task C). This difference was linked to the theory: control of a second-order element requires anticipation of the future position of the controlled element by inferring its velocity.

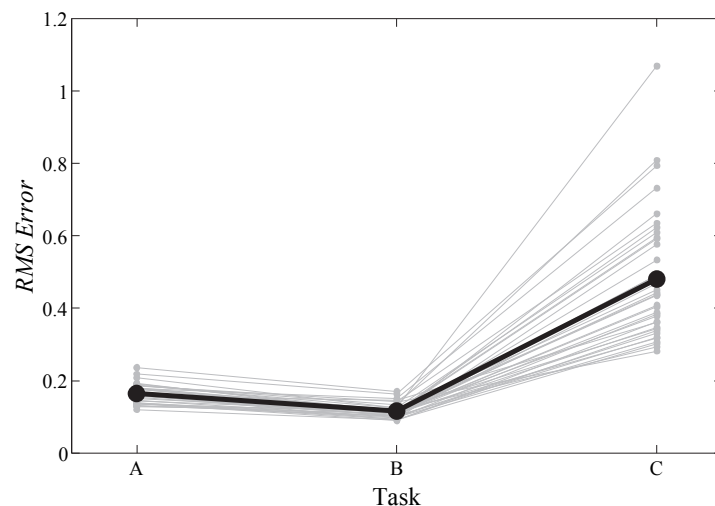


FIGURE 4. *RMS Error* of each student on tasks A, B, and C. The bold line represents the mean of students. Note. $n = 32, 37$, and 36 for tasks A, B, and C, respectively, due to missing data for tasks A and C.

To relate the order of control with the mouse movement, the lecturer presented a graph showing *RMS Error* as a function of the *SD Input* for all students and tasks (figure 5). The students had already explained the meaning of *SD Input* in the first question of the assignment. Clearly, the mean *SD Input* was largest for second-order-control, indicating that this task involved large mouse movements. It was explained that there were considerable individual differences; students could have acquired low *RMS Error* either with gentle pulse-like control (low *SD Input*) or with bang-bang-like control (high *SD Input*). For zero-order-control, on the other hand, the variation of *SD Input* was small because the mouse position (c) proportionally determined the position of the controlled element (m); therefore, there was only one effective input strategy possible, namely mimicking the forcing function (i) as closely as possible.

The Bode plots of tasks A, B, and C were also presented (figure 6). It was pointed out that, in all three orders of control, the MCM reliably applied in the crossover region, whereas individual variability increased for frequencies well below and above the crossover frequency. In one of the questions of the assignment, students had been asked to elaborate on their own Bode plots. The lecturer explained that, for first-order-control (figure 6(a)) and in accordance with the MCM predictions, the human acted proportionally to different frequencies in the error signal, whereas, as also predicted by the MCM, for zero-order-control (figure 6(b)), the strategy of

generating lag was adopted. This means that the human controller particularly responded to the lower frequencies and that the rate of change of control movement was approximately proportional to error. For second-order-control (figure 6(c)), model fit was poorer which is not surprising, since varying control strategies were used. The second-order system was difficult to control, as also evidenced by the very low phase margin. Even so, it could be clearly inferred that the human acted appropriately by generating lead; that is, responding to the middle and higher frequencies.

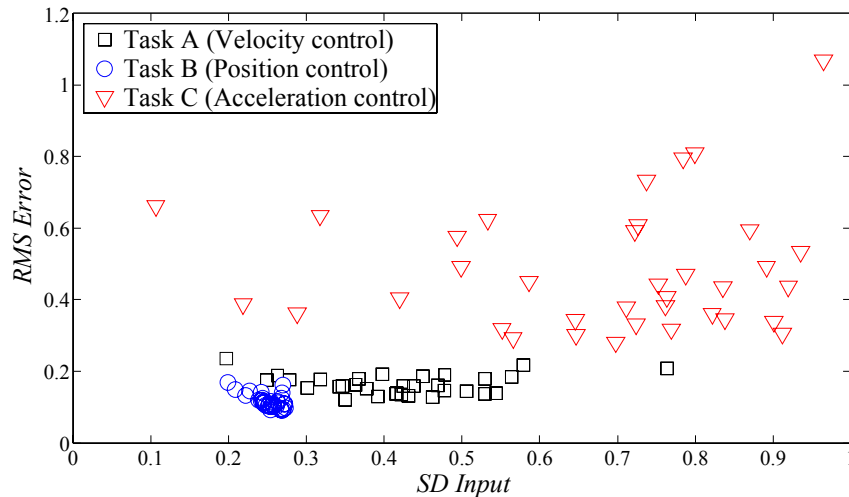


FIGURE 5. *RMS Error* versus *SD Input* for students on tasks A, B, and C.

Note. $n = 32, 37$, and 36 for tasks A, B, and C, respectively, due to missing data for tasks A and C.

Figure 7 shows the crossover frequency versus *RMS Error* for each student on task A. In accordance with the MCM predictions, lower *RMS Error* was associated with a higher crossover frequency ($r = -.57, p = .001$). Moreover, it was found that a higher effective time delay corresponded to higher *RMS Error* ($r = .80, p < .001$).

In short, by performing and analyzing tasks A, B, and C, students realised that they all were able to master zero and first orders of control. Controlling the second-order system was more difficult, and the results showed poorer fit to the MCM.

3. EVALUATION OF THE HOMEWORK ASSIGNMENT

The homework assignment was evaluated by means of a questionnaire as well as by analyzing the students' scores on the written exam. This exam was taken after completion of all lectures, 1.5 months after students had handed in their homework assignment. The exam was graded by an expert who had not been involved in the homework assignment.

In total, 50 students participated in the course. Thirty-two of them completed the homework assignment and the written exam, 5 completed the assignment but did not participate in the exam, and 13 participated in the exam without having completed the assignment.

3.1 Questionnaire

A questionnaire was handed out during the written exam, offering the students the opportunity to assess the homework assignment after having completed the human-machine systems course. The questionnaire investigated the students' opinion on the contribution of the assignment and the presentation lecture to understanding the theory. The questionnaire also investigated whether students found that they had become aware of the relevance of operator-centred variables, and whether the assignment increased their interest in manual control theory. The lecturer of the manual control theory was not present during the exam.

The questionnaire contained the following seven questions:

- Q1. How would you evaluate the value of the assignment in improving your understanding of manual control? (10-point scale with anchors at 1 (*Poor*) and 10 (*Excellent*))
- Q2. How would you evaluate the value of the in-class presentation/reflection on the results of the assignment in improving your understanding of manual control? (10-point scale with anchors at 1 (*Poor*) and 10 (*Excellent*))

- Q3. Were the concepts elaborated in the assignment well integrated with those taught in the lectures on manual control theory? (10-point scale with anchors at 1 (*No*) and 10 (*Yes*))
- Q4. One of the aims of the assignment was to let you become aware that mathematical equations of human behaviour (such as Fitts' law / the McRuer Crossover Model) should not be taken literally. Individual aspects, such as training, concentration, or chance effects, can play an important role in how humans behave, and how well the model fits the data. Did the assignment help you to become aware of this? (10-point scale with anchors at 1 (*No*) and 10 (*Yes*))
- Q5. Did the assignment increase your interest in manual control theory? (10-point scale with anchors at 1 (*No*) to 10 (*Yes*))
- Q6. I found the assignment (a) *too easy*, (b) *too difficult*, or (c) *just about right*
- Q7. I found the amount of time I had to spend on the assignment (a) *too little*, (b) *too much*, or (c) *just about right*

The questionnaire also offered the opportunity to provide suggestions.

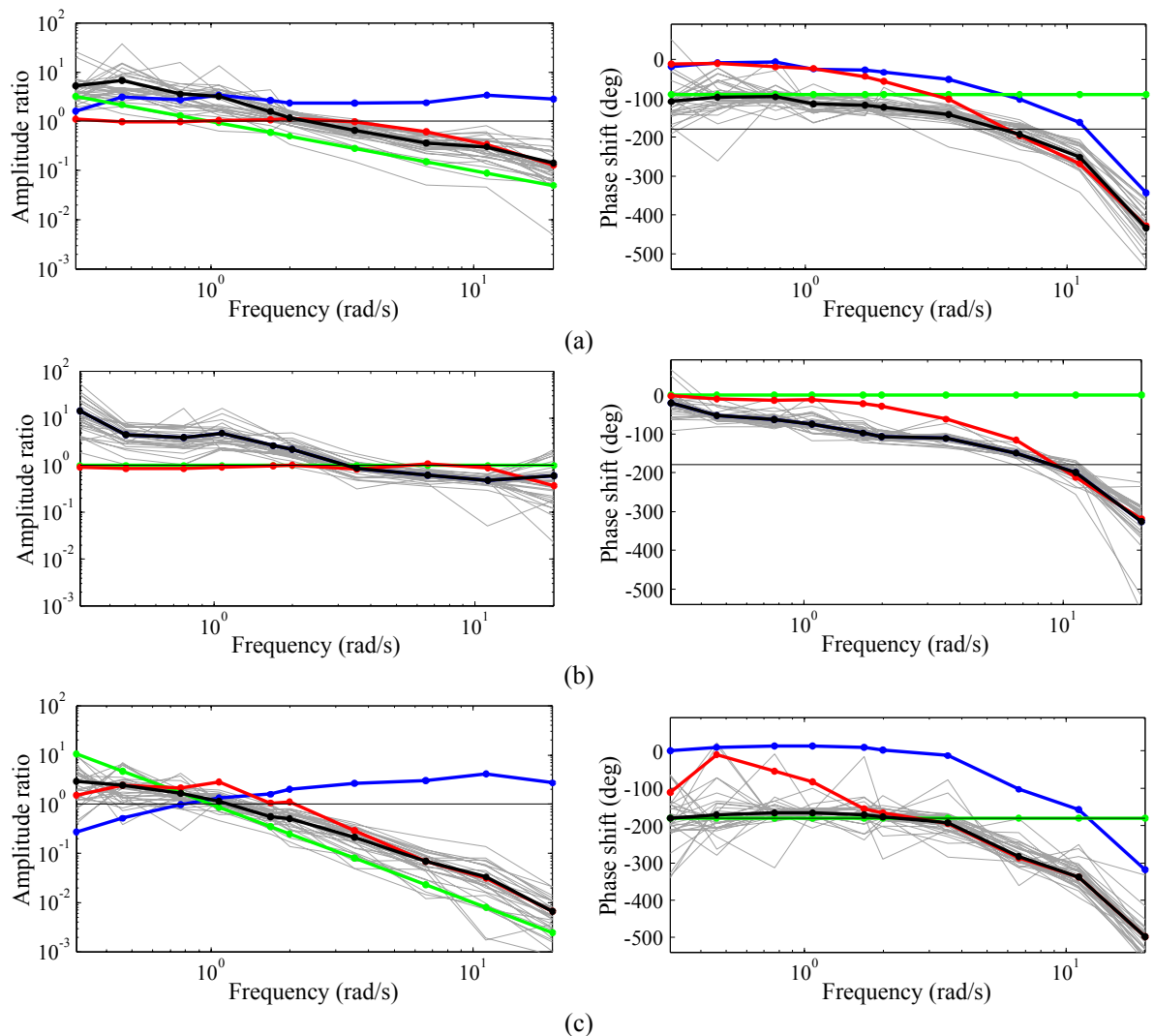


FIGURE 6. Bode plots of transfer functions of controlled element (Y_c , green), human (Y_p , blue), open-loop ($Y_p Y_c$, black), and closed-loop ($Y_{OL}/(1+Y_{OL})$, red). (a) Task A (velocity control), (b) Task B (position control), (c) Task C (acceleration control). Bold lines represent the mean amongst students per frequency point. Thinner grey lines represent the estimated open-loop transfer function of individual students.

Note. The human contribution (blue line) is not visible in (b): it lies exactly underneath the black line, since the gain of the controlled element equalled 1.

Table 2 shows that the mean ratings on Q1–Q5 were above 7. Students particularly appreciated the value of the assignment for improving their understanding of manual control (Q1) and for understanding that models of human behaviour should not be taken literally (Q4).

Table 3 shows that almost all students considered the difficulty of the assignment as just about right (Q6). Moreover, most students indicated that the amount of time that they had to spend on the assignment was just about right (Q7). However, seven students reported that they had to spend too much time on the assignment.

16 of 32 students had used the opportunity to provide written suggestions: 6 students suggested less tracking tasks and more in-depth theory/examples, 4 students suggested keeping the assignment in the course, 2 students would prefer other means of controlling the symbols such as two-dimensional tasks, and 2 students reported that they needed additional help to understand the assignment. The rest of the provided suggestions were not related to the assignment, but to the other lectures of the human-machine systems course.

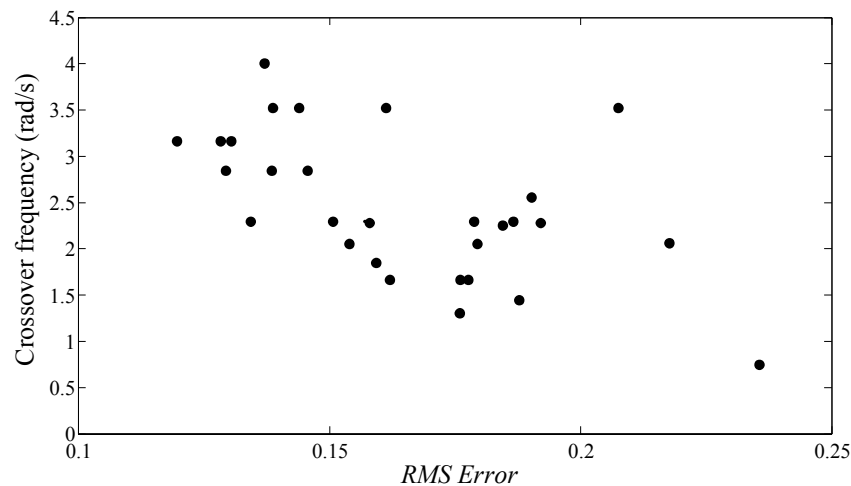


FIGURE 7. Crossover frequency versus *RMS Error* of each student (task A).
Note. $n = 30$; there were 7 missing values due to missing data or inappropriate model fit.

	Mean (SD)
Q1	7.80 (1.53)
Q2	7.06 (1.50)
Q3	7.28 (1.71)
Q4	7.56 (1.39)
Q5	7.00 (1.98)

TABLE 2. Means and standard deviations (SD) of questionnaire responses Q1–Q5 ($n = 32$).

	a	b	c
Q6 ^a	0	1	30
Q7 ^b	0	7	23

TABLE 3. Number of students per answer of questionnaire Q6 and Q7 ($n = 32$).
^aOne missing value. ^bTwo respondents encircled both b and c and were therefore excluded.

3.2 Exam results

The written exam comprised 13 questions. The first two questions (E1, E2) were about manual control theory. E1 was a multiple-choice question about remedying a pilot-induced oscillation. In E2, students had to draw a Nyquist plot to justify their answer in E1. Note that the homework assignment featured Bode plots instead of Nyquist plots; Nyquist plots had been taught by another lecturer. The remaining 11 questions of the exam (E3–E13) were not related to manual control theory.

The mean scores of the homework assignment and the questions of the written exam are shown in table 4. Students who had completed the homework assignment performed significantly better on E2 than students who had not completed the homework assignment. No difference was found for the mean score on the questions that were not related to manual control theory (E3–E13).

3.3 Correlations between scores

Table 5 shows the correlations between the *RMS Error*, the assignment grade, and the exam scores. There was no significant correlation between the homework assignment grade and the exam question scores. However, *RMS Error* had a significant negative correlation with the homework assignment grade, as well as with the questionnaire mean score. In other words, students with better tracking scores (i.e., lower *RMS Error*) had better answers to the questions of the homework assignment and rated the assignment higher. Note that the homework assignment was not judged on tracking scores because the assignment grade should not depend on a student's talent in manual control. A likely explanation is that students who were more motivated obtained a higher grade and practised more for lower *RMS Error*.

	Homework assignment (<i>n</i> = 32)	No homework assignment (<i>n</i> = 13)	
	Mean (SD)	Mean (SD)	<i>p</i> (<i>t</i> test)
Homework assignment (%)	74 (16) ^a	–	–
Exam question 1 (E1) (%)	81 (40)	62 (51)	.171
Exam question 2 (E2) (%)	73 (32)	44 (41)	.015
Exam question 3–13 (E3–E13) (%)	53 (20)	54 (24)	.869

TABLE 4. Mean and standard deviations (SD) of exam scores as a function of whether the students had completed the homework assignment.

Note. The values represent mean percentages of correctly answered questions.

^a *n* = 37. The pass rate of the homework assignment (more than 55% correct answers) was 89%.

	1	2	3	4	5
1. MMSlab2 mean <i>z</i> -transformed <i>RMS Error</i> among tasks A–H	–				
2. Homework assignment	-.44*	–			
3. Exam question 1 (E1)	-.11	-.16	–		
4. Exam question 2 (E2)	-.14	.15	.41*	–	
5. Exam question 3–13 (E3–E13)	.24	.12	.23	.27	–
6. Questionnaire mean Q1–Q5	-.39*	.54*	-.3	.36*	.17

TABLE 5. Pearson pairwise correlations between scores (multiplied by 100).

* *p* < .05.

4. DISCUSSION

Integrating the homework assignment in the human-machine systems course yielded beneficial results. The students found it helpful in understanding manual control and in realizing that mathematical models of human behaviour should not be taken literally.

The exam scores on questions relevant to manual control theory were significantly higher for the students who had completed the assignment than it was for students who had not completed the assignment. However, it is not possible to establish a causal relationship between participation in the homework assignment on the one hand and the exam scores on the other, because students were not randomly allocated to the assignment. Moreover, it was not known which students were present at the lectures, and why students chose to (not) participate in the assignment. Nevertheless, the students who had not completed the homework assignment scored poorer only on the exam questions related to manual control theory and not on the other exam questions, providing support for a causal effect.

There are some limitations to the present data. Inherent to a homework assignment, the order of the tasks was not randomised and students performed the tasks at home under uncontrolled conditions. Each student could practise as much as he or she wanted and students used different mouse devices. Moreover, results are dependent on the forcing function that was used: the present forcing function was not squared, but attenuated at higher

frequencies. Therefore, high frequency human control is probably estimated inaccurately in figure 6. This, however, is not problematic because the MCM is valid around the crossover frequency only. Moreover, none of these issues invalidates the fact that theoretically sound results were presented during the lecture, and that students could reflect on individual differences in manual control.

For active learning to be effective, it is important that the students are not only behaviourally active but also cognitively active [7]. For that reason, the assignment included questions requiring an understanding of manual control theory, followed by a lecture presenting the results of students' performance and behaviour to increase cognitive awareness. Nonetheless, the questionnaire responses showed that a number of students wanted more in-depth information and less tracking tasks. Therefore, it is recommended to maintain sufficient theoretical depth when including hands-on experience in an engineering course.

Acknowledgement

MMSlab2 has been developed by Coen de Visser, based on earlier work of Max Mulder. The authors thank these persons for their support.

References

- [1] W. Schaufelberger, "Design and implementation of software for control education," *IEEE T. Educ.* 33, 291–297 (1990).
- [2] M. Aldeen and R. Oxbrow, "Multimedia enhanced teaching of control systems", *IEEE Int. Conf. Multi Media Eng. Educ.*, 363–371 (1996).
- [3] V. Kroumov *et al.*, "Interactive learning tools for enhancing the education in control systems", *33rd Annual Frontiers in Education FIE 2003* 1, 23–26 (2003).
- [4] J. Lee and J.-T. Huang, "Motor drive control system for education and research", *Proc. 1995 Int. Conf. Power Electronics and Drive Systems* 1, 502–508 (1995).
- [5] H. Björnsson, "Editorial: Simulation in engineering education", *Eur. J. Eng. Educ.* 19, 3–5 (1994).
- [6] M. Ronen *et al.*, "Teaching and learning basic electronics with a professional circuit analyzer program", *Eur. J. Eng. Educ.* 20, 487–498 (1995).
- [7] R. E. Mayer, "Should there be a three-strikes rule against pure discovery learning? The case for guided methods of instruction", *Am. Psychol.* 59, 14–19 (2004).
- [8] C. C. Bonwell and J. A. Eison, "Active learning: creating excitement in the classroom", *ASHEERIC Higher Education Rep. No. 1*, George Washington University, Washington, DC (1991).
- [9] R. R. Hake, "Interactive-engagement versus traditional methods: a six-thousand-student survey of mechanics test data for introductory physics courses", *Am. J. Phys.* 66, 64–74 (1998).
- [10] R. K. Thornton and D. R. Sokoloff, "Assessing student learning of Newton's laws: The force and motion conceptual evaluation and the evaluation of active learning laboratory and lecture curricula", *Am. J. Phys.* 66, 338–352 (1998).
- [11] M. Prince, "Does active learning work? A review of the research", *J. Eng. Educ.* 93, 223–231 (2004).
- [12] P. J. Stappers *et al.*, "Learning control theory by experiencing dynamics", In H. Aoki (Ed.), *6th Asian Design International Conference. Journal of the Asian Design International Conference*, Tsukuba: Institute of Art and Design, University of Tsukuba (2003).
- [13] D. T. McRuer and H. R. Jex, "A review of quasi-linear pilot models", *IEEE Trans. Hum. Fact.* 8, 231–249 (1967).
- [14] N. Moray, "Ergonomics: Major writings", London: Routledge/Taylor & Francis (2005).
- [15] P. M. Fitts, "The information capacity of the human motor system in controlling the amplitude of movement", *J. Exp. Psychol.* 47, 381–391 (1954) (Reprinted in *J. Exp. Psychol.: General* 121, 262–269 (1992)).
- [16] R. J. Jagacinsky and J. M. Flach, "Control theory for humans: Quantitative approaches to modeling performance", Mahwah, NJ: Lawrence Erlbaum Associates (1993).