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ANALYSIS OF FACTORS INFLUENCING THE PERFORMANCE OF CADETS TRAINED TO OPERATE LOGGING MACHINERY

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The paper analyzes factors that affect human productivity when operating logging machinery. It assesses how training machines and simulators influence the results of training. The paper further describes novel methods for testing the psychophysiological traits of human beings that enable evaluating the precision of guiding the implement of the logging machine in horizontal plane as well as by boom extension. The results of testing a group of cadets are presented herein. The research team found the boundaries of the test results obtained by the author-developed methods as compared against the results of final examinations held to complete the logging machinery operation training. The paper will be of interest for human- machine interaction and logging machine training specialists.

Keywords: man-machine systems, industrial control, automatic control, machine, operator, performance, harvester, simulator

1 INTRODUCTION

Improving a human operator's performance might be quite challenging. From the system approach standpoint, an operator is a complex, dynamic, stochastic, non-linear, non-stationary, self-organizing open system. This gives rise to the problem of finding the informative parameters for accurate and reliable assessment of how the system performs as a whole.

2 RELEVANCE

When analyzing the human operator as a part of the logging machinery control system, researchers often rely on an anthropocentric rather than machine-centric approach [1].

In general, logging performance is based on three core factors: wood parameters, machine specifications, and human operator performance.

Today, the operator is deemed the most important factor and the key driver of performance improvement in wood harvesting [2]. This is due to the fact that harvester performance has in fact been at its potential peak since the 1960s [3].

Human operators working on modern technological equipment are challenged to control ever more objects and their parameters, to handle ever greater scope of sign-conveyed information, to manage faster and more complex control processes, which requires more accurate human action and faster response while also resulting in greater responsibility for such action [4].

This rising bar of human operator performance has led to the emergence and development of fundamentally novel forms and technologies of staff training [5], in particular to the use of virtual and augmented reality [6], cognitive and biomechanical operator support [7, 8].

Simulators and training machines have found extensive use in logging machinery operator training.

H Ovaskainen shows that in general, using a simulator is identical to the processes of real-world, physical equipment [9].

Operator training programs include ever more simulator hours. The positive effects of harvester simulation, namely more productive work and greater self-confidence in operating a real harvester, have been noted in many studies [10]. One benefit of simulation is that it enables the trainee to repeatedly practice their actions in the same situation. As a result, each operator makes their own individual algorithm, though its mileage may vary at different steps. Nevertheless, the common belief is that a good operator performs well at any step [11].

Simulator training is particularly important for countries or regions where the use of actual training equipment is not possible.

Freedman P. states that 25 hours of such training improves cadets' performance by 15% and cuts the equipment repair costs by 30% [12].

Hoss reports that 30 hours of simulator-based training corresponds to 10 hours of work with an actual harvester. However, simulators are associated with significantly lower equipment repair costs and training costs while being safer to train on. All of this speaks demonstrates the effectiveness of simulation in early training [13].

Yates found out that simulator-trained cadets were twice as productive in the first week of switching to actual logging machinery [14].

However, the virtual simulator always provides a simplified version of the actual working environment, and this might result in the cadet being taught wrong working models even if the difference is imperceptible in reality. Apparently, it is critical to make a simulator adequate to the actual equipment, or it will yield an opposite effect.

There are studies that cover the accuracy of operation in virtual environments [15].

One relevant problem lies in modeling the accuracy of harvester head travel within the operating area. Simulating the boom travel where the tree is too close to the unit, which limits the head travel, remains an open issue as well.

3 STATEMENT OF PROBLEM

Analysis of studies that sought to evaluate the logging machine operation process shows that logging is a complex multifactorial process, and the performance of this type of human-machine systems is greatly affected by the human operator's psychophysiological traits. Lackluster professional training of operators or lack of experience may lead to errors that result in lower-quality work or even in an accident [16].

4 THEORY

To formalize and detail the training of logging machine operators, one needs to represent the logging machinery operation on a flowchart. Literature analysis shows that the operator performs the following steps when cutting wood to length:

1. Find the tree;
2. Position the logging machinery;
3. Aim the harvester head;
4. Process the tree.

For human-machine interaction, the most difficult part is to aim the head of the logging machine, i.e. to position the implement against the tree being worked on. That is because implement guidance requires very accurate control while providing limited visibility; besides, the operator has to be used to the dynamics of the equipment.

Since an incorrectly aimed head may actually damage the trunk, we propose presenting the guiding process as the flowchart shown in Fig. 1.

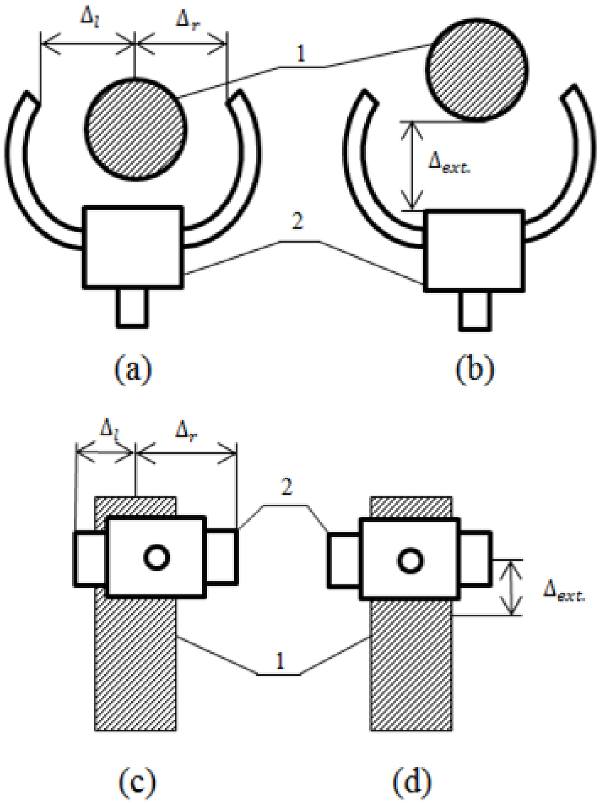

Figure 1. Head-to-tree guidance flowchart: (a) guiding the harvester in the horizontal plane; (b) guiding the harvester by boom extension; (c) guiding the forwarder in the horizontal plane; (d) guiding the forwarder by boom extension, where Δl, Δr are distances from the cutters to the trunk center, Δext. is the trunk-to-head distance, 1 is the tree trunk, 2 is the logging machine head (Complied by the authors)

Let us formalize these two problems as psychophysiological tests based on geometric primitives. Consider the method for detecting the accuracy of guiding the logging machine implement horizontally to the tree. In this test, the human operator sees a circle on the PC screen which has the target (2) and the movable point object (1) that travels on the circle as shown in Fig. 2.

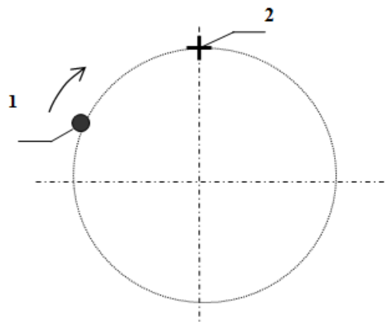

Figure 2. Testing procedure based on assessing the accuracy of guiding the logging machine implement horizontally to the tree (Complied by the authors)

When the moving point coincides with the target, the operator has to press STOP, which will stop the point and calculate the difference between its position and that of the target. Repeat the procedure as certain number of times and calculate the human reaction time T_r as the arithmetic mean by the formula:

$$T_r = \sum_{i=1}^{n} t_i \Big/ n, \tag{1}$$

where t_i is the ith point-target mismatch error, milliseconds; n is the number of times the point was stopped during the test.

For Stage 1, pressing STOP causes the point to pause and then resume moving on the circle; calculate the human reaction time T_r and notate it as T_{r1}. For Stage 2, pressing STOP does not cause the point to pause, and it simply continues moving; calculate the human reaction time T_r and notate it as T_{r2}.

The situational operation ability as then estimated as:

$$C = \left| T_{r1} / T_{r2} \right|. \tag{2}$$

Another test has been developed to assess the accuracy of guiding the logging machine implement to the tree. To assess such accuracy, the test takers were shown a circle on the PC screen with a round test object being placed inside that circle.

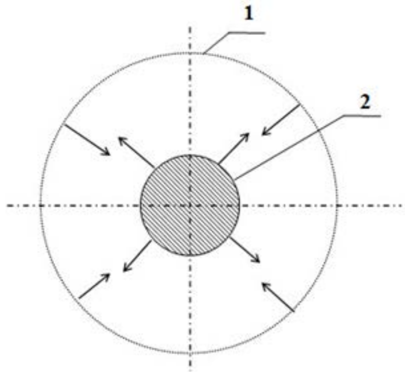

Figure 3. Testing procedure based on assessing the accuracy of guiding the logging machine implement by extension (Complied by the authors)

Fig. 3 shows the circle to be shown to the test taker, where 1 is a closed circle, the boundaries of which represent the target, with the diameter decreasing at a given rate; 2 is the test object that increases in diameter at a given rate.

The test object is thus growing larger while the closed circle around it is diminishing at the specified rate, which imitates movement towards the test taker. The task is to press the button when the circle and the object inside it become of the same size; this will stop the sizes from changing any further. The next step is to calculate the diameter difference between the circle and the test object; this indicates the reaction lag, if the sign is positive, or by preemptive reaction if the sign is negative. The next step is to calculate the reaction time T_r as the arithmetic mean by the formula:

$$T_p = \sum_{i=1}^{n} t_i \Big/ n, \tag{3}$$

where t_i is the ith circle-object mismatch error, milliseconds; n is the number of times the point was stopped during the test.

Sometime after, the test taker is shown both objects in their initial size; repeat the test a prespecified number of times.

Thus, the developed method for assessing the accuracy of guiding the logging machine implement to the tree by extension expands the capabilities of the method by finding the reaction time in a context where two objects are moving simultaneously in relation to each other.

5 EXPERIMENTAL RESULTS

To test the logging machine operation abilities by these methods, the research team invited 23 trainees aged 25 to 50 having normal or corrected vision.

To match the actual logging machine implement travel speed, the horizontal guidance accuracy test had the point moving at the same speed along the entire circle: 1 rad/s, the circle had a diameter of 200 mm.

In the extension accuracy test, the test object was growing in diameter by 100 pixels a second while the circle around it was diminishing at 10 pixels a second to simulate movement towards the test taker. The initial diameters were 100 pixels and 600 pixels respectively.

Depending on how well each member of the group passed the final exam, they were subdivided into two groups. Those who got an "A" in the exam were assigned to Group 1, while those who got a "B" were assigned to Group 2.

Fig. 4 shows the results of testing the group for horizontal guidance accuracy.

Non-parametric estimates were calculated to obtain group-wide scores:

pointwise estimate of the test result distribution median M;

confidence interval for the median [T1, T2], where T1 and T2 are the lower and the upper confidence boundaries, respectively, at 95%;

lower quartile (25% quantile) of the test results variation series QL;

upper quartile (25% quantile) of the test results variation series QH.

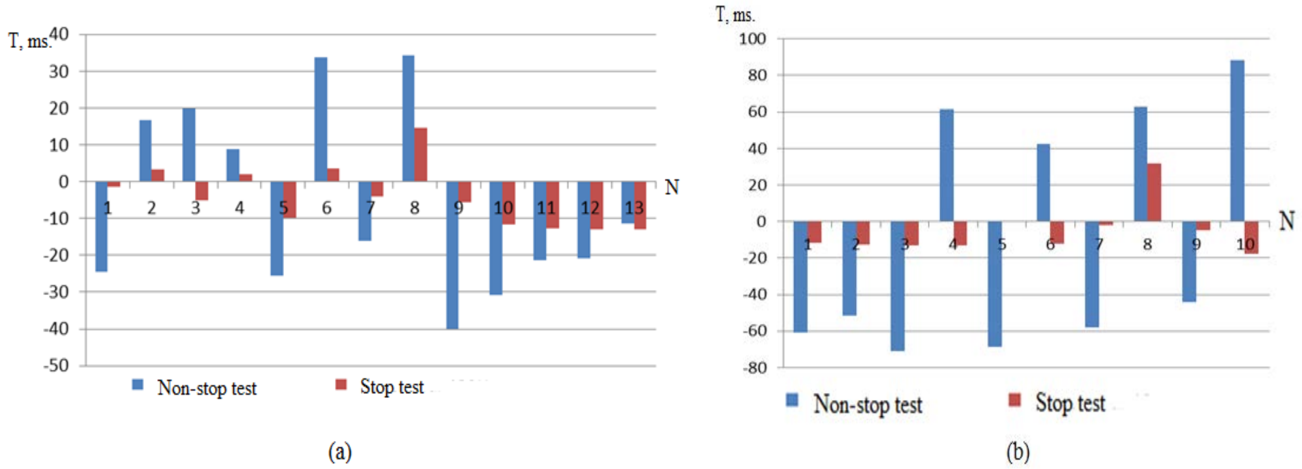

Figure 4. Distribution of test results: (a) Group 1, milliseconds; (b) Group 2, milliseconds; N is the person's number in the test group (Complied by the authors)

Table 1. Results of the statistical processing of horizontal implement guidance accuracy test results, 23 test takers, milliseconds

Time-based score	M	[T_1; T_2]	Q_L	Q_H
Non-stop test	-20.8	[-39.98; 19.88]	-44.02	33.76
Stop test	-5.61	[-12.8; -1.4]	-12.8	0.53

Fig. 5 shows the results of testing the group for extension guidance accuracy.

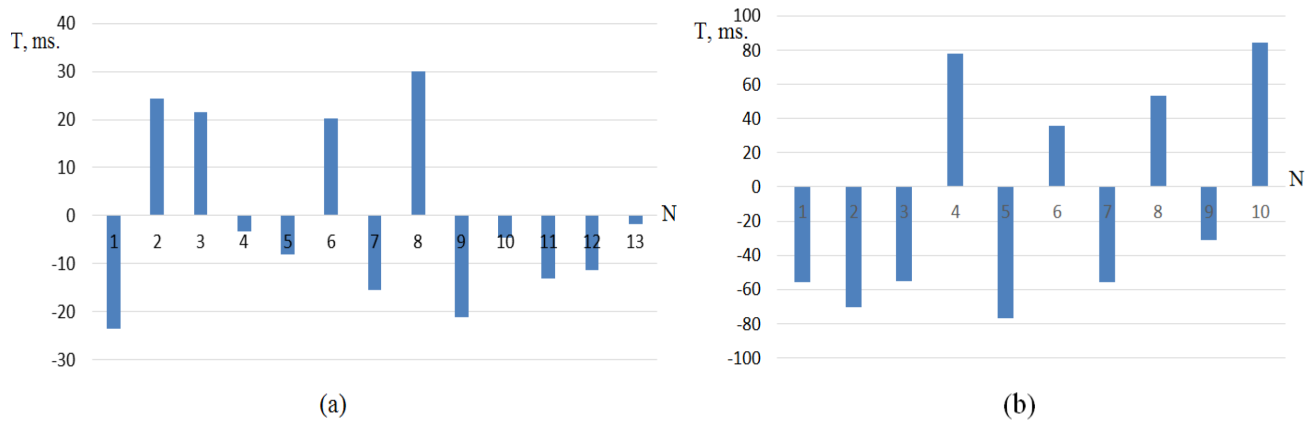

Figure 5. Distribution of test results: (a) Group 1, milliseconds; (b) Group 2, milliseconds; N is the person's number in the test group (Complied by the authors)

The same non-parametric scores were calculated as in the previous test.

Table 2. Results of the statistical processing of implement guidance-by-extension accuracy test results, 23 test takers, milliseconds.

Time-based score	M	[T_1; T_2]	Q_L	Q_H
Stop test	-8.12	[-23.5; 21.51]	-31.01	24.46

Using this data, let us build membership functions for test results / final exam results.

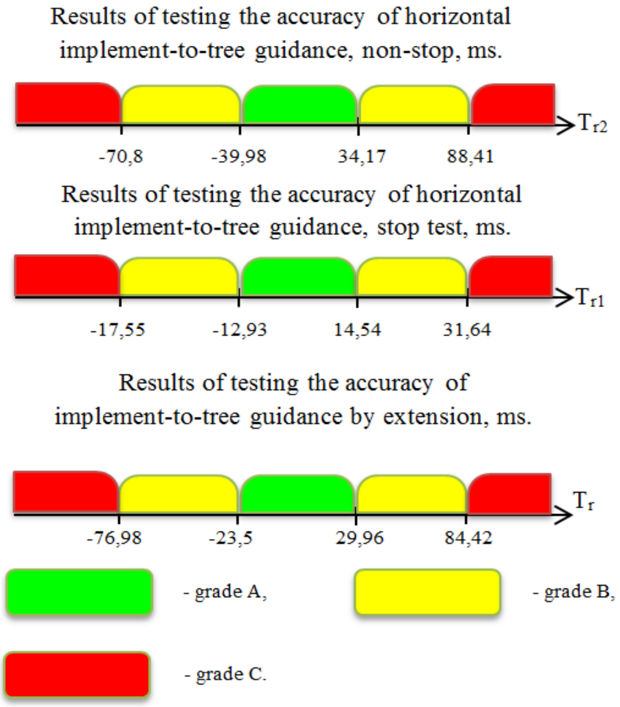

Figure 6. Test results/final assessment membership functions (Complied by the authors)

6 CONCLUSIONS

The collected data shows the limits of testing results in relation to the results of final exams of cadets who took courses on training with logging machines at the Volga State Technological University in Yoshkar-Ola. Thus, evaluation of the operator's control action development rate makes it possible to build a personalized approach to the training of logging machine operators. The proposed scheme of the professional training process for logging machine operators involving simulators and our test system on an exerciser is shown in fig. 7.

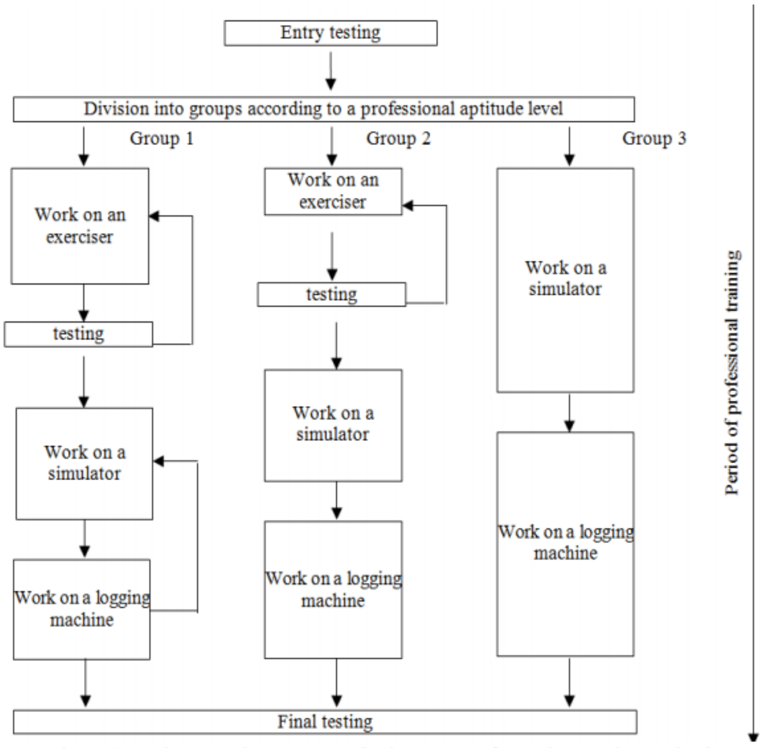

Figure 7. The scheme of the professional training process for logging machine operators (Complied by the authors)

It has been suggested that the training procedure be tailored based on the operators' degree of professional aptitude. In order to do so, the operators involved in the training process have been subdivided into three groups:

Group 1: operators with a professional aptitude level below 50%;

Group 2: operators whose professional aptitude level ranged from 50% to 75%;

Group 3: operators whose level of professional aptitude exceeded 75%

The peculiarity of this scheme is that a low initial level of the professional aptitude (Group 1) intends first of all development of the professionally important qualities using appropriate exercisers. Otherwise, as the practice proves, these trainees cannot develop professional skills and are dismissed. Work with our test system on an exerciser helps trainees to go to a more complicated stage of training, that is study of logging machine operation using simulators. Further research should be aimed at conducting experiments that increase the test base, and the introduction of fuzzy logic methods for classifying the degree of training of cadets.

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