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QUALITATIVE CONTROLLER

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This paper presents a qualitative controller design and evaluation of a balance control model. The human control of the reel on the moving bar is statistically and qualitatively analysed using the experimental results. The design of controller based on qualitative knowledge and the results obtained with the developed intelligent controller are satisfactory.

K e y w o r d s: intelligent control, qualitative controller, design; simulation, experiment

1 INTRODUCTION

Our research shows that conventional controllers are able to handle only the very limited interval for which they are designed. However, human beings often successfully handle the same task on a much bigger interval. Therefore we started an experiment using a laboratory balance model, with the aim of confirming this belief. We have tried to develop a controller with more human-like capabilities.

At the beginning, we analyzed human control to learn from it and to get results for final comparison. The next step was designing the controller. We carried out simulations using Matlab and also experimented in a real production plant. At the end, we evaluated our controller. It acted similar to a human being but has a similar disadvantage too: relatively big control error. However, we did reach a compact state space representation as well as a compact and fast program code for the controller. This requires less switching of the output and thus less energy than, for example, a fuzzy controller. The development process and the final qualitative controller are closer to expert systems technology than to fuzzy technology. The developed controller can be classified among intelligent control systems.

Intelligent control is a young discipline in the field of process control, marked by rapid development. Therefore, we must first define some basic concepts to make the text clearly understandable.

The term *conventional control* is used to denote the theories and methods that have been developed to control a dynamic system whose behavior is given by differential or difference equations.

The definitions of *intelligent control* can be derived from [1]:

– intelligence of the developed controller,
– the way in which biological systems perform a certain task,
– and the design of the controllers which perform tasks, usually performed by biological systems.

Why should we use intelligent control? Intelligent control is only an extension of conventional control. The methods of intelligent control have developed as a result of intensive attempts to solve problems that cannot be solved in a systematic way using mathematical modeling and differential equations.

Intelligent control is of interdisciplinary nature since it combines and extends the theories of system control, operational research and computer science. Apart from conventional control, it includes planning, learning, search algorithms, hybrid systems, diagnostics of errors and reconfiguration, Petri nets, neural networks and fuzzy logic.

One more difference between conventional and intelligent control should be noted. In conventional control, the controller and the controlled system are separated. The controller is designed for the given equipment. In intelligent control, the controller and the equipment cannot be separated easily. Control laws may be incorporated as component parts of the controlled system.

Definitions of intelligence differ strongly according to the field that discusses them. We can speak in terms of biological, psychological, and also engineering intelligence definitions. The most widely established is the approach that speaks of various kinds of human intelligence [2]. Intelligent systems can be described by understanding intelligence as the property of the system that becomes active when the procedures of attention focusing, combinatorial searching and generalization over the input information are used to generate the output. Thus, intelligence is inclined to reduce the complexity of mastering the controlled system. It increases functionality while reducing computation expense.

The structured nature of intelligence is very important. To master complex tasks, an intelligent system needs an adequate functional structure for efficient analyses and evaluations of control strategies and actions. Abstraction levels are used for reducing the complexity. The expression hierarchy refers to functional hierarchy, or to the hierarchy of the extent and resolution in the working space.

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The resolution of the control level is the size of the nonresolution zone for the representation of tasks, the model, the plan, or the law of the feedback loop. The resolution directly determines the computational effort. One level of resolution is not enough in complex systems and specific situations since the entire field of interest is usually large, and the final accuracy very high. First, the entire area of interest is treated at a much lower resolution. Only the subspace is treated at a higher resolution. Multilevel decomposition of the task is the result of sequential attention focusing. Sometimes the *expression abstraction* level is used instead of *level of resolution*.

Just like human intelligence, machine (artificial) intelligence can be understood as a vector with the following dimensions [3]: the processor's computation power, the number of processors, communications between processors, the size of the memory, memorizing functions, the mechanisms of knowledge representation, sensor resolution and processing, functional abilities, the ability to plan and predict, and the ability to learn.

Control methodology indicates a number of techniques used in the design and/or implementation of the controller for a dynamic system.

The controller design methodology of numerous intelligent control systems (fuzzy, neural, expert, learning, hierarchical intelligent controllers) is predominantly heuristic, based on the principles of artificial intelligence. Often intelligent controllers are designed to emulate some human functions in the complex dynamic system.

Two more definitions [1] of intelligent control methodology and an intelligent controller can also be found in literature:

A control methodology is *intelligent* if it uses biology based techniques and procedures (forms of representation and/or decision making) in the development and/or implementation of a controller for a dynamic system.

The physical device called a controller is intelligent if it has been developed and/or implemented using

– an intelligent control methodology, or
– a conventional control technique, so that it imitates/ implements the control functions that are usually performed by biological systems.

There is no clear line between conventional and intelligent controllers. As a rule, intelligent controllers include components of conventional controllers.

Usually the control plant is so complex that it is either impossible or inappropriate to describe it with a mathematical model. Analyzing is easier with higher level models. It is important to derive high level models so that only the essential information is active. It is evident from the experience gained that more can be acquired using abstractions than from designing and using more powerful computers.

We decided to build a qualitative plant model and thus designed a controller that is derived from the production plant model and the process of human control. Therefore it was necessary to observe human control of the same plant. The developed and implemented controller can be considered as an intelligent controller because its structure results from the way in which a human being performs a control task. The developed controller is also analyzed by simulation. In the final phase, we experimentally evaluated the designed controller and compared the results with a human control of the same plant.

Our study of the intelligent controller properties proves that it can be classified among controllers by a nonlinear static characteristic. The intelligent controller performance shows that it is comparable to human control.

2 QUALITATIVE MODELING AND INFERENCE

Certainly it is important to present some aspects of qualitative inference and the use of qualitative models in the process control.

Modeling is a procedure in which part of the real environment is represented by a model that includes all essential properties of the modeled object. With classical mathematical models, all treatments offered by mathematical procedures are possible. Models of the processes and devices are described by systems of differential equations. Also, the time responses of all state variables can be calculated provided that the initial conditions are known. The complexity of the representation increases rapidly with the complexity of the modeled object (or with the details of its presentation). We must also deal with systems that are too extensive for simulation, in particular, for real time processing. One of the possible approaches is to present the objects qualitatively. A presentation of this kind is reasonable since we know that the results of numerical simulations often require a qualitative interpretation.

The idea of using the basic general knowledge of reality to explain the events is not new. The objective of naive physics was to provide a qualitative description of reality with simple facts. With his paper entitled the "Naive Physics Manifesto", published in 1978, Hayes initiated research into the structure of the formalism of general knowledge about everyday physical reality, objects, substances, space, motion, time, etc. In this way, qualitative inference was founded.

The fundamentals of qualitative inference and the foundation for practically all of the relevant research are given in the works of Forbus [4], Kuipers [5], and de Kleer&Brown [6]. Their approaches differ substantially, although they have some common traits. Forbus derived his approach from processes, their connections through conditions and consequences. De Kleer used components as primitives that interact by connections and create the behavior of the composed device. Kuiper's qualitative simulation system QSIM does not include the ontology of the physical situation; rather, it uses mathematical abstractions, equations and relations connected to variables for system representation. The basic difference between approaches is in the ontology used in the description of the physical system.

The purpose of qualitative inference is to create and use simplified presentations of the world, leaving out the irrelevant details, but retaining the resolution and the interpretation of the important properties of behavior. The objective is a general and consistent system. Consequently, qualitative inference systems can also be treated using the definitions of qualitative mathematics: a strict methodology in which we infer the value of parameters and relations from the inaccurate qualitative knowledge. This is also done in continuous mathematics with accurate numerical values and differential equations.

How do we represent the *state of the system*? In continuous mathematics, the values of the variables are taken from a set of real numbers but the qualitative presentation breaks this space into a finite set of intervals called quantitative spaces. The value of the variable is given by its position in the quantitative space inside the interval or on the boundaries between the intervals. The simplest quantitative space includes only the boundary zero (0). The variable can adopt three values: it is on the boundary (0), higher $(+)$ or lower $(-)$ on the interval. If the boundaries are values where important events occur, we call them landmark values. Apart from determining the values in the quantitative space, the state variable also determines the direction of change (typical examples are the increasing, decreasing, or steady states). The direction of change indicates the landmark that the value is approaching. State transitions are when the states of variables are changing. The direction of the change assures the connection between the structure and the behavior, thus making the prediction of state transitions possible.

Physical laws say which combinations of state variables and which directions of changes are valid, and which transitions are possible. The formalism for presenting the *qualitative relationships* is made up of qualitative equations and the qualitative analogy to differential equations. The algebra of qualitative equations is weaker than usual algebra. De Kleer & Brown suggested a notation in which $[X]$ represents the sign of variable X and $[\mathrm{d}X]$ the sign of the time derivative. The quantitative space of both variables is composed of positive, negative and zero values $[+,-,0]$. Unfortunately, algebra provides no loop (there is no inverse in addition).

The next form of qualitative connections is a monotonic functional relationship that combines the values of derivatives of two variables. The functional connection between the two variables x and y is monotonically increasing if the change of the first one causes the change of the second one in the same direction, or monotonically decreasing if the change takes place in the opposite direction. The connections can be derived directly from the mathematical model of the system with the rules of qualitative algebra or can be obtained by having intuitive knowledge of the system. Qualitative inference is interesting for real time applications. Computing is faster than numerical computations because only integer values appear in computation with only logic operations. Qualitative inference is suitable for real time expert systems, where qualitative deduction is necessary and numerical computation too slow. The influence on the compactness of the code is also important.

What are the advantages of using qualitative inference in process control? The first advantage is the efficiency of these systems in specific applications where only qualitative information is available because measurements cannot be performed. They are also very efficient in cases when an enormous amount of data and the complexity of the system require a qualitative interpretation. Sometimes the methods of qualitative inference can be used to avoid time consuming numerical computations, particularly in cases when the accuracy of input data is not assured.

Qualitative inference provides the formal approach to two aspects of inferring physical events: as in traditional mathematics, the presentation and the inference using qualitative information provides a formal system for inferring numerical systems, and also modeling physical systems and causal explanations of behavior.

The greatest weakness of qualitative inference is the production of ambiguous, and even spurious solutions. The first ones result from the weak presentation and algebra, and the second ones represent the solutions that cannot be realized in the modeled domain. Neither can be easily avoided.

Methods of qualitative representation and inference sometimes cannot satisfy the requirements of the first control level and the control level [7]. Nevertheless, already on the next level, the monitoring level, they are a useful supplement to classical approaches. Their efficiency increases with the increasing complexity of the control level.

3 HUMAN CONTROL

We developed an intelligent controller. Conventional controllers can handle only a limited interval of the changes of the desired value. Often with hand control, better results are achieved for a wide range of the desired value. We decided to observe the human control of a system to perform control functions carried out by man, and to get an idea of how to solve the control problem. The experiment of human control of the reel on the bar has been described. We included the statistical descriptions of experimental results and a qualitative analysis. We used the description of the human system control to evaluate the system control performed by the developed qualitative controller.

3.1 Motivation

Almost all definitions of intelligent control include the idea of human control or human intelligence. They are restricted to the definition of the intelligence of the developed controller or the methodology of its development.

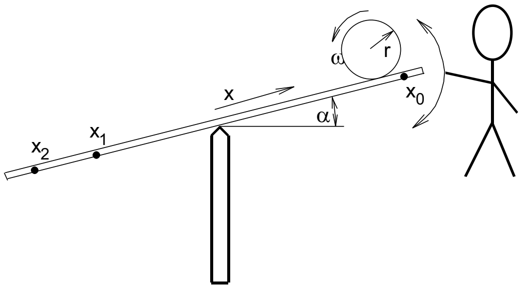

Fig. 1. Schematic representation of reel motion on a bar.

They point out the importance of human control actions. However, it is difficult to foresee and describe human behavior in a certain control task from the available models of human behavior.

Also, the analysis of intelligent systems includes many difficult problems. Therefore, direct comparison of human and artificial intelligence control could offer an acceptable solution. The experimental evaluation of intelligent control was the reason for analyzing human control. One of the tasks of our experiment was to test human control and its performance on a simple model. The results can be used in the development, analysis, implementation and verification of intelligent controllers.

3.2 The description of the model

In our experiment, we used a laboratory model in which we positioned a reel on a bar, as shown in Fig. 1.

A very simple mathematical model of the controlled system can be derived if small changes of the bar's angle are assumed. First, let us describe the reel's motion on the bar. We assume that:

- the equation of pure rotation is: $\omega r = -\mathrm{d}x/\mathrm{d}t$,
- the inertia of the reel is: $J = 1/2\,\mathrm{mr}^2$,
- the friction of rotation is neglected,
- it holds for small angles: sin $\sin\alpha \simeq \alpha$,
- and the centrifugal force acting on the bar is neglected.

Thus, the simplified equation of motion is: $\mathrm{d}^2x/\mathrm{d}t^2 = 2/3\,\mathrm{g}/\alpha$.

Here, x denotes the position of the reel on the bar. During the experiment, different people tried to attain the desired position of the reel on the bar. They affected the motion of the reel by changing the angle α of the bar. They held the bar with their hand at the extreme end of the bar at the initial position of the reel.

3.3 The results of the experiment

People who participated in this experiment were undergraduate students of automatic control engineering and the laboratory staff. Most of them had some experience with the laboratory model but had never practiced reel positioning.

At the beginning of the experiment, the reel was placed at the extreme positive (right) side of the bar, the position being denoted by x_0. The person tried to move the reel towards the desired position on the negative (left) side of the bar by changing the bar's angle α. The procedure was over when the person was satisfied with the attained position or when the reel crossed the extreme point of the bar. The set up time was the time from the beginning to the end of the experiment.

During the experiment, the position of the reel was recorded by a computer. Figure 2 illustrates a typical course of the experiment.

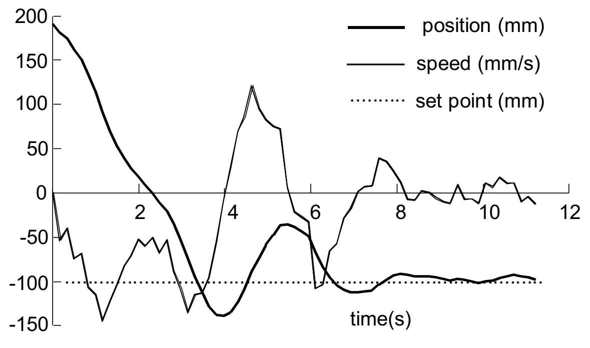

Fig. 2. Position and speed diagram for human controlled reel.

Each person made two positioning attempts. Two desired positions were determined. The jump from position x_0 to position x_1 or x_2 was required. Three attempts to reach the first desired position (x_1) out of 23 failed, meaning that the reel fell off the bar. The same number of attempts failed with the second desired value (x_2) but the persons were different.

The following quantitative statements result from the data on successful positioning in the first position (x_1). Qualitative statements are based on the analysis of all experiments.

The report is based on descriptive statistics. According to the central tendency and dispersion of data, we established that the standard deviation of the set up time was substantial. Thus, the median was a better data presentation than the mean value. The statistics of the maximal speed gave similar results for all persons; it was obvious that it was objectively limited by the human response time. This statement was confirmed by all unsuccessful attempts that were all performed at greater maximal speeds. The statistical errors resulted from the inadequate position measurements, its evaluation and the imperfect shape of the reel.

The relatively large control deviations, fast set up times and relatively low speeds indicated that human control abilities differ from the properties of conventional controllers.

Which elements of human intelligence played a role in the control experiment? The presence of logical- mathematical intelligence was the greatest [2]. It was essential to sort physical objects and estimate their behavior on the basis of experience gained with similar objects. The maximal reel speeds showed that the test person tried to maintain the low speed of the reel motion. The next most important element of human intelligence present during the experiment was the physical-kinesthetic intelligence: test persons had to move the reel by changing the angle of the bar that they held with their fingers. Very precise movements were necessary for this task. The experiment did not include control learning, although it is an important aspect of intelligent control — but it is not a condition for it.

We have established that human control is better when the previous experience and heuristics, as well as naive physics, can help to solve the given task. The complexity of our task is in the non-linearity and boundary conditions, although the control task itself is simple. The entire length of the bar was used in the experiment. The conventional state space controller was not successful in performing the same task but it mastered excellently the positioning in a relatively small domain. The controlled system is nonlinear and all simplifications of its description affect the control performance. We could not expect to totally eliminate the control error in human control merely because of the "sensor system". The same held for the physical constraints of the response speed in human control.

Table 1. Statistical report on the experiment.

	set up time	control error	max. speed	speed range
Mean	15.06	0.25	240.91	346.08
Median	12.45	-0.61	222.56	294.39
Standard Deviation	8.39	6.40	88.54	154.07
Variance	70.34	40.93	7839.58	23738.35
Range	33.30	30.88	344.73	464.60
Minimum	6.10	-17.04	141.63	186.69
Maximum	39.40	13.84	486.35	651.29
Count	20.00	20.00	20.00	20.00

Table 2. Statistical presentation of the experiment with the developed controller.

	set up time	control error	max. speed	speed range
Mean	17.77	-1.67	-125.00	200.73
Median	16.70	0.00	-136.36	181.81
Standard Deviation	4.82	8.35	91.17	59.54
Variance	23.19	69.70	8311.14	3545.13
Range	14.94	20.00	409.08	227.00
Minimum	11.21	-10.00	-318.18	136.36
Maximum	26.15	10.00	90.90	363.36
Count	12.00	12.00	12.00	12.00

4 THE QUALITATIVE PLANT MODEL

In order to design the controller properly and to reach the desired state, it is necessary to adequately present the state variables of the production plant.

One of the principal objectives of qualitative modeling is a simpler presentation of the problem than that obtained through continuous functions. In a continuous representation, the variables can be any real number, whereas in a qualitative representation the space is divided into a finite number of intervals called quantitative spaces. The value of the variable is given by its presence in the quantitative space. The simplest quantitative space has only one boundary and allows the variable to have three values. It can be on the boundary (0), on the interval above it $(+)$, or on the interval below it $(-)$.

We have modeled the motion of the reel on the balance control model. We did not derive a qualitative model from the mathematical model of the reel moving. The position of the reel, its speed and its acceleration represented the qualitative space. The qualitative state variables could be influenced by the angle of the bar. The choice of quantitative spaces was essential for the success of further work, which became evident in the design of the controller.

Only one boundary value was chosen for the position. This value represented the delimitation between the intervals and agreed with the real numbers in the space of numbers, which was the desired value. In the case of our implementation, this value could be changed dynamically. On the basis of our careful observations of control by a human, we have decided that this boundary should also be an interval. By doing this, we risked the danger of static control error but gained a lower dynamic near the desired value. This can be shown as the controller output $= 0$ on the laboratory model inside the chosen interval near the desired value. The value of the state variable x was: $x \in \{-, 0, +\}$.

The second qualitative state variable, the speed, also had only one boundary value in the beginning. This was the standstill point. Later it became obvious that two boundary values had to be added, namely, the points at which the speed was still safe and the system controllable. Another reason for doing so was an experiment that clearly indicated that a speed exists which represents the limit of successful control. Consequently, the value was: $x \in \{--, -, 0, +, ++\}$.

In the same way, acceleration has been limited. The limit is the point showing that there is no acceleration. The reel acceleration interval is denoted by $+$, and the braking interval $-$. Thus, we could write: $x \in \{-, 0, +\}$.

In the implementation the limits 0 were intervals of speed and acceleration.

5 QUALITATIVE CONTROLLER

In the designing of the controller we used the knowledge about: control by a human of the same system, the mathematical model of the plant and the experience gained in the operation of prototype controllers. Consequently, the final system can be classified among knowledge based systems.

The control algorithm was composed of two basic procedures:

– determining the qualitative states of the system,
– finding the appropriate control actions.

The first procedure was closely related to the model of the plant. Its task was to determine the qualitative state of the controlled system, in our case, the components of the state vector **X**. The state vector determined the control action and served as a basis for all subsequent decisions of the system implementing the control. This was the reason that it must be designed so carefully.

The second procedure provided an appropriate control action concerning the state vector **X** and the knowledge base. In our case, we simply coded the knowledge, as described in the following section.

5.1 Knowledge representation

In our case, the representation of knowledge was based on rules. However, due to the specific properties of the system, it was possible to present the knowledge more clearly with a decision tree, or in a more condensed form, with a matrix, which permitted simple coding.

A part of the rule-based knowledge expression was:

```
if  X == (0,0,0) | (0,0,+) | (0,0,-)
 then action = 0;
else if  X== (0,+,0)
 then action = -;
else if  X== (0,-,0)
 then action = +;
else if ...
```

Very quickly this expression became unclear, so a decision tree was used. It consisted of four levels: the position, speed, acceleration and decision level. The number of individual nodes was limited by the number of qualitative states in each level. A part of the decision tree is shown in Fig. 3. The output value was given in each leaf of the tree.

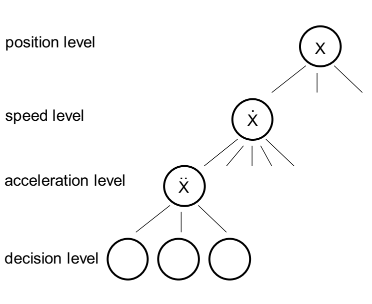

Fig. 3. A part of the decision tree.

However, the most condensed coding of knowledge was obtained by using the three-dimensional matrix. The number of elements of individual dimensions depended on the number of possible qualitative states. The elements of the matrix contained the value of the control action.

5.2 Simulations of controller operation

The presented simulation results were obtained through the program Matlab. The plant was simulated by using a mathematical model, and the controller's knowledge by creating a matrix.

To prove the controller's static non-linearity, only two qualitative state variables were assumed: the position and the speed of the reel. In Fig. 4 the controller's output is shown as a function of position and speed. The values have been chosen to make the interesting part of the static characteristic of the controller clearly seen. The width of the zero interval for the position was $2 * 0.012$, and for the speed $2 * 0.018$.

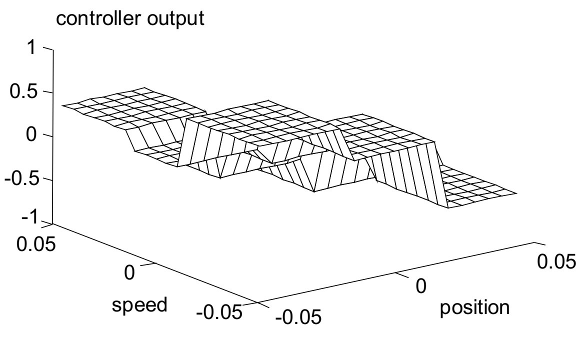

Fig. 4. The controller's static characteristic.

Both state variables could have three qualitative values. It was evident from the static characteristic that we designed a non-linear controller. The final controller would have a similar characteristic, but it was difficult to present it in three-dimensional space because of the three independent state variables and the one dependent variable.

The following figures show the simulation results of the developed controller. All parameter values are equal to those of the laboratory model test. Figure 5 gives the phase diagram, whereas Fig. 6, 7 and 8 show the time responses of the state variables. A matrix of size $(3*5*3*)$ has been used for representation of the knowledge. The initial position $x_0 = 0.2$ m, whereas the desired one was $x_1 = -0.1$ m. The sampling time was $t_s = 55$ ms.

5.3 Laboratory model control

Figure 9 shows the control of the reel with the developed intelligent controller. The figures below present the results of 12 automatic control procedures that were all discussed in the same way and with the same criteria as the human control described before.

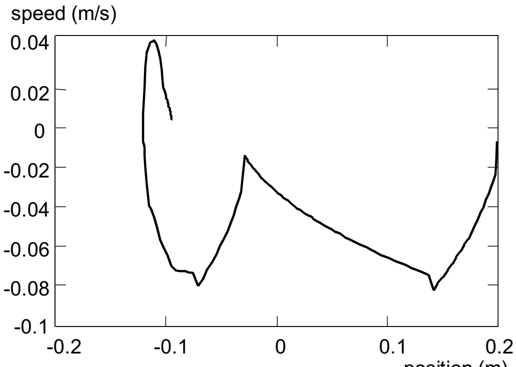

Fig. 5. Phase diagram.

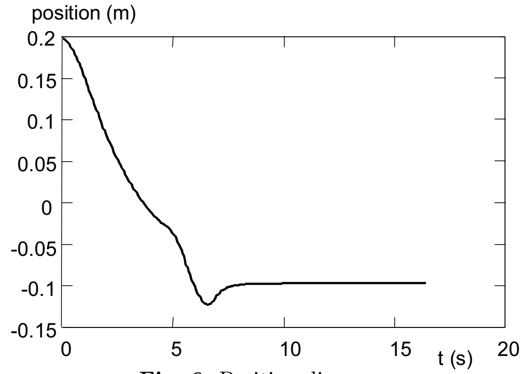

Fig. 6. Position diagram.

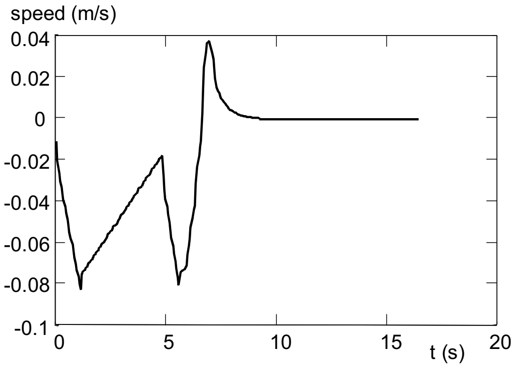

Fig. 7. Speed diagram.

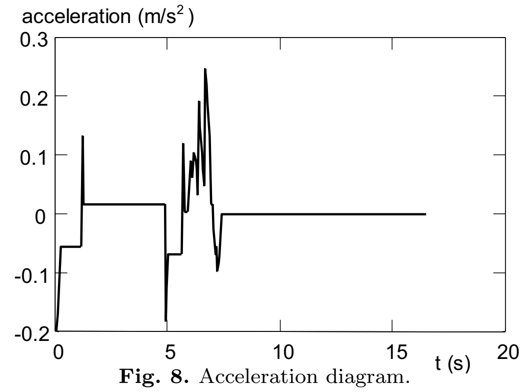

Fig. 8. Acceleration diagram.

6 EVALUATION OF THE INTELLIGENT CONTROLLER

For intelligent control systems, many elements of verification and validation methodology exist but these elements have not yet been assembled and standardized. Therefore, we have proposed some methods applicable for verifying intelligent control systems.

Verification and validation are actually composed of a number of activities that occur at the transitions between stages in a development process. In the validation process of the intelligent controller, simulation is commonly used [8]. The importance of evaluation via simulation cannot be ignored but actual implementation is preferred [9].

In our case we could get the results of the human control. Also, it was possible that human control of the plant was a reference for intelligent controller verification because of its performance on the discussed plant.

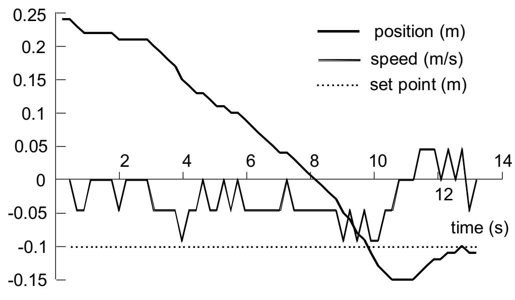

Fig. 9. Position and speed diagram for controlled reel.

The controller structure results from the way in which a human being performs a control task [1], [3] therefore it can be considered an intelligent controller. We tried to verify that a developed controller is an intelligent controller. We use human control results and implemented controller results for verification of the intelligent controller. The set up time, control error, reel sped and speed range were considered.

Qualitative validation that employs subjective comparisons of performance was performed. This does not imply that such an approach was informal. Quantitative validation employs statistical techniques to compare system performance against human or required system performances. Qualitative and quantitative methods can be combined, as in our case. A qualitative controller response can be quantified and quantitative or statistical methods can be used.

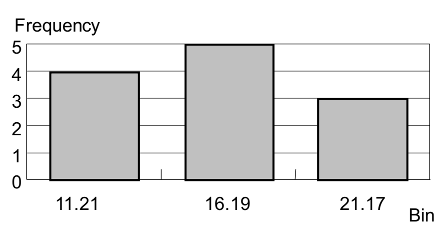

Fig. 10. Histogram of the set up time.

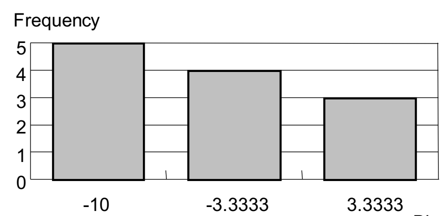

Fig. 11. Histogram of the control error.

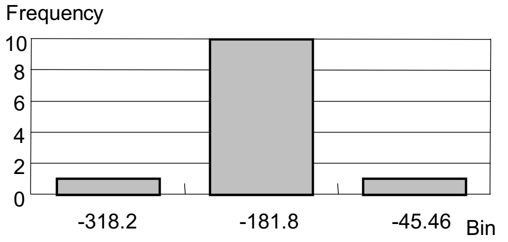

Fig. 12. Histogram of the maximal speed.

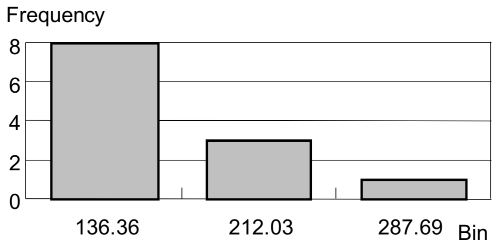

Fig. 13. Histogram of the speed rank.

Two qualitative validation approaches were combined: predictive validation and field tests. Predictive validation requires using historic test cases, and either known results or measures of human performance on those cases. Intelligent controller results were compared with corresponding results obtained from human control of the same plant. Field tests place an intelligent controller in operation in a real plant and then record the achieved results.

7 CONCLUSION

Statistically processed results indicated that the results obtained with the developed controller (set up time, control error, speed, speed range) are similar to the statistically processed results of human control. For the plant that we discussed, we know that for a wide range of the initial and desired positions, hand control is superior to conventional control (of course, conventional controllers are the best solution which come close to a successful working point).

The duration of experiments (from the beginning to the end of positioning) was longer in the case of automatic control, which was mostly due to the set speed limit. By setting it so low, the failures of automatic control were avoided. It should be noted that the test persons were directly informed about the angle of the bar, whereas in the case of automatic control, measurements could not be performed.

We proved that it was possible to develop an intelligent controller using qualitative conclusions. The results of automatic control were comparable with the results of human control of the discussed plant. We concluded that the designed qualitative controller achieved satisfied control properties on a balanced control model.

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