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A cognitive human operator model: the single-input single-output (SISO) case

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This paper presents experiments for finding a model of the cognitive behaviour of the human operator in some well-defined task. The task chosen is inventory control. Results of the modelling are compared with the performance of the human operator and these are discussed in the context of the optimal controller for the inventory control.

1. Introduction

The human operator in control of a dynamic system observes the system's inputs and/or outputs and, using his experience of the system (knowledge from the past and expectations for the future), chooses and executes an appropriate control action. This process of choice can vary from simply deciding whether a predetermined action should be carried out (simple decision) to a complex decision where a large number of possibly relevant circumstances must be evaluated in order to choose the optimal control action. Accordingly, if one attempts to build a model to describe the human operator's behaviour the complexity of the model must reflect the complexity of the decision-making process performed by the operator.

Modelling the behaviour of the human operator has been successful if the decisions taken were simple. In such a case the outcome of the decision process is more or less prescribed and, as a result of previous training, the operator in general will choose the correct action and will carry it out correctly, possibly constrained due to the speed of neuronal and muscular responses. Variations in operator behaviour usually result from variations in the way in which, and the moment when, the action is executed, not from failures in choosing the appropriate action. Therefore the behaviour can be modelled quite accurately, as shown in the field of manual control where a great variety of useful operator models are available (see, for example, Sheridan and Ferrell (1974) and Rouse (1973, 1977)).

As a result of technical developments in instrumentation and increasing automation however, the tasks of the human operator are shifting from classical manual control towards monitoring of controlled processes. This shift changes the characteristics of the operator task such that, gradually, it becomes a *cognitive control task* where processes such as expectation, planning, prediction, strategy-building and evaluation become the predominant elements.

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In general, the 'control action' which is performed by the operator results less from rule-based behaviour and more from cognitive behaviour and consequently becomes less predictable.

Exactly how the operator decides which action to take is not clear. It is clear, however, that his expectations about the system's present and future states, inputs and outputs will be extremely important for his control strategy and his control actions. These expectations emanate from the view held by the operator about the system: his '*internal model*' of the system (and its inputs and/or outputs). An internal model consists of all knowledge and experience about the system together with the goals and criteria used in evaluating the system behaviour. Conversely, the control actions chosen by an operator should be regarded as outcomes of his decision process and therefore can be used to study the structure and operation of his internal model.

In the experiments described here, the experimental task was designed to study prediction behaviour of human subjects and, possibly, to provide a linear model. The modelling was part of continuing work on the development of system-analytical methods for human control behaviour. In the experiments reported, single-input single-output (SISO) systems were used to generate time series which had to be extrapolated by the experimental subjects.

From the literature and earlier works (Rouse 1973, van Bussel 1980) we expected that the subjects should be modelled as simple zero-order extrapolators and therefore would base their extrapolations only on the most recent observation. Because we assumed that the subjects' behaviour would show a learning process which depends on the characteristics of the time series, they had to continue the task for a fixed period of time (encountering specific learning effects). We decided to use systems with a restricted range of eigenvalues (only positive, as opposed to experiments described in van Bussel 1980) where subjects were exposed to systems with positive as well as negative eigenvalues). Specific learning effects could now be expected to cause an even more pronounced tendency of the subjects to overestimate the positive dependencies between successive elements of the time series.

The paper is organized as follows: first a description is given of the inventory control problem and the place of the human operator in it. Calculation of the model of the human operator then follows. The last part of the paper contains experimental results, model validation and conclusions.

2. Description of the inventory control system

To make experiments more attractive to the persons involved, the task has been formulated as an inventory control problem. The inventory control task for a hypothetical shop owner can be defined as the task of choosing in every period an inventory for a product in such a way that his profit will be maximal. Because of the fact that the shop owner does not know the exact demand of his clients for the following period, he has to make a prediction of this demand and base the inventory for the next period on this prediction. Naturally his choice of an inventory is not based only on a prediction of the demand, but also on other variables such as storage costs, costs of the loss of goodwill and decay of his products during storage. By way of counting his profit at the end of a period, the shop owner gets some kind of feedback on the decisions he made at the beginning of the period.

2.1. *The processes in the inventory control system*

First we consider the demand process (see Fig. 1). We assume this process to be first-order filtered white noise so the demand in period i is

$$v(i) = v_0 + \alpha(v(i-1) - v_0) + \xi(i) \tag{1}$$

where α is an autoregressive parameter $(-1 \leqslant \alpha \leqslant 1)$, ξ a sample of a gaussian white noise and v_0 a constant.

For the sale process we have that the sales in period i are

$$a(i) = \min(x(i), v(i)) \tag{2}$$

where $x(i)$ is the inventory at the beginning of period i. The inventory at the end of period i can be written as

$$y(i) = x(i) - a(i) \tag{3}$$

The inventory at the beginning of period i depends on the amounts of the products remaining from the previous period, on the decay and on the purchases:

$$x(i) = (1-\lambda)y(i-1) + b(i-1) \tag{4}$$

where λ is a decay parameter $(0 \leqslant \lambda \leqslant 1)$ and $b(i)$ the purchase order at the end of period i.

The profit rate for period i will be calculated as follows:

$$w(i) = p_1 a(i) - p_2 b(i-1) - p_3 y(i) - p_4(v(i) - a(i)) \tag{5}$$

where p_1 is the price of sale, p_2 the price of purchase, p_3 the storage costs and p_4 the price of 'loss of goodwill'.

A block diagram of this system is shown in Fig. 1, where the element z^{-1} denotes a delay of one time sample.

For every period the person experimenting has to make a choice with respect to the size of the purchase order for the next period; this is in fact the only decision he has to make.

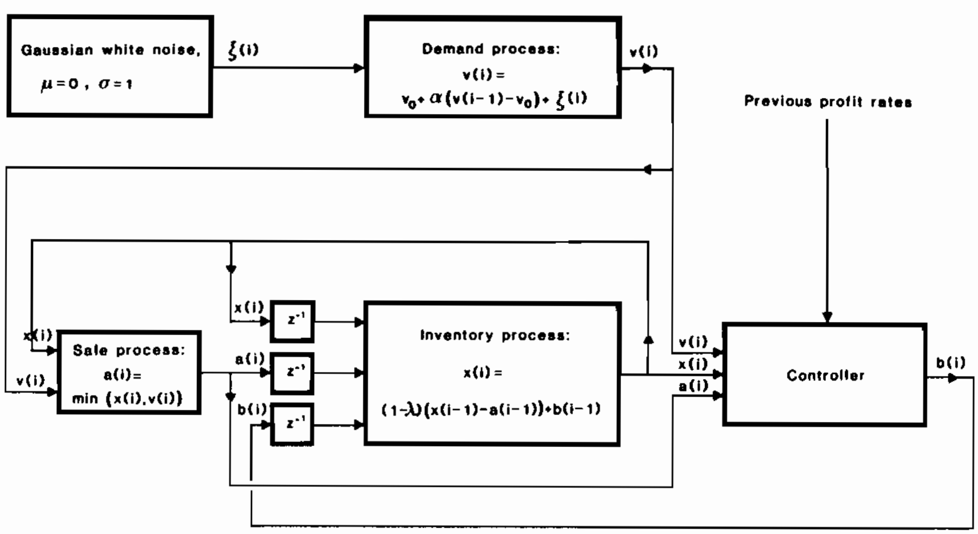

Figure 1. Block diagram of the inventory control system.

The system, drawn in Fig. 1, will be characterized by a few parameters. These are as follows

μ, σ	parameters of the noise generator
α, v_0	parameters of the demand process
λ	parameters of the inventory process
p_1, p_2, p_3, p_4	parameters that determine the profit rate

α determines the character of the demand, and is therefore the most important parameter. The other parameters just have to be chosen in a way that makes the inventory problem a realistic one. Basing our choice on this criterion and not going further into specific arguments for the test case, we chose the following values:

$$\mu = 0, \quad \sigma = 1{\cdot}0, \quad v_0 = 5{\cdot}0, \quad \lambda = 0{\cdot}1,$$

$$p_1 = 1{\cdot}0, \quad p_2 = 0{\cdot}5, \quad p_3 = 0{\cdot}05, \quad p_4 = 0{\cdot}1$$

2.2. *The optimal controller*

Knowing the structure and the parameters of the demand process, an optimal controller can be constructed that optimizes the expected profit rate. By using dynamic optimization techniques one can prove (Braakman 1980, Braakman and van Bussel 1980) that, given the inventory $x(i)$ at the beginning of a period i and the demand $v(i)$ during that period, an optimal choice for $b(i)$ can be found that optimizes

$$\sum_{j=1}^{\infty} w(j)$$

The optimal $b(i)$ can be written as

$$b^*(i) = v_0 + a(v(i) - v_0) - (1 - \lambda)y(i) + b_0 \tag{6}$$

The optimal choice for $b(i)$ can be transformed into an optimal choice for $x(i)$ by using eqn. (4):

$$x^*(i) = v_0 + \alpha(v(i) - v_0) + b_0 \tag{7}$$

where b_0 can be determined by

$$P(\xi(i) \leqslant b_0) = \frac{p_1 - p_2 + p_4}{p_1 - (1 - \lambda)p_2 + p_3 + p_4} \tag{8}$$

and $\xi(i)$ is the noise sample in period i.

We can see that $b^*(i)$ consists of three parts:

$v_0 + \alpha(v(i) - v_0)$	a one-step-ahead predictor of the demand for the next period
$(1 - \lambda)y(i)$	the inventory at the beginning of the next period
b_0	an extra purchase that is dependent on the density function of the noise and the prices on which the profit rate is based. It is a result of relating the costs for possible loss of goodwill to the costs for possible extra storage.

Taking the p- and λ-parameters as mentioned before, b_0 will be given by $P(\xi(i) \leqslant b_0) = 0{\cdot}857$. If $\xi(i)$ is sampled gaussian white noise with zero mean and unit variance, as in our case, b_0 will equal $1{\cdot}06$.

2.3. *The human operator*

As mentioned above, the human operator has to decide on the purchase $b(i)$ for the next period, based on the inventory x, the sale a, and the demand v of previous periods. Because of the fact that there is a unique relation between x, a and v given by $a(i) = \min(v(i), x(i))$ and that a choice for the purchase $b(i)$ is equivalent to a choice for the new inventory $x(i+1)$ when the old inventory is known, we may represent the process of the human operator as shown in Fig. 2.

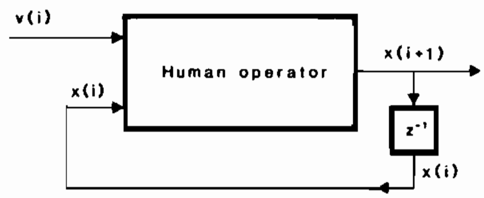

Figure 2. Human operator process.

So, what first seemed to be a MISO system, we can now write as a simple SISO system, considering the inventory $x(i)$ to be a state variable. This interpretation leads to the description of the process of the human operator shown in Fig. 3.

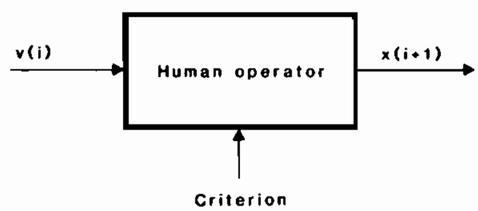

Figure 3. SISO human operator process.

Based on some criterion, the human operator will try to choose the inventory $x(i+1)$ in such a way that his profit will become optimal. However, to the human operator, the mathematical construction of the profit rate is unknown.

2.3.1. *The model of the human operator*

To construct a model for the behaviour of the human operator we have to visualize the way in which the human operator will make his decision. The following information is available:

(i) the demand v in period i and in previous periods; and

(ii) the value of the profit rate in period i and in previous periods.

Because of the construction of the profit rate, this function only has the task of giving the human operator a view on the optimal strategy: taking an 'over-inventory' to be able to serve all customers, or taking an 'under-inventory' to be sure that all products can be sold.

The essence of the human operator's choice will be his prediction of the demand in the next period. This prediction, together with the strategy induced by the profit rate as mentioned above, will determine the inventory for the new period.

The value of the profit rate in each period is partly dependent on the demand, on which the human operator has no influence. In this way, he gets hardly any feedback on the quality of his decision, and therefore the control task can better be considered as a *prediction task*.

Now the model of the human operator is chosen to be as follows:

$$x(i+1) = E(v(i+1)) + \tilde{b}_0 \tag{9}$$

with the expected value of the demand $E(v(i+1))$ as the prediction of the demand for the next period, and $\tilde{b}_0$ an extra inventory, based on the experience and strategy of the human operator in previous periods. With eqn. (1) this can be written as

$$E\{v(i+1)\} = v_0 + \alpha[E(v(i)) - v_0] + E(\xi(i))$$

Knowing the demand in period i, the expectation in the instant $i+1$ takes the form

$$E\{v(i+1)\} = v_0 + \alpha[v(i) - v_0] \tag{10}$$

Combining (9) and (10) we get

$$x(i+1) = v_0 + \alpha[v(i) - v_0] + \tilde{b}_0 \tag{11}$$

Because the human operator cannot distinguish between v_0, α and $\tilde{b}_0$, the model will become:

$$x(i+1) = cv(i) + b \tag{12}$$

with

$$c = \alpha$$

$$b = (1-\alpha)v_0 + \tilde{b}_0$$

2.3.2. *Determination of c and b (estimation of model parameters)*

The human operator has to enter data for N successive periods. After an experiment, two arrays, $x(i)$ and $v(i)$, are available, each of length N. Based on these two arrays, we can construct least-squares estimators for the c- and b-parameter, i.e. $\tilde{c}$ and $\tilde{b}$ in such a way that

$$\sum_{i=0}^{N-1} [x(i+1) - \tilde{c}v(i) - \tilde{b}]^2$$

becomes minimal. The result is very well known in estimation theory (see Eykhoff 1974) and leads to the following estimates:

$$\tilde{c} = \frac{N\sum_{i=0}^{N-1} x(i+1)v(i) - \sum_{i=0}^{N-1} x(i+1)\sum_{i=0}^{N-1} v(i)}{N\sum_{i=0}^{N-1} v^2(i) - \left(\sum_{i=0}^{N-1} v(i)\right)^2} \tag{13}$$

$$\tilde{b} = \frac{\sum_{i=0}^{N-1} x(i+1)\sum_{i=0}^{N-1} v^2(i) - \sum_{i=0}^{N-1} x(i+1)v(i)\sum_{i=0}^{N-1} v(i)}{N\sum_{i=0}^{N-1} v^2(i) - \left(\sum_{i=0}^{N-1} v(i)\right)^2} \tag{14}$$

Because of the character of the model (12) and since the noise is assumed to be white and additive, the estimates $\tilde{c}$ and $\tilde{b}$ are unbiased.

2.4. *Test cases—comparison of different systems*

The experimental results are based on a comparison of the outputs of different systems. More precisely, the validation of the model will be based on tests of residuals. These systems are represented by Fig. 4.

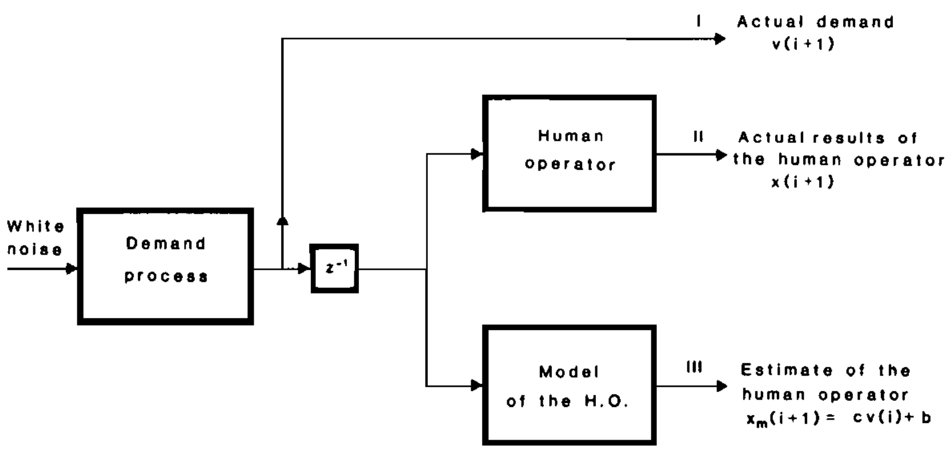

Figure 4. Comparison of the available systems.

For the results of the experiments, the following two residuals are evaluated:

$$\begin{array}{ll} \mathrm{II}-\mathrm{III} & (\mathrm{H-M}) \\ \mathrm{II}-\mathrm{I} & (\mathrm{H-D}) \end{array}$$

where H is the human operator, D the actual demand and M the model of the human operator.

The comparison of the actual results of the human operator and the results of the other systems is of interest: comparison of II and III tells us something about the quality of the model: the residual of II minus I shows the prediction-capability of the human operator.

3. Evaluation of the model

Estimation of parameters of the model of the human operator is performed according to the structure illustrated in Fig. 5. We assume that n is a signal of white-noise samples, and that n is an additive noise which the human operator adds to the results. Any possible correlated noise is assumed to be an internal process in the human operator system. In view of this, the model will be considered optimal if there are no more deterministic factors in the residual e, which means that the residual e is recognized as a 'white noise'. Therefore tests on the quality of the model will be based on testing the 'whiteness' of the residual e. For this purpose, the autocorrelation function of the residuals will be used.

The determination of the autocorrelation function is based on the assumption that the residual error may be seen as a stationary discrete signal being the realization of an ergodic process. We assume that

$$\Psi_{ee}(\tau) = \overline{e(i)e(i+\tau)}^{\text{time}} \tag{15}$$

When $e(i)$ is an array of white-noise samples, $\Psi_{ee}(\tau)$ will be a delta function $\delta(\tau)$. For

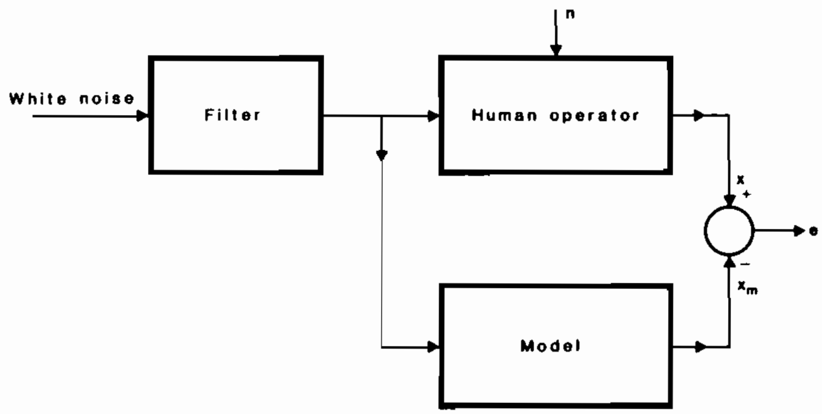

Figure 5. Layout of the experiment.

the residuals, we want to investigate whether or not the computed autocorrelation function can be regarded as a delta function.

Because of the fact that eqn. (15) is a mean value in the time-domain, and there is only a finite number of samples available in the array e, we can only compute an approximate autocorrelation function, defined as

$$\tilde{\Psi}_{ee}(k) = \frac{1}{N-k} \sum_{i=1}^{N-k} e(i)e(i+k) \qquad (16)$$

Using this approximated autocorrelation function we are able to determine the expected value and the variance of Ψ, which enables us to evaluate the delta-character of $\Psi_{ee}(k)$.

It is well known that in our case

$$E\{\tilde{\Psi}_{ee}(k)\} = \Psi_{ee}(k) \qquad (17)$$

The variance of the approximate autocorrelation function brings us more problems. It can be seen that

$$\text{var}\{\tilde{\Psi}_{ee}(k)\} = \frac{1}{(N-k)^2} \sum_{i=1}^{N-k} \sum_{j=1}^{N-k} E\{e(i)e(j)e(i+k)e(j+k)\} - \Psi^2_{ee}(k) \qquad (18)$$

Assuming that e is normally distributed, we can write (Laning and Battin (1956), p. 162)

$$\text{var}[\tilde{\Psi}_{ee}(k)] = \frac{\Psi^2_{ee}(0)}{N-k} + \frac{\Psi^2_{ee}(k)}{N-k} + \frac{2}{N-k} \sum_{\mu=1}^{N-k-1} \left(1 - \frac{\mu}{N-k}\right) [\Psi^2_{ee}(\mu) + \Psi_{ee}(\mu+k)\Psi_{ee}(\mu-k)] \qquad (19)$$

When $\Psi_{ee}(k)$ has the character of a delta function, the values of $\Psi_{ee}(k)$ for $k \neq 0$ will be much smaller than $\Psi_{ee}(0)$. Assuming this, an approximation of the variance can be given by:

$$\text{var}[\tilde{\Psi}_{ee}(k)] \cong \frac{\Psi^2_{ee}(0)}{N-k} \qquad (20)$$

By means of relations (17) and (20) we may test the delta-character of the approximate autocorrelation function. Usually we work with normalized autocorrelation functions, which means a choice of the value 1 for $k=0$. Assuming that $\tilde{\Psi}_{ee}(0) \gg \tilde{\Psi}_{ee}(k)_{k=0}$ and considering $\tilde{\Psi}_{ee}(0)$ to be a constant, we get

$$E\left\{\frac{\tilde{\Psi}_{ee}(k)}{\tilde{\Psi}_{ee}(0)}\right\} = \frac{\Psi_{ee}(k)}{\tilde{\Psi}_{ee}(0)} \tag{21}$$

and

$$\operatorname{var}\left[\frac{\tilde{\Psi}_{ee}(k)}{\tilde{\Psi}_{ee}(0)}\right] = \frac{\Psi_{ee}^2(0)}{\tilde{\Psi}_{ee}^2(0)}\,\frac{1}{N-k} \cong \frac{1}{N-k}$$

thus the standard deviation is

$$\sigma\left[\frac{\tilde{\Psi}_{ee}(k)}{\tilde{\Psi}_{ee}(0)}\right] = \frac{1}{\sqrt{(N-k)}} \tag{22}$$

Instead of the σ-value we can also work with the reliability interval, a more practical bound to test the function. For a gaussian distributed function, the 95% reliability interval can be computed by

$$\Delta\Psi_{95\%} = 1{\cdot}645\sigma$$

so

$$\Delta\left[\frac{\tilde{\Psi}_{ee}(k)}{\tilde{\Psi}_{ee}(0)}\right]_{95\%} = \frac{1{\cdot}645}{\sqrt{(N-k)}} \tag{23}$$

We will state that the evaluated autocorrelation function is considered to be a delta function when 95% of its values for $k \neq 0$ lie within the range

$$\pm\frac{1{\cdot}645}{\sqrt{(N-k)}} \tag{24}$$

as derived in the equation above.

4. Experimental results

4.1. *Organization of the experiment*

Thirty experiments were made with 30 different experimental subjects, who had never participated in such an experiment before. None of them had any knowledge, either of the method of generating the demand or of any other crucial information. The subjects were given a written instruction in which their task was described. They were asked to enter the inventory for 100 successive periods. After each period, the demand of the customers and the cumulated profit rate after the period were displayed on the screen. The subjects could take as much time as they wanted for the experiment: there was no time limit. Although they knew the variables that determined the profit rate, they had no information on the exact construction of the profit rate: the prices of sale; purchase, storage and loss of goodwill were unknown, just as the offset component of the demand v_0, the decay parameter λ, and evidently the autoregressive parameter α. One experiment is defined as the action of one experimental subject, entering the inventories for 100 successive periods.

The experiments started with the generation of the demand in period 0. This value functioned as an indication of the size of the demand. We expected that the participants would predict the demand of the next period when ordering the inventory. In doing so they would probably add some extra inventory $\tilde{b}_0$, based on the information of the profit rate. This extra inventory causes a higher profit rate because loss of goodwill is chosen to be relatively more expensive than storage costs.

One has to ensure that the experimental subject does not choose the inventory completely freely. He should not be allowed to choose the inventory for period i to be smaller than the inventory remaining from the previous period. In other words it is not allowed to sell products back to the wholesale dealer. This restriction is incorporated in the program.

4.2. *Results of the estimation of the model parameters*

The results of the estimated model parameters are listed in Table 1. Accuracy of the estimation of the parameter $\tilde{c}$ is strongly dependent on α; the standard deviation of the estimates decreases with increasing α. In all cases the parameter $\tilde{c}$ is overestimated. For $\alpha = 0{\cdot}6$ and $\alpha = 0{\cdot}8$ the estimates are, respectively, 0·73 and 0·87, which can be considered a good result, as in both cases the relation $\alpha - \sigma < \tilde{c} < \alpha + \sigma$ holds. It is noticeable that the estimation of $\tilde{c}$ for $\alpha = 0{\cdot}8$ gives a result very close to the true value, and with a small standard deviation. For $\alpha = 0{\cdot}0$ the estimator $\tilde{c} = 0{\cdot}56$ is not as good: the difference $\tilde{c} - \alpha$ is larger than σ. In this case, in which the demand is entirely white noise the human operator apparently 'wants to see' some kind of correlation in the demand, although there is none. The estimator $\tilde{c}$ is very large, and therefore it is advisable to consider the test situation very critically.

	$\alpha = 0{\cdot}0$		$\alpha = 0{\cdot}6$		$\alpha = 0{\cdot}8$	
$L = 10$	Mean	σ	Mean	σ	Mean	σ
$\tilde{c}$	0·56	0·29	0·73	0·21	0·87	0·10
$\tilde{b}$	2·62	1·59	1·61	1·08	0·71	0·63
$\tilde{b}_0$	0·41	0·34	0·26	0·31	0·06	0·46

Table 1. Results of the estimated model parameters, for each value of α averaged over $L = 10$ experiments.

The parameter $\tilde{b}_0$ may be recalculated from relation (12). In all cases the estimated value $\tilde{b}_0$ is far below the optimal one—in this case $b_0 = 1{\cdot}06$. This result might be an indication that subjects did not discover the fact that an optimistic choice for the inventory leads to higher profit rates than a pessimistic one.

Apparently the information that the human operator should receive via the profit rate does not function very well. The following two facts may have contributed to this underestimation of b_0:

(1) The profit rate is presented to the human operator on the screen in a cumulative form. In this way it functions as a stimulation for the subject to fulfil the task and to optimize the total profit rate. On the other hand this way of presenting the profit rate makes it more difficult for the subject to receive information on the quality of his choice of the inventory. A profit rate, presented as an account in one period, could be a more direct way of giving feedback to the subject.

(2) The profit rate, as calculated in this experiment, depends on the demand, which is not controllable by the subject. In other words: the level of the profit rate is dependent on the level of the demand, and therefore it is not a direct measure of the performance of the subject. It would be more correct to relate this profit to the maximal profit rate that could have been achieved. In that way the subject would get direct information on his performance

4.3. *Test on the quality of the model—model validation*

The two residuals, as defined in Fig. 4, have been tested:

(i) H–M: (Human operator) – (Model of the human operator)
SHM: mean square of the residual H–M averaged over the number of samples.

$$\mathrm{SHM} = \frac{1}{N} \sum_{i=1}^{N} (x(i) - x_m(i))^2$$

(ii) H–D: (Human operator) – (actual Demand)
SHD: mean square of the residual H–D averaged over the number of samples.

$$\mathrm{SHD} = \frac{1}{N} \sum_{i=1}^{N} (x(i) - v(i))^2$$

SHM and SHD are evaluated for all experiments. The mean values of SHM and SHD are determined, averaged over the number of experiments and denoted by $M(\cdot)$. The results of this test are listed in Table 2.

	$\alpha = 0{\cdot}0$		$\alpha = 0{\cdot}6$		$\alpha = 0{\cdot}8$	
$L = 10$	$M(\cdot)$	σ	$M(\cdot)$	σ	$M(\cdot)$	σ
SHM	0·88	0·66	0·24	0·17	0·27	0·26
SHD	2·63	1·93	1·41	0·28	1·45	0·58

Table 2. Mean squares of the two residuals for each value of α averaged over $L = 10$ experiments.

Results of the approximate autocorrelation functions are presented in Figs. 6, 7 and 8.

Remarks

(i) In the optimal case the autocorrelation function of the residuals H–M would be a delta function. The values of the autocorrelation function for small k, however, fall outside the reliability interval. This occurs in all three cases. However, there are some differences for different values of α: for $\alpha = 0{\cdot}8$ and 0·6 only for $k \leqslant 4$ the values of $\tilde{\Psi}(k)$ are beyond the 95% reliability interval. For $\alpha = 0{\cdot}0$ the model does not seem to fit very well, according to this picture. Moreover, one has to take into account that because of the fact that $\tilde{\Psi}$ is not purely gaussian distributed, the 95% reliability interval is larger than the assumed factor 1·645 multiplied by σ. (eqn. (23)).

(ii) The residuals H–D can tell us something about the learning effects of the subject. A tendency towards making choices in the optimal direction causes a decreasing of $\tilde{\Psi}(k)$ for increasing k. A relatively small decrease of $\tilde{\Psi}(k)$ can be seen in

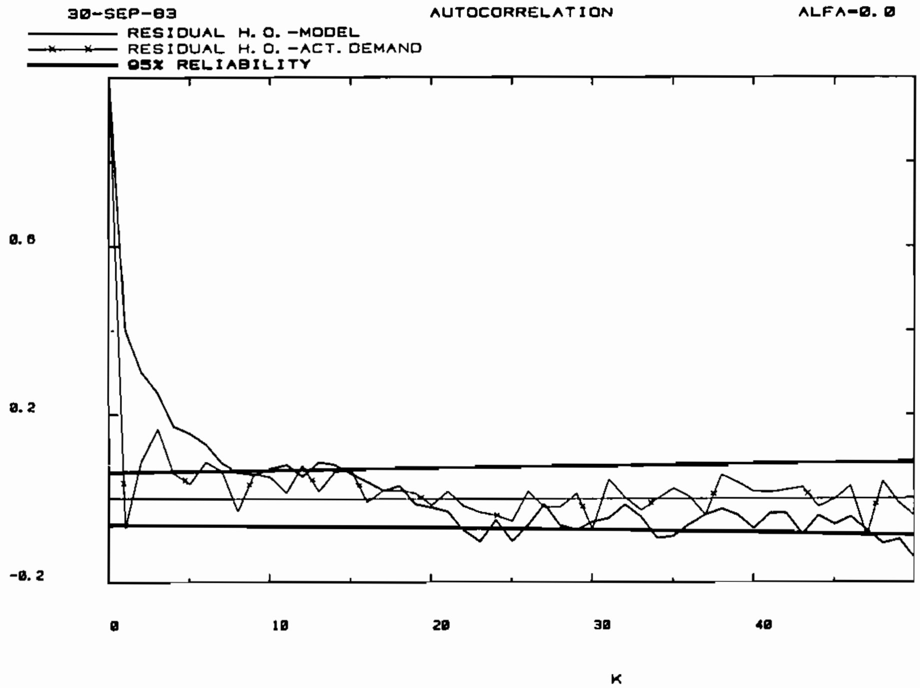

Figure 6.

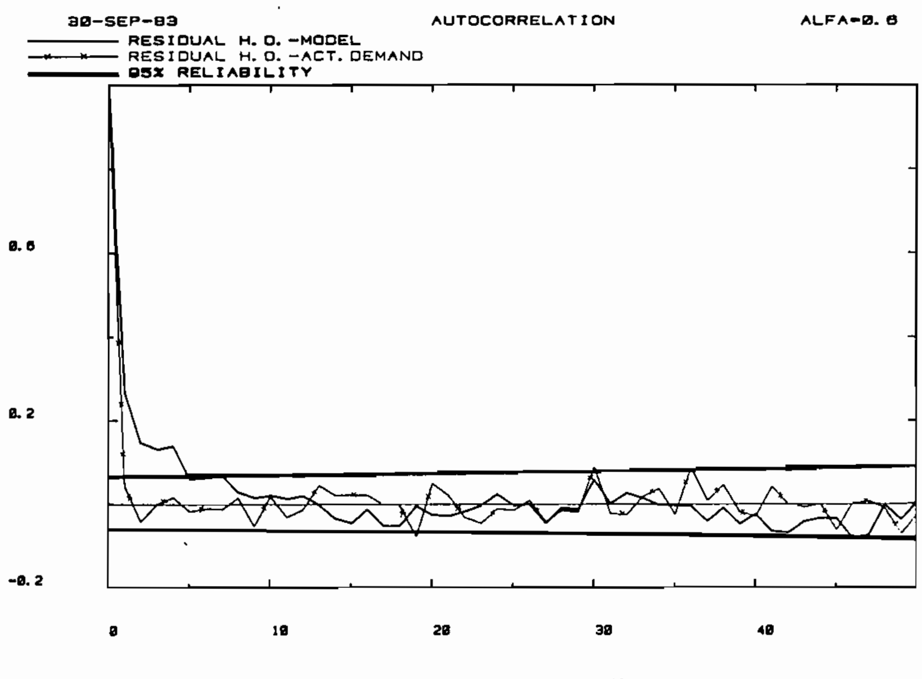

Figure 7.

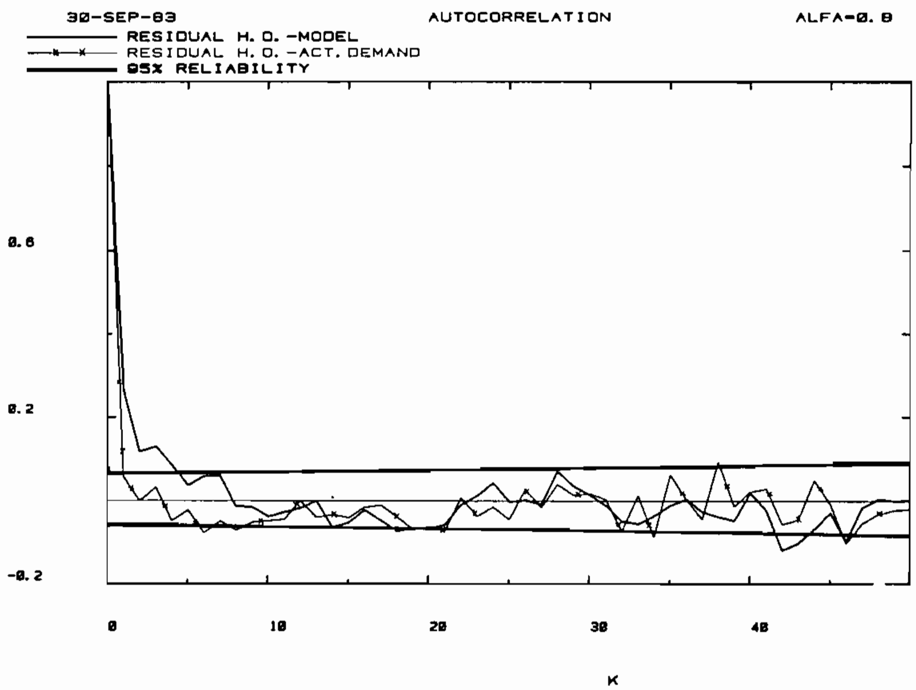

Figure 8.

all cases. The decrease in the case of $\alpha = 0{\cdot}8$ for $k > 50$ is the clearest one, although it is not very convincing either. Anyway, evaluation of this residual with window techniques will be a better strategy for obtaining knowledge about the learning effects.

5. Conclusions

Our purpose was to determine whether a simple zero-order model could be a sufficiently exact description of the behaviour of a human operator in a specific control task, recognized as a cognitive control (prediction task).

To attain this purpose, a computer program has been written that is able to test such a model, and to estimate its parameters in an experimental situation. Thirty experiments have been run in three groups of ten, and based on the results of these experiments we can state that:

(i) The zero-order model can be a satisfactory model to describe the principal aspects of the behaviour of the human operator.

(ii) Extension of the model to a first- or, perhaps, second-order model may improve the description of the behaviour.

(iii) As it seems now that the profit rate did not serve its purpose sufficiently in guiding an operator in making successive decisions; this conclusion forces us to reconsider the function of the profit rate as used in the experiment. Profit as such is an important criterion in inventory control. However it is often very difficult to see a (direct) relation between decisions and the profit which results from them. Profit rate can only give information that is additional to the prediction errors which are clearly visible to the operator. In our experiments the profit rate, if interpreted correctly, would cause the operator to choose the inventory to be slightly too large. This strategy, however, is intuitively contradictory to the obvious strategy of the inexperienced operator to minimize the difference between his inventory and the demands from his customer. In other words, one needs much more experience with the test to make full use of the information provided by the day-to-day changes of the profit rate.

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