

MODELLING THE HUMAN OPERATOR'S SUPERVISORY BEHAVIOR

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ABSTRACT

The investigation reported here deals with the description of the behavior of the human operator performing the supervision of a setpoint controlled process under steady state condition. The description will be given in terms of a mathematical model.

In verifying the model structure, certain task variables have been defined. Then, to each of these task variables, the particular influence of the variable on the parameters of the human operator model has been postulated. The data analysis is based on statistical and stochastic procedures.

It is shown that the model structure is applicable to the description of the human supervisory behavior. However, the parameter estimation procedures are complicated, time consuming and thus expensive.

1. INTRODUCTION

The proper functioning of technological systems, diverging from very simple to very complex, needs the ability of human intervention in most cases. More specifically, it can range from a direct manual control to a supervisory control mode.

Because of the ever increasing automatization in industry, new demands have been put on now-adays operators. They are no longer functioning as direct, manual controller; their tasks became more and more the supervision of multi-variable, slowly responding, and complex systems. As a consequence, this task is composed of monitoring the displayed system outputs, controlling the setpoints of the automatic controllers and performing the fault management.

Due to sudden process changes or disturbances, the output variables might exceed the boundaries which are specified by the management or by safety regulations. Based on the perceived deviations, the supervisor decides to change one or more setpoints. Moreover, when the information needed to supervise the plant is insufficient, the operator might decide to ask for additional information which may lead to a setpoint correction. This steady state control aspect of the supervisory behavior is in general important in process control, that is in the control of continuous processes. It is called tuning. The shut down and start-up procedure, also an important control mode, is mostly executed by special teams or automatic controller systems.

In nuclear power plants, however, tuning is far less important than fault management. These plants are highly automated, and the main task of the operator is to search for malfunctions, fault diagnosis and fault management.

In this investigation the attention is focussed on the tuning task of the supervisor.

2. MODELLING HUMAN CONTROL BEHAVIOR

The behavior of an operator performing a supervisory task, or any other manual /cognitive task, can be described in different ways.

For many years, scientists try not only to describe the behavior of the subjects

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of interests *after* the experiments, but, they also try to make predictions upon the behavior to be expected, thus *before* the experiments. Among the many theories which are applied in order to predict human operator behavior during manual control tasks, the cybernetic models are well-known.

In this philosophy the human operator is regarded as a system, a central processor, with inputs and outputs. So, human operators can be described as input - output relations. This idea is not new; back in the twenties, the behaviorists already described human beings as data processors with an unknown central processor, the so-called "blackbox", which transferred stimuli into certain responses. By the application of a wide variety of stimuli and by measuring all responses, the input-output relationships could be determined. On the basis of system theory, from the input-output relations a model, that is a model structure and model parameters, can be derived. Consequently the "black box" is whitened.

Although in manual control situations cybernetic models can be applied successfully to predict human behavior [ACMC 1964 - 1981], up to now it is still not possible to develop such prediction models for supervisory control situations. The major differences between direct manual control of vehicles and the discrete characteristics of supervisory control in process industry can be illustrated by Table I. [Beaverstock, Stassen, Williamson, 1977]

Data Processing Aspects	Vehicle Control	Process Control
INFORMATION Type Dimension Time constants Abstractness Origin disturbances System properties	Direct About 10 From sec. to min. Low Known Linear Constant	Indicative Between 100 and 1500 From min. to hours High Unknown Non-Linear Time-varying
PRESENTATION Integration Parallel/series Number of displays Time window Modes Overview	Integrated displays Mostly parallels Low Instantaneous and predictive Visual, auditive, vestibular Good	Non-integrated displays Parallel and/or series High Instantaneous and history (trend) Visual, auditive Poor
MANIPULATION Direct feedback Response Strategies Accuracy	Proprioceptive Immediate Error correction More or less consistent Quantitative	No proprioceptive Next shift Boundary control Variable More or less qualitative
CONFIGURATION Physical size Personnel training Human factors	Small Highly and consistently Well developed	Large Less rigorously Very little developed

TABLE 1: COMPARISON BETWEEN VEHICLE CONTROL AND PROCESS CONTROL
 After Beaverstock, Stassen and Williamson [1977]

3. MODELING HUMAN SUPERVISORY BEHAVIOR

3.1 Definition of the system state and model description

The human operator's supervisory behavior in a stationary control mode, where a dynamic, slowly responding, and complex system is setpoint controlled is characterized by periods of waiting and of observing output variables followed by periods of executing control actions.

The process to be supervised is described by a linear, dynamic system with state $x(k)$. The system is disturbed by a noise $w(k)$. It has a controlled input $u(k)$ whereas the output $y(k)$ consists of a linear combination of the state variables $x(k)$; the system can be observed by the human operator via a display. This observation can be a continuous observation or an additional sampling of a particular system output.

System theory defines the state of a discrete system as *"some compact representation of the past activity of the system complete enough to allow us to predict, on the basis of the inputs, exactly what the outputs will be and also to update the state itself"* [Padulo, Arbib, 1974]. *"So the future values of the state as well as the outputs are only determined by the initial values of the state and the following inputs"* [Kok, Van Wijk, 1978]. Therefore, the input-output relation of a dynamic system can be described by two equations: One equation yielding the progressive change in time of the system state due to the inputs, and a second equation associating the outputs of the system to the actual value of the system state, thus:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Gw(k) ; \\ y(k) &= Cx(k). \end{aligned}$$

The matrices A , B and G can be regarded as system parameters, and the matrix C is the display parameter.

In order to describe human operator's supervisory behavior, the model suggested by Kok and Van Wijk [1978] will be applied. This model is based on the philosophy that the human supervisor acts as some kind of sub-optimal controller, taking into account the inherent limitation that his observation of the output process variables can be inaccurate. This limitation is modelled by a noise $v_o(k)$, called the observation noise. It is assumed that the human supervisor possesses exact knowledge of the generated control signals $u(k)$. Hence, the model consists of three subsystems: an *observer*, a *controller* and a *decision making element*, *DME*, the last one acting on each of the two other subsystems (Fig. 1).

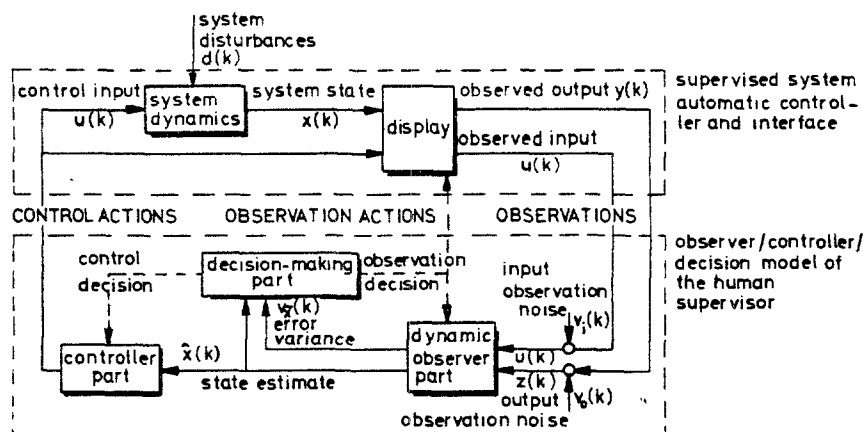


Fig. 1: Structure of the observer/controller/decision model

The structure of the *observer* is depicted in Fig. 2; it is modeled as a Kalman filter, thus it contains a replica of the system including the display. Based on the observed output variables, on the knowledge of the dynamics of the system, on the knowledge of the statistical properties of the noise acting upon the system, and on the setpoint changes which have been made already the observer estimates the state of the system $\hat{x}(k)$ and the associated variance of the estimation error $V_{\hat{x}}$. In this part of the model, the noise vectors $v_o(k)$ with the covariance matrix ψ_{v_o} is assumed to be white and normally distributed. As a consequence the matrix ψ_{v_o} is a diagonal matrix. The quantity ψ_{v_o} models the rate of uncertainty of the supervisor about the perceived outputs of the system. The quantity is a parameter of the observer subsystem.

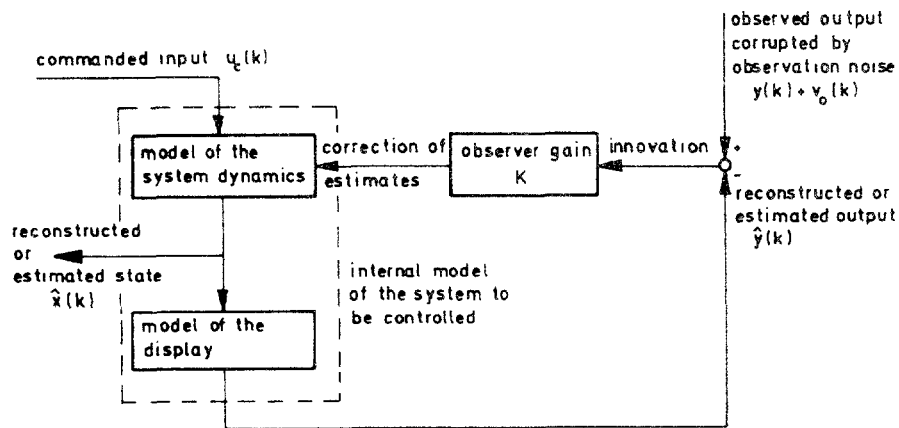


Figure 2: Structure of the observer

The subsystem, the *controller*, can be regarded as a variant of the optimal control law. It is supposed that the human operator will control deviations, from outside the limits, back to the nominal value in a certain period. Hence, when the period, in which the output variable will reach the nominal value, is determined, then the amplitude of the setpoint correction is also fixed; a short period requires a larger amplitude than in a longer period. This trade-off between period and amplitude is modeled by the parameter "p" in the single step control law which will be used as *controller*.

From this control law: $u(k) = u_{nom}(p) - L(p)\hat{x}(k)$, where u_{nom} denotes the nominal input value, L denotes the gain factor and $u(k)$ the magnitude of the corrective action, all the quantities are known except p , the model parameter, while the gain factor, L , is dependent of p . It is supposed that the human operator bases the quantity $u(k)$ on the estimation of the actual system state, $\hat{x}(k)$, and is supposed not to take into account effects of the system noise during the period in which the action is kept constant. With the single step control law it will be possible to reach in p time steps an output vector $y(k + p)$ which is equal to the nominal output vector, y_{nom} , as long as the system noise is zero within that period. Because the system noise is probably not zero a "subgoal" will be reached.

The *DME* provides two functions: Firstly it models the moments on which an additional sample has to be taken and secondly it models the instants in time on which

a setpoint correction has to be performed. The inputs of the DME are the system state estimate $\hat{x}(k)$ and its variance $V_{\hat{x}}$; the first function makes use of $\hat{x}(k)$ and $V_{\hat{x}}$, the last one uses $\hat{x}(k)$ only.

The additional observation sampling is modeled according to a hyperbolic decision rule (Fig. 3). Whenever the combination of the absolute value of the estimation of the deviation $|\hat{y}_i(k) - y_{nom,i}|$ with regard to the nominal value, $y_{nom,i}$, of an output, $y_i(k)$, and the uncertainty about that particular estimation, $\sigma_{y_i}(k)$, exceeds a criterion value, a sample will be taken. The quantities $\hat{y}_i(k)$ and $\sigma_{y_i}(k)$ are derived as a linear function of the state estimate, $\hat{x}_i(k)$, and the associated variance, $V_{\hat{x}}$, respectively. The modeling parameters are the curvature of the hyperbolic line, CE_i , and the asymptot value or minimal accepted uncertainty, $\sigma_{y_i \min}$, where i denotes the i -th output variable.

The controller decisions are modeled as a straight line (Fig. 4). Whenever, the absolute value of the deviation between the estimated output and the nominal value, $|\hat{y}_i - y_{nom,i}|$, exceeds the line q_i , a corrective action will be made. The upper or lower tolerance limit, q_i , is thus also model parameter.

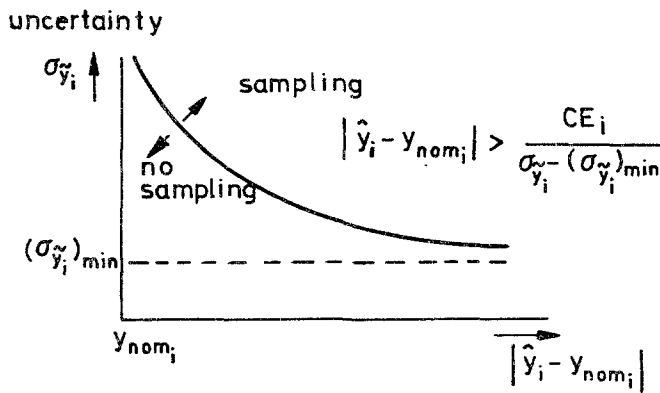


Figure 3: The hyperbolic decision-rule

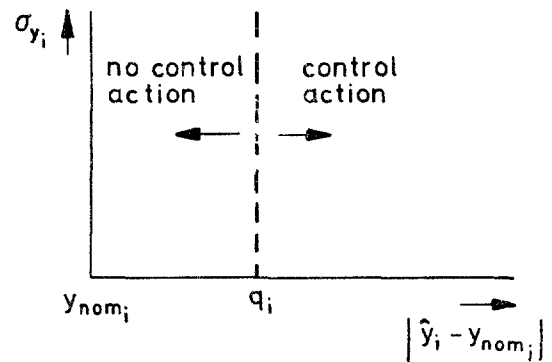


Figure 4: The linear decision-rule

3.2 Separation Theorem / Model hypotheses

As pointed out already in the preceeding section, the Observer/Controller/Decision-model, OCD-model, is based on the conceptual framework of the Optimal Control Model of Baron, et.al [1969], Kleinman, et.al [1970,1971]. The basic assumption of this model is that a well-trained and highly motivated human operator will act in a near optimal way, subject to his internal constraints which limit his performance, and subject to the extend to which he understands the task objectives. This model can appropriately be used to predict manual control behavior ACMC,[1964 - 1980]. The OCD-model is an extension of the Optimal Control Model, just by the introduction of a DME. It is also different by the fact that a single step control law as a modification of the optimal control law is proposed, instead of the optimal, continuous control law. Finally it differs by the fact that most of the internal constraints which were taken into account in the OCM are assumed to be neglectable. This assumption seems sensible due to the large time constants involved in the steady-state supervisory control mode; hence aspects like reaction times of 0.1 sec and neuromuscular dynamics with time constants of 100 to 200 msec,important in the OCM, can be neglected in the OCD-model.

In the case of the Optimal Control Model the well-known separation theorem is valuable as a basic tool. No arguments can be found, to proof that the separation principle can also be applied in the case of the OCD-model, since with the introduction of the DME, the model becomes non-linear, whereas linearity is one of the necessary conditions in order to be allowed to apply the separation principle. The importance of the separation theorem, however, makes that it may be fruitful to study to what extend the DME influences this important principle; therefore the following hypotheses have been stated:

- . Variations in the intensity of the system disturbances are changing the parameter values of the observer; they are not influencing the parameters of the controller. Changes of the parameter values of the decision making element for observation actions will also take place.
- . Variations in the display structure are also changing the parameter values of the observer, and the decision making element for the observation actions; they are neither changing the parameter values of the controller, nor the parameters of the decision making element for the controller actions.
- . Variations in the task to be performed are changing the parameter values of the controller and the decision making element for the controller actions; they are not changing the parameter values of the observer and the decision making element for the observation actions.
- . Variations in the dynamics of the system to be supervised are changing all the parameter values in the model.

In Table II the postulated relations between the task variables and the parameters of the model are represented, where a plus, +, denotes a dependency and where a zero, 0, denotes independency.

Table II: Postulated relations between task variables and model parameters.

Parameters of:	Observer part	Observer Decision part	Controller Decision part	Controller Part
Task variables:				
System Disturbances	+	+	0	0
Display Structure	+	+	0	0
Task Requirements	0	0	+	+
System Dynamics	+	+	+	+

Since the parameters themselves are difficult to interpret, and since they cannot be identified easily, a smooth way of verification of these hypotheses cannot be found directly. Therefore, it is worthwhile to transform the hypotheses to directly measurable quantities. Since quantities like the number of observation actions, the number of controller actions and the amplitude of the control actions can be measured, and since they are directly related to the structure of the system to be supervised, one can reformulate the hypotheses as follows:

- . Variations in the intensity of the system disturbances will be reflected in the number of observation actions, and will be reflected in an additional way in the number of controller actions. However, it will not be reflected in the mean amplitude of the controller actions.
- . Variations of the display structure will only be reflected in the number of observation actions; they will neither influence the number of controller actions nor the mean of the amplitudes of the controller actions.
- . Variations in the task requirements will be reflected in the number of controller actions; they will not be reflected in the number of observation actions (Table III and Fig. 5).

Two remarks have to be made in relation to these hypotheses:

In the first place the task variable "system dynamics" will not be taken into

account here, because the verification of hypothesis on the influence of the system dynamics as a task variable will increase enormously the number of experiments.

In the second place the supplementation "in an additional way" in the first hypothesis needs some explanation. To verify the separation theorem, it has to be shown that optimization of the filtering and the control problem, separately, will lead to the same results as optimization of the combined problem. Referring to the model first-discussed, and taking into account the influences of the task variables just-mentioned, a consequence of the separation theorem is that the super-position principle should hold. Hence, the task variable system disturbances is thought to contribute, in an additional way, a number of controller actions which is independent of the number of controller actions attributed by the task variable task requirements.

Table III: Postulated relation between task variables and direct measurable quantities.

Quantity:	Number of Observation actions	Number of Controller actions	Mean Amplitude of Controller actions
Task variable:			
System Disturbances	+	+	0
Display Structure	+	0	0
Task Requirements	0	+	+

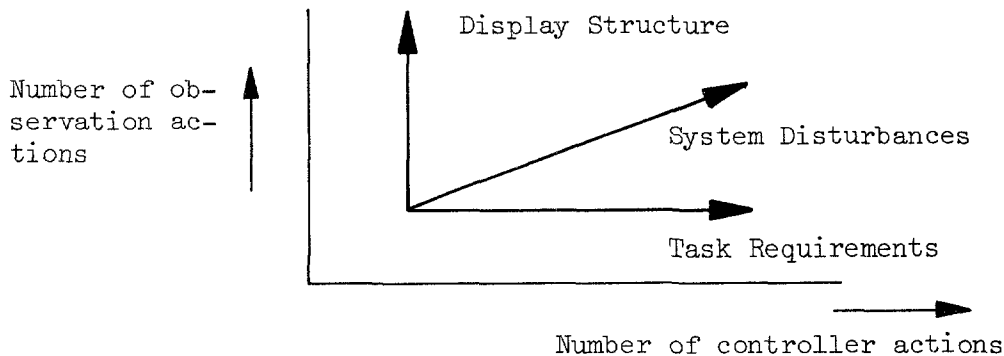


Figure 5: Postulated relation between task variables and direct measurable quantities

4. EXPERIMENTAL DESIGN

4.1 Description of the research vehicle

In trying to verify the hypotheses stated in the last section, one needs a research vehicle on which experiments can be performed. For this reason a setpoint controlled process simulation has been implemented on a PDP 11/34 computer. The process, a Utility Plant, is considered to be a linear system and it consists of a Boiler, a Back Pressure Turbine and a Condensing Turbine. The Boiler produces high pressure steam which is pressure controlled. The Back Pressure Turbine consumes H.P.-steam and produces low pressure steam and electrical power; this low pressure steam is flow controlled. The Condensing Turbine consumes H.P.-steam and produces only electrical power. The total amount of electrical power produced is power controlled (Fig. 6).

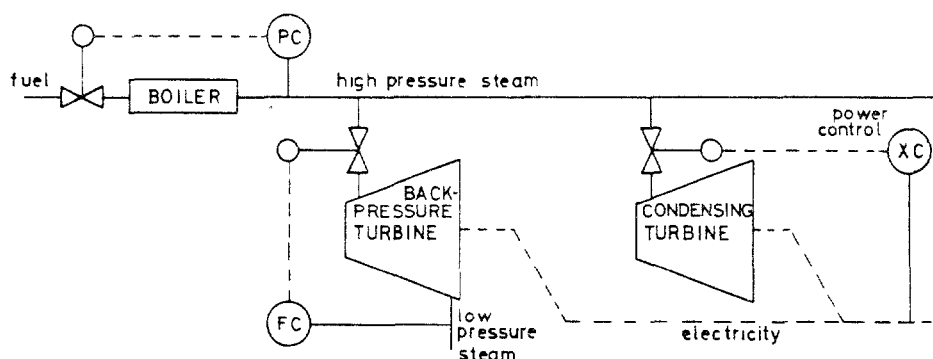


Figure 6: Structure of the Utility Plant

4.2 Description of the task of the supervisor

The task of the human operator is to keep the three output variables, i.e. the pressure of the H.P.-steam, the flow of L.P.-steam and electrical power which are corrupted by system disturbances, within specified boundaries. These boundaries are symmetrically located around a certain nominal value. The outputs are displayed digitally; the boiler output can be observed continuously whereas the two other outputs can be sampled only on request. The task of the operator is to sample as few as possible, and to correct the set-points as few as possible. The control should be performed only with small corrective actions.

The operators will be master students of the Lab. for Measurement & Control of the department of Mechanical Engineering.

4.3 The experimental set-up

Three task variables have been chosen for the experimental set-up, i.e. a variation in system disturbances, in display structure and in task requirements.

Variations in the *system disturbances*: Each output variable is disturbed by a first order noise with a low intensity, denoted as n , or with a high intensity, denoted as N .

Variations in the *display structure*: Each deviation between output and a specified boundary can be indicated in one of the two following ways. By the local alarm structure, denoted as d , a direct indication is given which output is out of the boundaries and in what direction the variable is changing. By the central alarm structure, denoted as D , it is only indicated whether one of the output variables is deviated from one of the specified limits. The human operator has to investigate which output is deviating and in what direction the output is changing; he even has to make sure that there is only one output deviating from the specified limits. More information can be asked for by means of taking additional samples.

Variation in the *task requirements*: The lower and upper limits of each output variable are specified. For the case that lower and upper limit are close to each other the task is difficult (B); for the case they are far away from each other, the task is rather easily (b).

In the experimental set-up each condition consists of a combination of one of the two levels of the three task variables involved. Therefore, eight conditions can be formed. In the first verification phase four conditions were considered, they were: n.d.b; n.D.b; N.d.b; N.D.b. In the second verification phase the conditions were: n.d.B; n.D.B; N.d.B; N.D.B.

5. TESTING THE HYPOTHESES

In trying to verify the hypotheses, one needs to be sure to base the verification on a robust set of data of well-trained operators. The criteria in order to conclude whether the data is originating from well-trained subjects, are twofold. At first, the number of samples taken and the number of corrective actions performed should approach a constant level for each condition. Secondly, the computed absolute value of the deviation integrals, based on the time that the signal is outside the specified boundaries, should be as close as possible to zero.

For testing the hypotheses on the basis of the first four conditions the data of nine trials were considered. The necessary conditions in order to apply parametric statistics were checked. Thereafter, an investigation whether the collected data were statistically seen, influenced by possible learning effects was performed. No learning effects could be detected. As an indication, more than 100 (catch) trials preceded the actual 36 trials. Fig. 7 shows the 99% confidence interval of a T-Student distribution of the number of samples taken and the number control action performed, for each of the four conditions. The figure shows that a change in the display structure effects only the number of samples taken and not the number of controller actions executed; Table IV reveals the exact results.

Table IV: Results of a T-test

Variable	Number of cases	Mean	SD	2-tail prob
Sampl group n,d,b	9	0.7	2.0	0.000
group n,D,b	9	21.7	3.1	
Contr group n,d,b	9	77.2	3.6	0.353
group n,D,b	9	79.8	7.4	
Sampl group N,d,b	9	14.8	6.5	0.000
group N,D,b	9	47.0	11.0	
Contr group N,d,b	9	115.9	16.6	0.242
group N,D,b	9	108.2	9.1	

Furthermore it can be seen, that variation in the intensity of the system disturbances is reflected in the number of observation actions, whereas it is also additive in the number of controller actions; Table V shows the exact results.

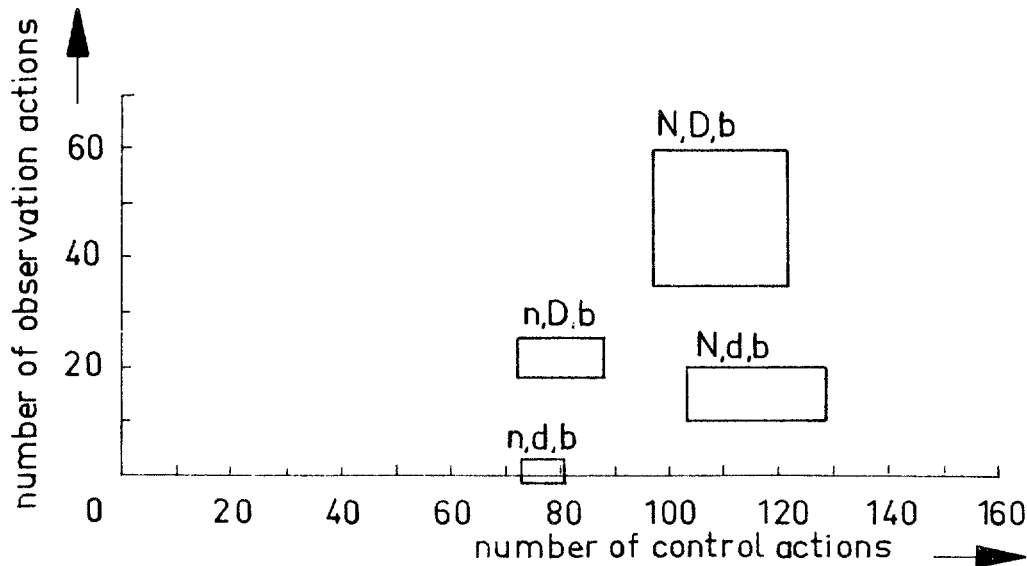


Figure 7: Obtained results of four experimental conditions

Table V: Results of a T-test

Variable	Number of cases	Mean	SD	2-tail prob.
Sampl group n,d,b	9	0.7	2.0	0.000
group N,d,b	9	14.8	6.5	
Contr group n,d,b	9	77.2	3.6	0.000
group N,d,b	9	115.9	17.6	
Sampl group n,D,b	9	21.7	3.1	0.000
group N,D,b	9	47.0	11.0	
Contr group n,D,b	9	79.9	7.4	0.000
group N,D,b	9	108.2	9.1	

As long as the task requirements have not been changed in the four conditions, the mean amplitude of the controller actions was supposed to remain constant. For verification the results of the T-test showed no significant difference between the four conditions (Fig. 8). So the hypotheses with respect to the task variables, display structure, and system disturbances, can be accepted completely.

The third task variable the "task requirement", is supposed to have only a effect on the number of controller actions and not on the number of observation actions. By comparing Fig. 9 and Fig. 7, it can be seen that only in one case the results of a variation in the task requirements deviates from the postulated effects; in condition n,D,B more samples are taken than in condition n,D,b.

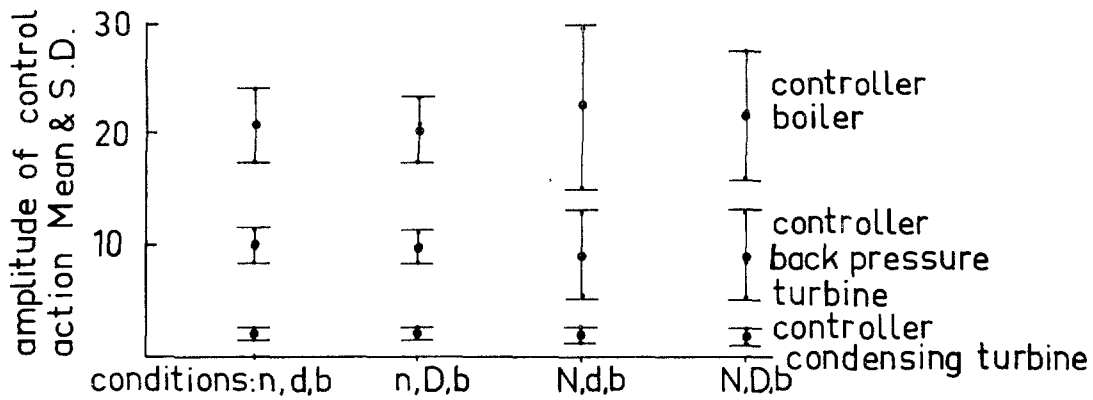


Figure 8: Number of set-point corrections of three output variables in four experimental conditions

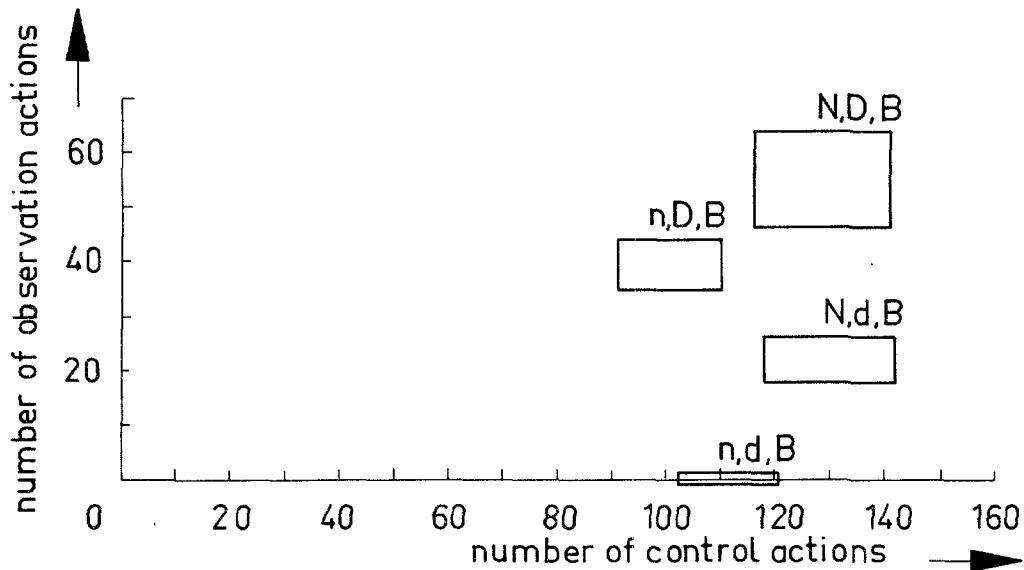


Figure 9: Obtained results of four experimental conditions

Results obtained with a less trained subject were similar with respect to the task variables, display structure and system disturbances in the conditions: n,d,b; n,D,b; N,d,b; N,D,b. The results were slightly less significant ($p < .02$). The results with respect to the task variable task requirements do not agree with the hypotheses; even the results in the conditions n,d,B; n,D,B; N,d,B; N,D,B where the task variables display structure system disturbances were varied systematically, were rather poor, although the trends were in the predicted direction.

In trying to understand why the highly significant results with the well-trained subject were not replicated by the less-trained subject, and in particular for the case of the task variable task requirement, an additional investigation was made.

Due to the fact that the second subject sampled about three times more than the well-trained subject in each condition and due to the fact that he also controlled about 1.3 times more than the first subject, the idea of a roof or ceiling effect, spoiling the expected results, was probed. In a new experimental set-up the well-trained subject was excluded from any alarm indication when he was supervising the Utility Plant. So the task variable display structure got a third level. Here it should be noted that no alarm indication in the other two levels, local alarm and central alarm, carries at least the information that none of the outputs is out of the boundaries. In the new, experimental situation, he even did not get this information, so the subject had to sample much more than before, independent of whether the system disturbances were high or low, and whether the boundaries were small or large. The number of samples became about equal to the number of samples of the second subject. The results, obtained from more than 90 trials, indicated very strongly that a roof effect could have been the cause of the differences between the results obtained with the well trained subject and those with the less trained subject.

6. PARAMETER IDENTIFICATION

In order to verify the hypotheses with respect to the parameters of the model, no analytical method for parameter estimation could be derived. Therefore, certain iteration procedures have been used. During the parameter identification, many difficulties showed up. One difficulty appeared in the problem of not converging to a minimum of one of the accepted criteria, another difficulty appeared with the large computing time of 45 seconds CPU of a large scientific off-line computer system for only one iteration step. Therefore, much effort has been put in reducing the number of iterations.

The main parameter of the Observer part, ψ_{VO} , has been chosen constant; the parameter value was chosen 1% of the variance of the associated observer output variable according to results obtained with the Optimal Control Model [Levison, et.al., 1969]. This parameter will be identified in the near future.

The parameters for the observation part of the DME, the curvature parameter CE_i , and the asymptote $\sigma_{y \min i}$ of this curve, had to be identified for each of the outputs to be sampled. Therefore, an adaptive random search method became too expensive. For this reason a graphical method was proposed.

Suppose the human operator sampled the i-th output variable at time: $t_{i1}, \dots, t_{ik}, \dots, t_{in}$. By applying the observer part, the absolute value of the deviation between the estimation of the i-th output variable, $\hat{y}_i$, and the nominal value of the i-th output variable, $y_{nom i}$, and the associated uncertainty about this estimation σ_{yi} , can be derived; respectively:

$|\hat{y}_{i1} - y_{nom i}|, \dots, |\hat{y}_{ik} - y_{nom i}|, \dots, |\hat{y}_{in} - y_{nom i}|$ and $\sigma_{yi1}, \dots, \sigma_{yik}, \dots, \sigma_{yin}$. The k-th sample is located on the hyperbolic decision line:

$$|y_{ik} - y_{nom i}| = \frac{CE_{ik}}{\sigma_{yik} - \sigma_{y \min ik}}$$

For the k-th sample, the quantities $\hat{y}_{ik}$, $y_{nom i}$ and σ_{yik} are constants; so the relation of these quantities with the parameters CE_{ik} and $\sigma_{y \min ik}$ is known. This relation can be given as the straight line,

$CE_{ik} = -|y_{ik} - y_{nom i}| * \sigma_{y \min ik} + |y_{ik} - y_{nom i}| * \sigma_{yik}$, and can be plotted in a $\sigma_{y \min i} - CE_i$ plane. This relation can be given for all samples of the i-th output variable.

Fig. 10 shows the envelop lines of all the n "decision lines". In the area of convergence of the envelop lines, the optimal parameter set is supposed to be located. This idea can be explained when 2 samples are taken; the crossing of

the two lines, Fig. 11, shows the only solution for two samples to be located at the same hyperbolic line with the associated asymptot. In this case convergence is narrowed down to one point, and the variance is reduced to zero.

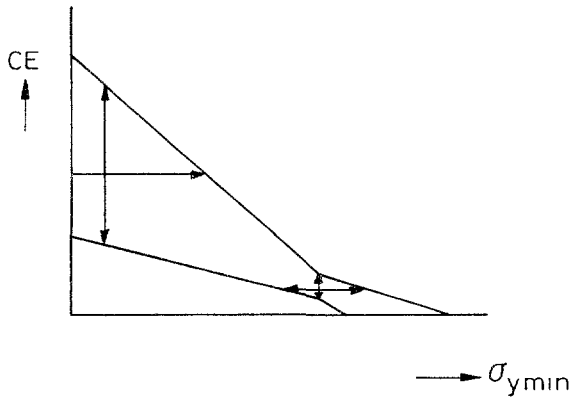


Figure 10: Envelop lines in a $CE-\sigma_{y \min}$ plane

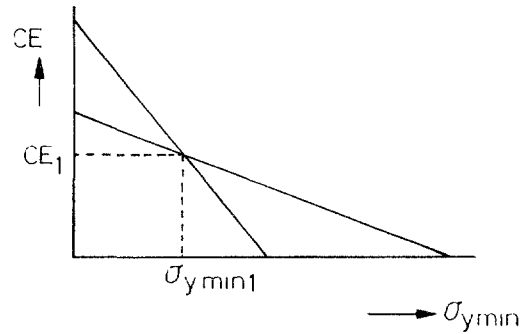


Figure 11: Two decision-lines

By applying this method, very good results were obtained, i.e. the number of samples, taken by the model based on the acquired parameter set, agreed with the number of operator samples taken in the same condition. This result however, does not guarantee that the instants in time of operator sampling and the instants in time of sampling of the model agree with each other. Therefore, the distribution of the sampling intervals of the model, given certain parameter values of CE_1 and $\sigma_{y \min 1}$, is compared with the distribution of sampling intervals of the human operator. The distributions have the shape of binominal distributions. A close resemblance between the two distributions of operator sampling and model sampling for the two to be sampled outputs is illustrated in Fig. 12 and Fig. 13.

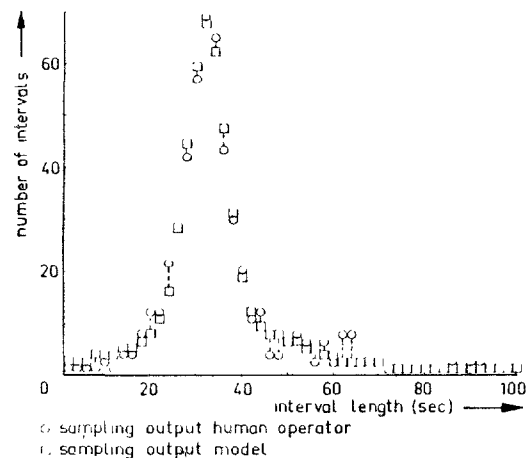
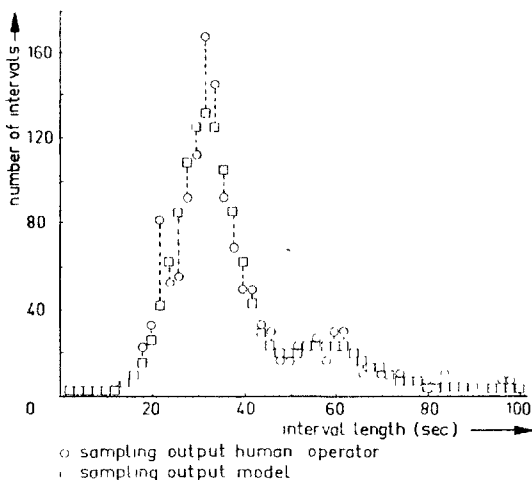


Figure 12, Figure 13: Distribution of sampling intervals of two outputs

The parameter, p , of the controller subsystem, determines the number of time steps, the setpoint correction will remain constant and determines the amplitude of that correction; that parameter, p , have to be identified. In this investigation different parameter values have been used, whereas $p = 22$ turned out to be the lowest value before instability of the H.P.-steam control loop occurs. With $p = 22$ also the best control performances were obtained. In order to relate these results with other control situations. Table VI shows the absolute value of the deviation integrals of the three output variables of the supervisor system for several control situations.

Table VI: Deviation scores of system outputs

Deviation score of:	Boiler output	Back Pressure output	Condensing output
Situation:			
Non operator intervention	400	106	50
Optimal operator control	0.0	0.01	0.001
OCD-model control;	137	73	58
Single step control law ($p=22$)			
OCD-model control;	0.35	10	9.5
Optimal (continuous) control law			

The results are clear: The optimal (continuous) control law deviation score agrees mostly with the deviation score of the human operator. However, the characteristics of the way of controlling of the model do not agree at all with the discrete action pattern of the human operator. The number of controller actions, initiated by the OCD model ($p=22$), agrees with the number of control action executed by the human operator; also, the discrete action pattern of the single step control law agrees with human operator control actions, but the overall performance of the model expressed by the deviation scores, is still somewhat troublesome.

7. CONCLUSIONS AND FINAL COMMENTS

Whether the separation theorem is valid or not for the OCD-model, cannot be answered right now. However, it can be said that the results obtained with a highly trained and motivated subject showed the postulated independency of observation and control.

It can also be said that most of the model parameters can be identified, although the computing time is still alarming.

Therefore, the research will be continued with highly trained subjects; it will deal with changes in the parameter choice of the controller part or even accepting another control law and it will deal with optimizing the parameter identification procedures.

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