HUMAN SUPERVISORY CONTROL
BEHAVIOR: verification of a cybernetic model

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HUMAN SUPERVISORY CONTROL
BEHAVIOR: VERIFICATION
OF A CYBERNETIC MODEL

Proefschrift

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door

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In the present time, scientific investigations are in many cases no longer the work of one man but the work and effort of groups of people. The work on a project, presented in this thesis is no exception. Therefore, I like to acknowledge the contributions of all those who have taken part in the project or contributed to the progress of it.

In the framework of fulfilling the requirements for their master degree, Jan de Wit and Wim Verbeek made a computer simulation of an existing distillation column. Erst Peter Tamminga used their software to make a utility plant simulation. Besides, contributions to the parameter estimation techniques used were made by him. Karel Frieling evaluated several parameter estimation procedures and suggested the grid method. Rolf van der Veldt modified several of the estimation procedures, worked on the subject of reduced order observers and executed some of the experiments. Gijs van Oostveen made procedures to compare sample and control interval distributions of the human operator and those obtained from the model. Paul van Dorp made computer software for the trend recording presentation on the Visual Display Unit and suggested several presentation forms. Peter Lute implemented Van Dorp's software in the Plant simulation and performed some of the experiments. Finally, Bart van Rixel investigated the effects of displaying derived output information on the operator output estimations.

Display and control modules were developed and realized by the staff members Leo Beckers and Leo Brinkman. Also Jaap van Dieten contributed substantially to the realization of the modules. The simulation software was mainly realized by students under the supervision of Jaap van Dieten who also contributed significantly to the software development.

I am indebted to Jan Kok and Ron van Wijk for using their model. Both Jan Kok and Henk Schneider are thanked for their helpful discussions.

I want to acknowledge Aad Gutteling for drawing the illustrations and all those members of the Laboratory of Measurement and Control who have contributed directly or indirectly to the progress of the project.

I am indebted to the Dutch Organization for the Advancement of Pure Research for their financial support of the project for a period of four years. I to want to acknowledge the Department of Mechanical Engineering for their hospitality and facilities needed to carry out the experiments.

Thanks to my next-door neighbour, Jan Huizinga is justified for the excellent cover lay-out. Moreover, I want to thank my friend Herman Wessel for the insightful cover drawing.

I like to thank my parents for always being parents to me. Finally I want to thank my friends for supporting me carrying the loss of my late partner Jeltje.
Humans are intrigued by the behavior of others and that of their own. About such behavior, a variety of descriptions have become available. Within the human description methods, the cybernetic approach belongs to one of the latest forms; it will result in cybernetic or system approach-oriented models. The models are thereby restricted to observation and control behavior in relation to dynamic systems. The first models were dealing with control behavior of fast responding systems such as automobile driving and flying aircrafts. Hence, a large number of manual control data became available. One of the milestones in manual control modeling is certainly the Optimal Control Model. It is therefore not pure coincidence that it has been tried to apply this model in the, until recently, neglected area of supervisory control.

In supervision situations the system to be supervised, and eventually controlled, is relatively slow and multi-variable. Typical systems are distillation columns in chemical and petrochemical industries and, in a particular sense, supertankers.

In a previous investigation a supervisory control model, based on the structure of the Optimal Control Model, was suggested and preliminary tested. The model as such was found to be a successful contribution, although the model had been tested in only rather simple task situations. The investigation reported here deals with the validation of that particular supervisory control model.

In the model several assumptions had been made; one assumption seemed cardinal, i.e. the separation of observation and control. This assumption yields the application of the separation principle. The Optimal Control Model was fully based on this principle.

However, in order to extend this model to supervisory control, some modifications had to be included; it resulted in the Observer Controller Decision Model, the OCDM. In particular the introduction of a non-linear function, to represent discrete human decision making, required the separation in observation and control. Due to the non-linear function, a proof, of this separation could not be obtained on the system theoretical basis. Therefore, it has been investigated to what extent the separation could be accepted validly on the basis of psychological theories.

In experimental psychology, a paradigm is regularly applied to search for independency of parts in visuo-motor models. This paradigm has been regarded as an adequate tool for indications with regard to the validity of the separation between observation and control. The paradigm itself is thereby principally based on the superposition principle, known from system theory.

To obtain appropriate data, a slowly responding and complex multi-variable system, a display device, and experienced supervisor behavior are required. It has been decided to apply a computer simulation of a system with digital and/or trend recorded output information. Controls are set-point type controllers. The operators of the supervised system were master students at the Laboratory for Measurement and Control; these students have been trained extensively.

In the model as such, three characteristic functions can be recognized, viz. observation, control, and discrete decision.
The observer in the model deals with the reconstruction of the state of the supervised system. Apart from this estimation of the system state, the variance of the estimation error is an additional output of the observer. It should be mentioned thereby that the modeling is formulated in state space notation. Two decision functions are encountered in the decision making part. The first decision function deals with determining the instants of taking samples of the non-continuously presented output information. For this observation decision mechanism the state estimate and the error variance are required. The second decision function deals with the determination of the instants of introducing control corrections. The determination is based on the state estimate. The third and last part in the model fixes the control amplitude on the instants that control corrections are to be made. The control amplitude is thereby based on the state estimate.

In the model structure, a number of parameters is present. These parameters are available for making a fit between the model behavior and the measured operator data. By means of search procedures the best parameters values can then be determined on the basis of a sensible chosen criterion. In this case the well-known quadratic criterion was not applicable, due to the multi-objective character of a supervision task. Therefore, a vectorial criterion has been applied.

In order to keep computer time low during the fitting procedure, it is sensible to keep the number of parameters as small as possible.

Task conditions have been chosen such that principally the separation theorem can be indicated as valid for the Optimal Control Model. It is thereby postulated that for the OCDM the principle also should yield under these task conditions. One consequence of accepting the separation principle is to treat small sets of parameters separately without loss of optimality. Therefore a sequential optimization of the parameter sets can be applied to find at the end model behavior equal to the case that the parameters were determined all at the same time.

Data for which it could be said, on the basis of statistics, that no further operator learning could be detected, has been used to test the hypotheses.

It was found that, with the aid of the superposition principle, some task conditions could be indicated as acceptable for a sequential optimization. Then the parameters were estimated. The optimization showed several inconveniences. The adjustment procedures used, to find optimal parameter sets, required much computation time. All kind of procedures have been tried to reduce this computation time. Some procedures resulted in a reduction of time, others failed completely in this particular situation.

Therefore an extensive search for parameter optimization could not be performed. During the parameter optimization other aspects showed up. These aspects indicated that with several in- and outputs the model could probably be dealt with, but that system interaction to some extent could not be coped with. The practical utility of the supervisory control model in its present form is therefore found to be rather limited.

Final comments, in order to understand the applicability of this model, are given.
SAMENVATTING


De eerste modellen hadden overwegend betrekking op het regelen van snel reagerende systemen zoals auto's en vliegtuigen. Hiermede kwam een groot aantal gegevens beschikbaar. Een mijlpaal in het modelleren van de zogenaamde directe handregeltaken is zeer beslist het optimale regelmodel. Niet zonder reden is getracht dit model tevens toe te passen in het, tot voor kort weinig onderzochte, gebied van het supervisieregelen. Kenmerkend voor dergelijke supervisiesituaties is dat de gesuperviseerde systemen relatief langzaam zijn en bovendien multivariabel. Voorbeelden van te superviseren systemen zijn te vinden in de chemische- en de petrochemische industrie zoals distillatiekolommen en, tot op zekere hoogte, supertankers. In een voorgaand onderzoek is een supervisormodel opgesteld gebaseerd op het optimale regelmodel en vervolgens aan een eerste onderzoek onderworpen. Hoewel het model is toegepast voor het beschrijven van relatief simpele taaksituaties kan toch van een geslaagde opzet gesproken worden. In het onderhavige onderzoek wordt de verificatie van dit supervisor modellnader besproken.

Met betrekking tot het model zijn een aantal aannamen gedaan. Slechts één aanname was beslissend voor een mogelijk verdere toepassing; te weten de scheiding tussen waarnemen en regelen. De aanname staat in de systeemtheorie bekend als het separatiebeginsel. Enige modificaties waren echter noodzakelijk om het model geschikt te maken als model van de supervisor. Dit resulteerde uiteindelijk in het Waarnemer-Regelaar-Beslisser-Model. Met name het toepassen van een niet-lineaire functie ten behoeve van diskreet beslisgedrag maakte de scheiding van waarnemen en regelen weer actueel. Op systeem-theoretische gronden is namelijk een dergelijk bewijs van het separatiebeginsel, gezien de niet-lineaire functie, niet te leveren. Derhalve is onderzocht, op basis van psychonomische benaderingen, in welke mate en onder welke omstandigheden de scheiding tussen waarnemen en regelen toch geaccepteerd kan worden.

In de experimentele psychologie wordt regelmatig een zogenaamd paradigma toegepast om eventuele onafhankelijkheid van delen in visuo-motorische modellen te onderzoeken. Het betreffende paradigma wordt daarbij als een geschild stuk gereedschap toegepast als indicator van ondermeer waarneem- en beslisaspecten. Aan het paradigma zelf ligt het superpositiebeginsel ten grondslag, zoals bekend uit de systeemtheorie.

Om het onderhavige supervisormodel te verifiëren zijn een traagreagerend complex en multivariabel systeem, een interface, en ervaren operatorgedrag noodzakelijk. Er is daarbij besloten gebruik te maken van een computersimulatie van een systeem met uitgangsinformatie op basis van digitale en/of trend presentatie. De regeling van het gesuperviseerde systeem vindt plaats door middel van setpointinstelling. Afstudeerstudenten,
verbonden aan het laboratorium voor Werktuigkundige Meet- en Regeltechniek en Cybernetische Ergonomie, traden, na een grondige training, op als proefpersonen.

Zoals reeds opgemerkt, zijn drie karakteristieke functies in het model te onderscheiden; t.w. waarnemen, regelen en discrete besluiten.


In het supervisorkader model zijn diverse modellparameters aanwezig. Deze parameters kunnen dienen om een overeenkomst te bewerkstelligen tussen het geregistreerde supervisorgedrag en het gedrag van het supervisornmodel. Op basis van een geschikt kriterium worden de best mogelijke parameter waarden, als resultaat van zoekprocedures, vastgesteld. Daarbij bleek het algemeen gebruikelijke kwadratische kriterium niet geschikt te zijn. Derhalve is een meervoudig kriterium toegepast.

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Bij het verwezenlijken van overeenkomstig modelgedrag met dat van de supervisor is, in verband met de benodigde reken tijd, het aantal parameters zo klein mogelijk gehouden. Als consequentie van het van toepassing zijn van het separatiebeginsel, bestaat de mogelijkheid groepjes parameters los van elkaar te optimaliseren zonder dat daarbij de uiteindelijke optimaliteit van het gehele model in gevaar komt.

Derhalve zijn taakkondities voor de operator gekozen zodanig, dat in ieder geval voor het optimale regelmodel, het separatiebeginsel aan te tonen zal zijn. De hypothese wordt daarbij geformuleerd dat ook voor het supervisornmodel het separatiebeginsel van kracht is, onder dergelijke taakkondities.

Om deze hypothese te testen is uitsluitend operator gedrag van getrainde personen toegepast, dat is vastgesteld op grond van statistische technieken.

Met behulp van het vaststellen van superpositie in bepaalde taakkondities, en dus het separatiebeginsel accepteren, zijn voor die kondities de parameterwaarden als groepjes parameters geoptimaliseerd. De gebruikte procedures vergden daarbij veel computerrekentijd. Er is derhalve getracht deze rekentijd zo veel mogelijk te beperken aan de hand van alternatieve optimisatietechnieken. De diverse technieken hadden daarbij een wisselend succes.


Opmerkingen met betrekking tot een beter begrip van de toepassingsmogelijkheden van het model worden ten slotte gegeven.
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CHAPTER I: INTRODUCTION.

1.1 GENERAL INTRODUCTION.

Systems such as chemical plants, nuclear power stations and
aircrafts, are now-a-days partly or fully automated. As a
consequence of this trend and, moreover, due to the introduc­tion of process computers on a large scale, the question has
been raised as whether the human operator is finally being
replaced by these computers or not; as far as it can be
overseen, this replacement seems not likely to take place. Even
with so-called 'unmanned' process operation man is supervising
the system(s), but at a remote location. The task of the human
operator, however, has changed; in fact it has shifted from
direct manual control, with man 'in' the control loop, to
supervisory control, with man 'above' the loop; the computer
functioning as the direct controller. Therefore, the main
questions to be answered are:

- Who is informed about what, in which way, and when?
- Who does what, how, and when?

These questions are directly related to the problem of task
allocation between man and machine. In order to answer these
questions, knowledge about the operator's capabilities and
limitations should become available in the near future. As
human operator performance depends on a large number of
variables, a classification of those variables can be helpful.

In the case of pilot-vehicle systems, Mc. Ruer and Jex
(1967) classified four different groups of variables, i.e. task
variables, environmental variables, operator-centered
variables, and procedural variables. This classification is
very general, and it has been applied in many human operator
investigations. As a consequence, the classification is a good
starting point in this investigation.

In the design of man-machine systems one is concerned with
the influence of task variables such as different forms of
displays, controls, controlled element dynamics and forcing
functions, whereas one tries to minimize the effect of other
variables on the performance of the overall man-machine system.
Although environmental variables such as vibrations,
temperature and atmospheric conditions are not of direct
concern, and the operator-centered variables such as
motivation, stress, workload, training, and fatigue, together
with the procedural variables such as instructions and
practice, are very important, the main concern of this study is
the task variables. Hence, the effect of different task
variables on the behavior of the human operator in supervision
will be investigated in detail.

1.2 GENERAL PROBLEM DEFINITION

In Human Factor research, as in experimental psychology in
general, the task variables or independent variables are
manipulated, and the dependent variables can be considered as
potential performance measures. The non-experimental variables
are kept as constant as possible; if this is impossible, particular methods are used to compensate for their effects on the dependent variables. Roughly speaking two methods can be distinguished to investigate the effects of task variables in man-machine studies:

- Descriptive modeling techniques in order to fit, according to a certain criterion, the human input and output to empirical models.
- Prescriptive or normative modeling in which a model structure is postulated and in which the model parameters are to be estimated from experimental data.

In the first method, the performance of subjects is measured given a set of task variables. The different performance measures under different experimental conditions are determined in order to describe the relation between task variables and measured task performance. This method has led to many practical improvements in the design of Man-Machine Interfaces, MMif's.

The second method describes what the input-output relation as a function of time should be by manipulating the task variables. This research method enables, after the considered model has been verified, predictions of the overall man-machine system performance, which includes the causal relation between input and output.

1.3 HUMAN OBSERVER AND CONTROLLER STUDIES

As long as the human creature dealt with tools, the urge of teaching other members of the human species and of learning from them can be recognized. First imitating the other's behavior and expanding this behavior to one's own purpose could be sufficient. Thereafter, the sequence of actions became more formalized; one became first apprentice, then a journeyman and at the end a teacher oneself. In the early days of the industrial development, behavior became even more structuralized. Men and women had to adapt to the functioning of the technical machines and their products. Thereafter, the stationarity of one's behavior started to be an important factor. Product quality got closely connected to a high degree of reproducibility and small tolerances. Ultimately, with a high level of automation, other human operator abilities, such as pattern recognition and problem solving capabilities are of increasing importance. Models elucidating one or more of these aspects, are very useful in contributing to understand human's functioning under different environmental conditions.

1.3.1 Psychological approach

Although the psychological literature very probably does not offer directly applicable results, known investigation methods can be very helpful in order to solve some of the many problems encountered in supervisory control investigations.

Well-known models in experimental psychological research can be used when they are relevant to problems such as: which tasks can be handled by human operators and how well can these tasks, relevant to the control of large and complex processes, be performed. In principle, psychological models can elucidate the human operator's abilities in performing multi-tasks. Results
from those models can be fruitfully used as a contribution for solving the problem of task allocation between human operator and automatic control device. The basic question here is:

Given a certain set of tasks, in what manner can the human operator perform these tasks simultaneously in an optimal way?

In order to give an answer to such questions, various combinations of tasks have to be investigated. The idea is that if two simultaneous tasks compete for the same human information processing resource(s) while the demand exceeds the available resource(s) capacity, then a degradation of performance will take place. Therefore, the performance measures attained are likely to be better when these tasks are performed separately, rather than simultaneously.

In literature many combinations of tasks are considered. The review by Wickens (1979) of 65 dual task studies, offers an estimation procedure whether or not two tasks will result in degraded performance, assuming they are performed simultaneously.

Although many results are concurrent and other results are in conflict with each other, still one can make a fair quantitative determination how alternative allocation of tasks will effect performance. Extrapolating the results from reaction time experiments in which the subjects have to perform rather easy tasks which require no a priori knowledge of the observed signals, to supervisory control situations where large time constants are involved and where system knowledge is essential, remains troublesome. As the concept of processing stages has obtained considerable acceptance through the application of the additive factors methodology in reaction time experiments, the paradigm of Sternberg (1969), the concept will be elucidated in a separate section.

1.3.2 The cybernetic approach

In man-machine systems, encompassing manual as well as supervisory control, three subsystems are of importance. These are:

- The system to be controlled together with the disturbances.
- The human operator, executing a certain task, or a combination of tasks.
- The interface between human operator and system, consisting of controls and displays.

The performance of the entire man-machine system loop depends on each of the subsystems. In trying to understand, and moreover, to predict the behavior of the overall man-machine system, one must be able to describe the subsystems individually. One advantage of models originating from system theory above other models is that all subsystems are described in one common language.

In attempting to model human operator behavior, a fundamental as well as a practical or pragmatic motive can be advanced. From the purely scientific point of view, the use of
models provides a succinct way of explanation of the experimental data. While developing a model, the scientist's thought about the issue connected to the subject of investigation becomes more structuralized. From the practical point of view, models are useful in order to obtain, or to contribute to obtain quantitative predictions. These quantitative predictions are essential in the process of designing technological systems. It is rather important to know how supervisors interact with large complex systems, before these systems are actually built.

It should be noted that cybernetic models are not intended to represent a replica of the mental activities of the human operator. When the human operator is modeled in the cybernetic sense it does not mean that the operator is thought to be identical with, for instance, a servo controller, an ideal observer, or a time shared computer. The models are meant to derive relations between human inputs and outputs as a function of well-defined task variables.

Often the cybernetic approach is based on the Internal Model concept. It is postulated that all forms of human operator control behavior are based on knowledge about the system under control, the task to be executed and the disturbances acting on the system. This is true for manual as well as supervisory control (Veldhuyzen and Stassen, 1977). This knowledge is called the Internal Representation. When the Internal Representation is described in one way or another, it is called the Internal Model. Overseeing these approaches, the Internal Model concept as well as similar research methods in fundamental psychology may help in investigating the human operator's behavior in supervision tasks.

1.4 CYBERNETIC MODELS

1.4.1 Introduction

Since the human operator can be regarded as a very flexible system, he is thought to be able to choose his control strategy according to the task requirements. This is especially the case in controlling the various technical systems known from industry. In order to describe the different man-machine interactions, many modelling forms and techniques are at hand or can, in principle, be generated. When we restrict ourselves to cybernetic modelling, a global classification indicates the large variety of modelling possibilities, even in this restricted area. Nonlinear models are mostly limited to very specific tasks and systems and will be, due to that reason, outside the scope of this short review. The linear models can be subdivided among others into describing function models and optimal control models. The describing function models are especially suited to tasks where the human operator is part of a servo loop, in particular, for the control of relatively fastly responding systems. The optimal control models are also developed to describe servo tasks. However, their main advantage lies in a more general application and the possibility to extrapolate the model to supervisory control situations, where response speed is slower, and probably even to extrapolate to other tasks, e.g. fault detection.
1.4.2 Describing Function Model

One of the well-known cybernetic models is called the describing function model (for more information, see: Sheridan, Ferrell, 1974). This descriptive model was generated in order to design servo-systems including the human operator as a system controller. Tracking experiments were executed with different dynamic systems and input signals, both aspects serving as task variables.

Instead of looking only at the mean squared tracking error, the investigators tried to describe the relation between the human controller's input (the displayed system output) and his output (the system input) by means of a linear model and an additional noise or remnant, (Fig. 1.1).

The remnant represents the part, which is uncorrelated with the input stimulus and which is added to the linear part of the human operator model. The remnant, modeled as acting at the human operator's input or at his output can be interpreted to represent the next phenomena:

- The human's limited observation capabilities.
- The human's limited motor control capabilities.
- The human's non-stationary behavior, due to changes in motivation, fatigue, attention etc.
- The human's nonlinear behavior.

This remnant can be modeled as a filtered white noise, whereas the human operator behavior, as a whole, can be described by a dynamic linear model including the remnant. It was found that the structure of the model and the parameters of the model could be related to the human operator's inherent limitations and to the task variables involved. The model itself, however, cannot be generalized, hence it has no predictive value for design.

![Figure 1.1: The human describing function model](image)

1.4.3 Crossover Model

During the fifties and sixties many pilot behavior studies were published, all using the describing function model (Russell, 1951; Krendel, Barnes, 1954; Elkind, 1956; Seckel et al, 1957; Hall, 1958; Mc Ruer and Krendel, 1959). These
investigations were all focussed on the relation between the human operator describing function and a number of task variables, such as the controlled element dynamics and the statistical properties of the external forcing function. These investigations were summarized by McRuer and Jex (1967). McRuer and his colleagues, (1965) suggested a normative model, based on the reviewed investigations, to predict human operator behavior during compensatory tracking tasks with one unpredictable input and one output. The idea that the human operator adapts his own dynamics in order to realize good overall man-machine system characteristics, is reflected in this model. The human operator's control behavior was characterized by a transfer function, $H_p$, having four parameters and a remnant. The transfer function then has the following form:

$$H_p(\omega) = K_p \frac{1 + j\omega \tau_1}{1 + j\omega \tau_2} e^{-j\tau_e}$$

where

- $\tau_e$ [sec] = The effective time delay. This delay models the operator's reaction time including the effects of the operator's neuromuscular time constant.
- $K_p$ = The adjustable gain.
- $\tau_1$ [sec] = The adjustable lead time constant.
- $\tau_2$ [sec] = The adjustable lag time constant.

Depending on the time-invariant controlled element dynamics, $H_c$, the structure of the human describing function could be reduced in such a way that a two parameter model was obtained. This could only be obtained near the so-called crossover frequency where the open loop gain, $|H_p(\omega)H_c(\omega)|=1$. Therefore, the model includes both the human operator and the controlled process, (Fig. 1.2).

The model describes human operator behavior in terms of a servo-controller, in which the open loop gain is based on amplitude margin and phase margin considerations.

![Figure 1.2: The crossover model](image)

This crossover model has been successfully applied in a wide range of investigations such as:

- Tracking tasks (McRuer et al 1969, 1980)
- Vehicle control (Costello, Higgen, 1966)
An extension of the model to predict human operator manual control of a two inputs and a one or two outputs system have been reported, among others, by McRuer and Weir (1969) and by Van Lunteren (1978). Although positive results have been obtained, still the crossover model is difficult to apply to describe multi-variable control tasks. A prediction of the manual control of such two input and two output systems already raised difficulties. Extensions in complexity would, because of the considerable increase in cross-coupling terms, not be desirable.

1.4.4 Optimal Control Model

There are many situations, in which the task of the human operator involves more than just acting as a component of a single-input single-output servo system.

The model suggested by Baron and Kleinman (1968), and modified by Kleinman, Baron and Levison (1969) to its present structure, is a very valuable normative model. The model can directly be used to describe human behavior in the control of multivariable, time-varying, but linear, systems. In the model as such, the term state variable takes a central part.

The model is based on the assumption that the human operator can be modeled as an optimal controller, taking into account the inherent human limitations which are:

- A data processing time modeled by a time delay.
- Observation errors modeled by an observation noise.
- Neuromuscular control dynamics modeled by a first order system.
- Motor control errors modeled by a motor noise.

The model itself consists of two mutually independent parts, i.e. an observer part and a controller part. The observer part, which estimates the system state, is based upon the perceived system outputs, the internal model of the system including the statistics of the disturbances acting on the system, and the system inputs as generated by the controller part. The controller part generates a control output, which is based on the system state estimate, the internal model of the system to be controlled, and that of the task to be executed.

Such a division into two parts looks very sensible from a psychological point of view. Humans are thought to react, predominantly, on externally presented stimuli, also called perceptual inputs. These perceptual inputs are then processed in the brain. After such an input-processing phase, an output-motor phase is thought to take place. This output phase can be composed of any form of muscle action, ranging from reflexes to voluntary executed complex movements. In reaction time modeling terms, the two phases often referred to, are called stimulus phase and response phase. The cybernetic division in two parts
is also sensible due to the separation principle (see for instance: Kwakernaak and Sivan, 1972). This principle states that, for quadratic criteria, for normally distributed signals and for linear systems, the optimization of the combination is equivalent to optimization of each of the separate parts. The controller part is, according to the separation principle, independent of the statistical properties of the noises involved (Fig. 1.3).

Figure 1.3: Relation between task variables and inherent limitations in the OCM (Kok and Van Wijk, 1978).

The optimal control model, OCM, as shown in Fig. 1.4, consists of five subsystems and two noise realizations. The subsystems are: a time delay, a Kalman filter, an optimal predictor, an optimal controller, and a neuromuscular system. The time delay is taken into account for the human data processing time and the Kalman filter generates the estimates of the delayed state variables. This estimation is based on a noisy version of the displayed output variables which are time delayed. The predictor then compensates for the time delay. The optimal controller makes use of the real time state estimate in order to generate a control signal. Before this control input reaches the system to be controlled, it is filtered by the neuromuscular system and disturbed by a motor noise. Both observation noise and motor noise are considered to be white, normally distributed noise realizations.

On the one hand, the number and the kind of system outputs to be presented to the human operator can be expected to influence the actual system state estimate. The selection in displaying the system outputs might only have consequences for the Kalman filter, as long as the observability is guaranteed.
The way of presentation of these system outputs will have effects on the accuracy with which the operator can perceive the output variables. Therefore, the way of presentation is thought to influence the intensity of the model observation noise. On the other hand, the task requirements will effect the way of controlling the system and may be expected to influence primarily the optimal control law i.e. the controller part.

![Optimal Control Model Diagram](image)

Figure 1.4: The Optimal Control Model (Kleinman et al, 1969)

Although the model is meant to describe human operator manual control tasks of a multi-variable, time-varying system, it is unrealistic to expect that this model will hold in general. Especially, processes such as supertankers and chemical plants respond often very slowly and have such a complex functioning that it is rather unlikely that the human operator will have a perfect knowledge of all aspects of these processes at any time. Besides, the discrete action pattern of the human operator can hardly dealt with. The application of an optimal observer can easily be misinterpreted as that the human operator makes state estimations. This needs definitely not to be true. What is tried to suggest here is that the human operator cannot possibly have complete system knowledge of complex systems. The application therefore of an observer which does have perfect system knowledge and only noisy system output information is luxurious and perhaps also very unrealistic. The application however of a non optimal observer makes the whole modeling so much more complex that still an optimal observer has been applied here.

1.4.5 Supervisory control modeling

The main activities of the human operator in supervisory control tasks such as production control, quality control, energy saving and off-normal handling are after Beaverstock, Stassen and Williamson (1977):

- Learning, understanding and interpreting the externally imposed task performance criteria.
- Monitoring the system outputs so that an identification can be made of the system dynamics and disturbances acting on the system.
Planning and determining which control actions should be performed.

Inputting the appropriate data to the control system for both initialization and on-line adjustments, so teaching the control system or the process computer.

Intervening in order to switch from supervisory control to manual control and vice versa.

Characteristic for a supervision situation is the large time constants involved in the system to be supervised and the discrete action pattern of the supervisor. Tasks to be performed by the supervisor can differ rather in a qualitative sense. A process tuning task can be identified next to tasks such as fault diagnoses and fault management.

In order to describe the human supervisory control behavior in a tuning mode, a supervisory model is suggested by Kok and Van Wijk (1978). The model is a discrete version of the optimal control model in the sense that a decision-making mechanism is introduced. This decision mechanism was applied to model the selection of output variables to be observed and the instant in time of the observation for improving state estimation. The mechanism was also necessary to model the operator interference by means of setpoint control actions. In a steady state supervision control situation, the human operator task can therefore be summarized as keeping the output variables within specified limits and with a minimum of control actions and sample requests. Furthermore, the model is a simplified version of the optimal control model in the sense that the neuromuscular system is neglected, and that no motor noise is assumed to be added to the control signal; only observation noises are to be considered. The omission of the motor noise is induced by the fact that there are no direct indications to expect, a priori, difference between the internally commanded control signal and the control actually applied by the human operator. Further, the motor noise cannot be identified separately from the observation noise in the model (Kok, Van Wijk, 1978). The omission of the neuromuscular time constant is motivated by the fact that the large time constants of the system to be supervised are dominating in process tuning tasks.

In order to control slowly responding systems, fast control movements do therefore not make sense. For the same reason, also the human perceptual time delay is relatively small. As a consequence, the predictor, for compensation of the time delay, will not be needed. In the Optimal Control Model, it is assumed that all state variables can be estimated; hence a Kalman filter, that is an optimal observer has been applied.

The large computation time in the model identification, to estimate all state variables, makes it plausible to identify only those variables which are strictly necessary for the human operator modeling.

In order to obtain optimal reduced-order filters, for instance, only in some cases a solution can be obtained for continuous stochastic systems (Sims and Asher, 1978). When the systems to be observed are discrete and stochastic, also only in some special cases a solution can be found in literature (Sims and Stotts, 1979), otherwise a set of nonlinear equations is obtained with no explicit solution. Next to these
limitations, a very important aspect was reported by Kondo et al (1979). They found that, although applying an optimal reduced filter, still the separation principle remained valid. Although the separation principle was found to be valid, stability could not be guaranteed. Another way to reduce the order of the filter can be obtained by reducing the dimension of the system to be observed by means of estimating only a set of elements of the state vector. The result of this optimal model reduction process will be a set of nonlinear equations which are hard to solve with no unique solution (Wilson, 1970). Although an iterative method is provided by Wilson (1974), it remains still very difficult to choose the initial system matrix of the reduced model, whereas, up till now, no proof has been found for convergency of this method. In order not to complicate the research too much, it seems fairly reasonable to model the human supervisor, for this moment, by accepting a full-order observer and keeping the supervised system at a low order.

1.4.6 Fault detection modeling

Due to the fact that a full-order and optimal observer is based on the Internal Model, that is a replica of the system to be controlled, it can be shown that, as long as the disturbances acting on the supervised system are Gaussian white noises, the innovation process is a zero-mean Gaussian white noise (Mehra, Peschon, 1971). As follows from Fig. 1.5, this innovation process is the difference between the actually observed output and the reconstructed output which after multiplication by the observer gain $K$, will serve as a correction on the state estimate.

![Figure 1.5: Structure of the observer (Kok, Van Wijk, 1978).](image-url)

There are two reasons to expect a non-white innovation process. Firstly it can be due to a wrongly chosen Internal Model, in which case the system can still be functioning alright. In the case that the right Internal Model has been used, the non-white innovation process indicates a dysfunction in the technical system. Structurally seen, such a check on the whiteness of the innovation process in order to establish a mismatch, is very similar to ideas how human fault detection can take place. In order to design a specific failure sensitive filter, a survey on a variety of failure detection methods including comments on the characteristics, advantages and disadvantages and trade-
offs involved in the various techniques is provided by Willsky (1976). Methods such as mentioned in the survey of Willsky may be still further extended to the field of man-machine modeling (Gai and Curry, 1976).

1.5 THE FOCUS OF THE THESIS

Although much attention has been given lately to human's control activities in Man-Machine Systems research, still less attention has been paid to supervisory control tasks. There are several reasons to mention why supervisory control is step-childly treated:

- The supervision of large and complex processes is relatively new. Cycle riding modeling, for instance, has a history of over more than hundred years.

- The supervision activity is merely composed of knowledge based (mental) activities whereas manual control can predominantly be seen as skill and rule based (subcortical) activities and, due to the repetitive character, therefore it can be more easily measured.

- The systems to be supervised are mostly multi-variable, highly complex and therefore hard to describe and to understand in full detail.

- The systems to be supervised are slowly responding which require merely different control activities than the fast responding systems known from manual control tasks.

Irrespectively the troubles to be encountered, Kok and Van Wijk suggested a supervisory control model in which the operator's supervision activities are taken into account as an integral part of the Man-Machine Systems loop. They have developed a dynamic model that the relationship between man and machine describes.

In cases that a dynamic model can be validated and moreover be utilized generally, this would lead to a substantial progress in understanding supervisory control behavior.

The investigation reported in this thesis has to be regarded as a set-up for the validation of the promising dynamic supervisory control model. Whereas the preliminary conclusions of Kok and Van Wijk (1978) pertain to the control of a very simple supervised process, a more complex process will be applied here.

As it is thought that the application of the model stands or falls with the correctness of a fundamental assumption made, this assumption, dealing with the so-called separation principle, will be explicity examined. Because the theories underlying the cybernetic approach cannot appropriately be applied to accept this basic assumption, another theoretical approach is found to test the extent to which the assumption can be practically be accepted for application. In order to be able to start the validation of the before mentioned model, theories accepted in different disciplines will be shortly discussed and actually used. The status of the theories is taken for granted; only the practical utility in the chosen control situation is examined and evaluated. Possible suggestions for refinement of or changes in the model are
finally given.

1.6 THE OUTLINE OF THE THESIS

The objective is an investigation to validate a cybernetic model describing human operator supervisory behavior. Before finally the model is described, a short review on models has provided in Chapter I.

In Chapter II the functioning of the entire model is elucidated, as well as the different mechanisms in the model. Then, the model structure and the model parameters are discussed. Furthermore, the characteristics of the inputs and the outputs of the human operator model are described.

In Chapter III, the structural implications of the model are discussed. As the model structure gives rise to a number of fundamental questions, the basic principles underlying a paradigm, extensively used in experimental psychology, are discussed.

The application of the principles to be able to validate the model is then taken in serious consideration in Chapter IV.

When the model is to be applied, the validation has to be executed in supervisory task situations. It is therefore that supervisory control as term is defined. Moreover, Chapter IV deals with the description of supervision tasks and the description of the research vehicle used in the investigation. Besides, this chapter deals with the task specification of the human operator and a discussion of the experimental conditions which are used.

In the next chapter, the statistics in the validation process are discussed.

Chapter VI is reserved for the results which are obtained in the different task conditions. All results are then discussed and conclusions are given whether or not the postulations can be accepted.

In Chapter VII, the parameters of the model, already discussed in Chapter II, are identified. Results of the identification are discussed and conclusions are given.

In the final chapter, general conclusions are formulated about the investigation, about the experimental results, and about the parameter adjustment procedures used. Further application of the model is then discussed by summarizing pro and contra arguments. A modification of the model is considered.

---BIBLIOGRAPHY---


Chapter II: VALIDATION OF A SUPERVISORY CONTROL MODEL.

2.1 THE OBSERVER CONTROLLER DECISION MODEL

In applying the Observer/Controller/Decision-model, the OCDM, of Kok and Van Wijk (1978), supervisory control situations as given in Fig. 2.1 can be considered.

The supervised system consists of a dynamic process, on which are acting external disturbances, and an automatic controller. In addition, the state of the system is observed by a measurement system. This measurement system provides on the one hand feedback to the controller and on the other hand it transfers relevant information to the MMIf. Some of the system outputs can then continuously be available to the operator, whereas other system outputs can be sampled.

In such a supervisory control situation, the human operator's task is to keep the values of certain variables within specified limits. Although most parts of the variations in the output variables, due to system disturbances, are suppressed by the automatic controllers, there is still an operator task consisting of changing setpoints. His control actions are thought to be based on his Internal Representation of the current state of the system. The model considered here is restricted to supervisory control situations which are stationary; hence the situation of process tuning has been considered. Therefore start-up, shut-down, and change-over procedures as well as aspects such as failure detection, failure diagnosis, and failure management will not be taken into account.

As it was mentioned earlier, the human operator behavior is
characterized by periods of intermittently observing continuously displayed outputs, followed by periods of sample taking and control. The inputs of the human operator then are observations of the displayed output variables and his outputs are control actions and sample requests. Based on these aspects, the operator behavior in supervision situations can be modeled to establish his input-output relation.

Underlying the application of the OCDM, two model aspects are considered to be important, i.e. the causal aspect and the remnant aspect. In order to be able to describe human supervisory control behavior, these aspects are postulated to be sufficient. The causal model and the remnant model are described by Kok and Van Wijk (1978) as follows:

The causal model which describes the human supervisory control behavior, consists of three parts: A dynamic observer part and a controller part in cascade, and a decision-making part acting on each of the other parts; in fact two decision functions can be recognized. The inputs of the decision-making part are the system state estimate and its error variance as generated by the dynamic observer part. Based on this information, and regarding the given supervisory task, the decision-making part derives the instants in time of the control actions as well as the instants of sample taking. The sample decisions are then transferred to the observer part for appropriate adaptations of the state reconstruction mechanism to the additionally available system outputs. The control decisions, on the other hand, are transferred to the controller part to trigger the controller mechanism, which then determines the proper amplitude of the necessary control action (a set-point correction, for instance).

The remnant model which describes the human supervisory behavior is formed by two additional normal white noises; the first operates on the observed output $y(k)$ and is called the output observation noise, $v_0(k)$, and the second operates on the observed input $u(k)$ and is called the input observation noise, $v_1(k)$, (Fig 2.2).

The model exclusively reflects the discrete action pattern of the human operator in steady state supervisory control situations. Consequently, the outputs of the model are series of sampling requests, with subsequent time intervals and series of control actions. Two aspects are considered in a control action, i.e. the amplitude of the control action and the moment of that particular action in relation to the state of the supervised system. From a sample request, only the instant of that particular request related to the system state is considered.

For the Optimal Control Model, OCM, the separation principle is valid. Since the OCDM is derived from the OCM, the best supposition that can be made is, that this principle is also valid for the OCDM. However, from the theoretical point of view, this assumption is rather questionable since nonlinear decision mechanisms have been introduced in the linear model. The extent to which the model still 'behaves' linearly and to which it can be regarded practically as such remains a very important topic.
When dealing with the OCM, the separation principle states that the controller part is determined by the task variables, system dynamics and task requirements whereas the observer part is determined by the task variables, system dynamics, system disturbances, and display structure. The latter task variable represents the information configuration displayed on the man-machine interface, MMIF. To verify whether the separation principle is valid for the OCDM, the next relations between task variables and the model structure are now postulated:

- Variations in the display structure will affect the parameter values of the observer and its decision element, whereas it will not influence the parameters of the controller and the parameters of the control decision element.
- Variations in the intensity of the system disturbances will affect the observer and the observation decision element parameters, whereas these variations will not be reflected in the values of the controller and control decision element.
- Variations in the task to be executed by the operator will be reflected in the controller and control decision mechanism parameters, whereas the parameters of both other mechanisms will remain unchanged.
- Variations of the system dynamics will be reflected in the parameters of all mechanisms found in the structure.

The postulated effects are represented in Table 2.1, where a + denotes dependency and where a o denotes independency. As it can be seen in Table 2.1, the decision making element has been sectioned into the before mentioned two functional parts. One part contributes to the observing mechanism, whereas the other part is incorporated in the control mechanism.
Table 2.1: Postulated relations between task variables and model parameters

<table>
<thead>
<tr>
<th>Task variables:</th>
<th>Parameters of:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Observer part</td>
</tr>
<tr>
<td>Display structure</td>
<td>+</td>
</tr>
<tr>
<td>System disturbances</td>
<td>+</td>
</tr>
<tr>
<td>Task requirements</td>
<td>0</td>
</tr>
<tr>
<td>System dynamics</td>
<td>+</td>
</tr>
</tbody>
</table>

2.2 THE OBSERVER

2.2.1 The observer part.

In comparison with the general supervisory control model in Fig 2.1, a more specific model has been proposed. In this model the dynamic process, the automatic controller, the measurement system, the sampling system and some parts of the interface has been combined into one dynamic system with system state x(k), control input u(k) and system disturbances d(k) Fig(2.2). Moreover, the displayed output y(k) is a combination of the permanent outputs and the sampled outputs. As a consequence of sampling, the display parameters in the model has become time varying. Besides, the system output y(k) also the control input u(k) is presented on the display. The output y(k) includes directly or indirectly the quantities to be supervised.

Instead of a motor noise, such as found in the OCM, only an additional observation noise v(k) has been introduced which operates on the observed inputs as presented on the display. The observation noise v(k) is very similar to the output observation noise; it is therefore treated likewise.

The input situation for the observer is now complete and can be depicted as in Fig. 2.3.

In the OCDM, it was postulated that all sample and control decisions and all control amplitudes are based on the state estimate and corresponding error variance which quantities are both derived from all information available from the observation of the systems in- and outputs. The state estimate and error variance are the outputs of the observer part of the model which is thought to be modeled independently of the other parts in the model. The independency is based on assuming the validity of the separation principle in the considered model. Then the task variables of concern for the observer are the system dynamics, the statistical properties of the system disturbances and the additional noises. For the observer part of the model it is assumed that the human operator has an exact Internal Representation of the supervised system, the statistical properties of the system disturbances and the noises. Although this assumption is rather unlikely, particularly when very complex systems are to be supervised, still the exact Internal Representation is accepted as a starting point. Thereby it should be realized that the modeling of any non-optimal behavior is far more difficult. As a consequence of accepting an exact Internal Representation, this
has to be modeled by an exact Internal Model which can be achieved by means of the application of an full order observer. In the given observation situation, Fig. 2.3, linear system dynamics are assumed.

The equation for a linear dynamic discrete system in state space notations is:

\[ x(k+1) = Ax(k) + Bu_c(k) + Dd(k), \]  
(2.2.1)

where \( x(k) \) is the system state vector, \( u_c(k) \) is the control input vector, and \( d(k) \) is the system disturbance vector. The matrix \( A \) is the system matrix, \( B \) is the input matrix, whereas the matrix \( D \) represents the gain factor of the white noise system disturbances. As the disturbances are assumed to be normal white noises and independent of the system state, it follows that:

\[ E\{d(k)\} = 0; \]  
\[ E\{d(k)x^T(l)\} = 0; \quad 1 < k; \]  
(2.2.2)

\[ E\{d(k)d(l)\} = \phi_d \delta_{kr} (1-k). \]  
(2.2.3)

The observed outputs \( y(k) \) of the system are linear combinations of the system state:

\[ y(k) = Cx(k). \]  
(2.2.5)

The matrix \( C \) is the output matrix, representing the display parameter. The observed outputs of the display are assumed to be corrupted by output observation noise \( v_o(k) \), hence:

\[ z(k) = y(k) + v_o(k). \]  
(2.2.6)

The observation of the control input is accompanied by
observation noise \( v_i(k) \):\]
\[
\begin{align*}
    u(k) &= u_c(k) + v_i(k) , \\

\text{The observation noises are considered to be independent normal white noises:}
\end{align*}
\]
\[
\begin{align*}
    \mathbb{E}\{v_o(k)\} &= 0; \quad \mathbb{E}\{v_i(k)\} = 0; \\
    \mathbb{E}\{v_o(k)v_o^T(1)\} &= \phi_{v_o} \delta_{k_1}(k-1); \\
    \mathbb{E}\{v_i(k)v_i^T(1)\} &= \phi_{v_i} \delta_{k_1}(k-1); \\
    \mathbb{E}\{v_o(k)v_o^T(1)\} &= 0; \quad \mathbb{E}\{v_o(k)d_i^T(1)\} = 0; \\
    \mathbb{E}\{v_i(k)d_i^T(1)\} &= 0; \quad \forall k, 1; \\
    \mathbb{E}\{v_o(k)x_i^T(1)\} &= 0; \quad \mathbb{E}\{v_i(k)x_i^T(1)\} = 0; \quad 1 < k.
\end{align*}
\]

For the sake of convenience, a vector \( w(k) \) is defined. This vector is called the overall system noise and is composed of the system disturbances \( d(k) \) and the input observation noise \( v_i(k) \):

\[
\begin{align*}
    w(k) &= \begin{bmatrix}
        d(k) \\
        v_i(k)
    \end{bmatrix}; \quad \psi_w = \begin{bmatrix}
        \psi_d & 0 \\
        0 & \psi_{v_i}
    \end{bmatrix}
\end{align*}
\]

The noise distribution matrix \( G \) is composed of matrix \( D \) and matrix \( B \) in the following relation:

\[
G = (D - B),
\]

It brings Eqs (2.2.1), (2.2.5), and (2.2.6) in the following form:

\[
\begin{align*}
    &x(k+1) = Ax(k) + Bu(k) + Gw(k) ; \quad \text{with}, \\
    &y(k) = Cx(k).
\end{align*}
\]

If all the output variables are available in a supervisory situation and all variables can be observed at all time, the system output equation has the following form:

\[
z(k) = Cx(k) + v_o(k).
\]

A time-varying output matrix \( C(k) \) is needed in the case where occasionally one or more of the outputs are sampled by the human operator. In such a case the Kalman filter is supplied with a modified noise vector \( v' \). This vector is composed of the appropriate elements of the original noise vector \( v_o(k) \). Therefore, the system output equation then becomes:
To obtain a minimum variance state estimate $\hat{x}(k)$ and the corresponding covariance of the error in that estimate, $V_x(k)$, the modified Kalman filter is used. Due to the normal distribution of the applied noises, the pair $[\hat{x}(k), V_x(k)]$ is a sufficient statistic for testing hypotheses about the state of the system. The error variance models thereby the uncertainty the operator has about the accuracy of the observed in- and output signals. In the given situation, the elements of the input and output observation noise vectors are unknown. As a consequence, the elements are parameters of the observer part and as such the elements have to be identified. As it was indicated in the equations, the elements of the observation noise vectors are mutually independent, only the diagonal elements of the noise intensity matrices $\Psi_v$ and $\Psi_v$ are to be identified.

In order to obtain the pair $[\hat{x}(k), V_x(k)]$ for a given supervisory control task the matrices $A$, $B$, $C$ and $G$ have to be known. For the task situation to be discussed in Chapter IV, the matrices are given in Appendix A.

2.2.2 The decision mechanism for observation actions.

In supervision situations, the human operator often has the possibility to improve his knowledge about the system state by sampling the non-continuously displayed system outputs. It is also expected that the uncertainty about the system state knowledge decreases when appropriate additional process information is gathered. In relation to the human operator's overall control objective, a trade-off between costs of sampling and the degree of uncertainty accepted will be made.

Most of the available literature applies to monitoring and detection tasks, whereas no control tasks are involved. The verification is mostly achieved in statistical terms such as average sampling interval time and the associated variance. In such investigations, the human action pattern as a function of time is not considered.

To describe the dynamic aspects in sampling, several sampling mechanisms were proposed and actually used by Kok and Van Wijk (1978).

As a consequence of the operator sample actions, the operator's estimate about the systems functioning will probably be updated and the uncertainty of the estimate will decrease. When it is supposed that all outputs are supervised quantities, a supervised output variable $y_i$ consists of a linear combination of the state variables of that system with the general form:

$$ y_i(k) = c_i^T x(k), \text{ where is } c_i^T = [C]_i, $$

and when the state estimate $\hat{x}(k)$ is normally distributed, a normal distribution will also result for $\hat{y}(k) = c_i^T(k)$.

Then only the pair $[\hat{y}_i, S_{\hat{y}_i}]$ is needed to have sufficient statistic to test the state $x(k)$.

The pair $[\hat{y}_i, S_{\hat{y}_i}]$ has the following relation:
\[
\hat{y}_i = c_1^T \hat{x}_i ; \quad (2.2.18)
\]
\[
S_{\hat{y}_i}^2 = c_1^T V_x c_1 . \quad (2.2.19)
\]

Therefore a decision rule which is based on the occurrence of a given event with respect to a variable \( y_i \) will consequently be a function of the parameters \( \hat{y}_i \) and \( S_{\hat{y}_i} \). On the basis of each sample request of an output \( y_i \), the pair \( [\hat{y}_i, S_{\hat{y}_i}] \) becomes updated. When plots were made of the moments of the operator sampling, applying realistic values for the parameter \( \phi_v \) and \( \phi_{v_i} \), the best results were obtained by accepting a hyperbolic decision rule having the following form:

\[
\frac{|\hat{y}_i - y_{\text{nom}}_i|}{S_{\hat{y}_i}} > \frac{C_{p_i}}{S_{\hat{y}_i} - S_{\hat{y}(\text{min})_i}} \quad (2.2.20)
\]

where \( y_{\text{nom}}_i \) represents the nominal value of the output variable \( y_i \), \( C_{p_i} \) and \( S_{\hat{y}(\text{min})_i} \) represent respectively the curve parameter of the hyperbolic line and the horizontal asymptote of the line, being the minimally accepted uncertainty before a sample taken.

Based on the plotted pairs \([\hat{y}_i, S_{\hat{y}_i}]\) for each sample request of output \( y_i \), the parameters in this part of the model, \( C_{p_i} \) and \( S_{\hat{y}(\text{min})_i} \), can be identified. The hyperbolic decision line as such is depicted in Fig. 2.4.

![Figure 2.4: The hyperbolic decision rule (Kok and Van Wijk, 1978).](image)

After the decision rule has become true, a sample is taken which will decrease \( S_{\hat{y}_i} \) to low value. Then further sampling is postponed until \( S_{\hat{y}_i} \) has sufficiently deviating from \( S_{\hat{y}(\text{min})_i} \) and \( \hat{y}_i \) has deviated from \( y_{\text{nom}}_i \).
2.3 THE CONTROLLER

2.3.1 The decision mechanism for control actions

To avoid that the output variables exceed the specified tolerances, the operator has to change one or more set-points from time to time. Although no direct applicable suggestions from the man-machine systems literature were at hand, two different models for control decisions were suggested. The overall control objective, in both models, is assumed to maintain the supervised variables within a given region symmetrically situated around the nominal value and modeled as:

\[ |\tilde{y}_i - y_{\text{nom}i}| < d_i ; i = 1, \ldots, n \]

In order not to complicate the model parameter estimation procedures too much, the easiest decision rule has been accepted it is based on the estimate \( \tilde{y}_i \) only, in formula:

\[
\text{if: } |\tilde{y}_i - y_{\text{nom}i}| > q_i, \text{ then: } \] (2.3.1.)

a control action is taken.

In this respect, \( q_i \) is a model parameter. In order to compensate for the time lags in the controlled system, and taking into account the control objective, the parameter \( q \) will probably be smaller than the tolerance value \( d \) and is called the subjectively accepted tolerance width. A decision rule like the one mentioned here, has been represented in figure 2.5 as a straight line.

![Figure 2.5: The controller decision rule](Kok, Van Wijk, 1978)

2.3.2 The controller part

As the instant in time of a control action is determined by the control decision mechanism, the function of the controller is to determine the amplitude of that control action.

In order to perform supervisory control, at least two control situations can be mentioned i.e. the situation in which the operator produces single control actions, and the situation in which the operator produces multiple control actions. In the single control case, the supervised variables are brought to
the desired nominal value, \( y_{\text{nom}} \), by one single control action. The action is induced at the moment \( k_1 \), (Fig. 2.6) the moment that one of the supervised variables crosses the subjectively accepted boundary value \( q \). The control amplitude \( u(k) \) is determined by the actual state \( x(k_1) \), the endgoal value \( y_{\text{nom}} \) and parameter \( p \); the nominal time to reach \( y_{\text{nom}} \). The control action can be terminated at time \( k_2 \) if no disturbances have effected the variables during that interval \( k_1/k_2 \), and if no other supervised variable has reached one of its subjective boundaries. Otherwise a new control action is required. Similar to the decision rule (2.3.2), a rule can be used which terminates the time of control when all output variables are within their target area \( \varepsilon_i \) of \( y_{\text{nom}_i} \), in formula:

\[
\text{if: } |\hat{y} - y_{\text{nom}}| < \varepsilon_i, \quad \text{then terminate control action.}
\]

(2.3.2)

The tolerance parameter \( \varepsilon \) is a vector involving the elements \( \varepsilon_1, \ldots, \varepsilon_n \). Each of these parameters is determined by the task to be performed such as given to the human operator.

The so-called 'multiple control strategy', a sequence of control actions, which brings the system in the desired state are thought to be applied by the supervisor in those cases where it is not possible to reach the desired state by only one single control action. The endgoal then will be achieved by choosing a proper sequence of actions, resulting in the achievement of a sequence of subgoals. The Figs 2.6 and 2.7 illustrate the two control situations mentioned above. The amplitude \( u_i(k) \) of the control action is determined by the current state value \( x(k) \), the endgoal \( y_{\text{nom}_i} \) and the parameter \( p \).

![Diagram of control action](image)

Figure 2.6: Single control strategy
(Kok, Van Wijk, 1978).

In this investigation the supervised system is chosen in such a way that the number of inputs is at least as large as the number of outputs. As a consequence, a single step control law can be utilized in order to correct the supervised outputs so that in \( p \) steps the nominal value \( y_{\text{nom}} \) will be reached.
2.4 SUMMARY OF MODEL PARAMETERS.

In the investigation, a utility plant simulation with three inputs and three outputs has been used (See section 4.3). Two of the three outputs are to be sampled whereas whereas three control inputs can be applied. Then the parameters in the different parts of the model are such as summarized below.

The observer part:

1. $\psi_{v_{oi}}^i, i = 1, 2, 3$
   - The diagonal elements of the observation noise intensity matrix related to the system outputs. The matrix is supposed to be a diagonal matrix.

2. $\psi_{v_{ii}}^i, i = 1, 2, 3$
   - The diagonal elements of the observation noise matrix related to the system inputs. The matrix is a diagonal matrix.

The decision making part:

1. $C_{p_i}, i = 2, 3$
   - The curvature parameters of the hyperbolic line in relationship to sampling.

2. $S_{\bar{y}}(\text{min})_i, i = 2, 3$
   - The minimum accepted uncertainty in relationship to sampling; the horizontal asymptote of the hyperbolic line.

3. $q_i, i = 1, 2, 3$
   - The subjectively accepted control boundaries in relationship to controlling.

The controller part:

1. $p$
   - The number of time steps with a constant control signal.

The summary shows thus 14 parameters which are to be estimated. The parameters of the observer part are the intensity matrices of the output observation noise $v_{oi}$ and the input observation noise $v_{ii}$, respectively $\psi_{v_{oi}}^i$ and $\psi_{v_{ii}}^i$. As it was assumed that the observation noise vectors are mutually independent and also that the elements are uncorrelated, $\psi_{v_{oi}}^i$ and $\psi_{v_{ii}}^i$ are diagonal matrices.
As the initiated setpoints are digitally represented, the uncertainty about the perceived input signals, the setpoints, is regarded as negligible small and therefore the elements are chosen equal to zero.

For $\psi_v$ also an assumption has been made, this assumption is based on investigations of Levison et al. (1969). They showed, in their case, that an observation noise of 1% of the variance of the observed output signal can be regarded as an appropriate choice. In related investigations, this parameter turned out to be not very sensitive (Sastra, 1978 and Van Oostveen, 1982). Therefore the parameter has been fixed and consequently has been kept outside the identification procedure. In order to be completely sure about the insensitivity of that parameter, some parameter values have been tried. Because only very slight differences in estimation of the state could be observed, the fixation of that parameters was found to be completely acceptable. Due to this fixation, again three parameter values could be kept outside the estimation procedure. The parameter values as chosen can be found in the Appendix A. Due to the assumptions for $\psi_{v^o}$ and $\psi_{v^i}$ eight parameters remain to be estimated.

2.5 SIGNALS OF A DISCRETE CHARACTER.

In order to accept the model to describe the supervisor's behavior, the differences between the output signals of the model and those signals originating from the human supervision have to be small. Therefore one first has to define a criterion on these differences and thereafter one has to optimize those parameters which minimize this criterion. When optimizing the OCDM parameters, a complicating factor occurs. In the case of control activities, these activities are composed of combinations of discrete time aspects and control magnitude aspects. When operator and model control activities are compared, the combination of these time and magnitude aspects have to resemble each other. Because no a priori means are available to bring amplitude and time aspects together into one single quantity, the optimization of the model output has thus to be regarded as a multi-objective problem. As a consequence, one cannot easily apply the generally used quadratic criterion. As an example of which model output is selected when a quadratic criterion is used, Fig. 2.8 shows two possible model outputs, $\hat{u}_1(t)$ and $\hat{u}_2(t)$, to be compared with the human operator control activities (Kok and Van Wijk, 1978)

The criterion is defined as follows:

$$J(u_i) = \frac{1}{T} \int_{0}^{T} [u(t) - \hat{u}_i(t)]^2 dt, \ i=1,2$$  \hspace{1cm} (2.5.1)

By measuring the difference between model and operator data by means of the quadratic criterion, it is apparent that the chosen parameter set belonging to $\hat{u}_1(t)$ would give a better description of the supervisor's output on the basis of the quadratic criterion. However, due to the fact that the number of actions in $\hat{u}_1(t)$ is far too high to resemble the human operator's action pattern, the output $\hat{u}_2(t)$ can be regarded as a much better match with those responses. Taking into
account one variable and disregarding the other(s) will not serve the purpose of matching this supervisory control model outputs with actual operator data. Therefore a vectorial criterion, instead of a scalar one, has to be used in this investigation.

Figure 2.8: Comparison of two possible model outputs $\hat{u}_1(t)$ and $\hat{u}_2(t)$ with a given supervisor response $u(t)$ using a quadratic criterion.

-BIBLIOGRAPHY-


Chapter III: STRUCTURAL IMPLICATIONS OF THE MODEL

3.1 STERNBERG PARADIGM

In order to investigate the consideration of dealing with independent parts in the OCDM, whereas no direct theoretical support is available, some more insight can probably be obtained from literature of other disciplines which might be helpful in finding new ways.

Sternberg proposed the use of reaction time measurements to distinguish so-called stages, independent functional parts, in the human information processing process. As postulated, these independent parts mean that the total reaction time equals the sum of constituent reaction time contributions of these parts. If we restrict ourselves to reaction time measurements of the 'premotor' phase, as distinct from the motor execution time of the 'motor' phase, three stages of information processing can be assumed in a visual stimulus and manual response task. The stages can be summarized as follows:

- Stage 1: The stimulus is read and encoded. Let us assume that this stage of stimulus encoding or pattern recognition takes e milliseconds.
- Stage 2: The encoded form of the stimulus is successively compared with each member of a memory set. This comparison consists of the determination whether the encoded form matches with a member of the memory set. Let us assume that each comparison takes c milliseconds and that there are N members in the memory set. This serial comparison stage takes therefore c.N milliseconds.
- Stage 3: In this stage a binary decision is made whether a match was found or not, and consequently, whether a 'yes' or 'no' response has to be executed. This decision is assumed to take place in d milliseconds. So, the total reaction time, RT, can be expressed as:

\[ RT = e + c.N + d, \]  

(3.2.1)

or for the sake of convenience as:

\[ RT = c.N + (e + d), \]  

(3.2.2)

where c is the slope of the function and (e + d) is the RT-intercept of the linear function.

Sternberg's model predicts a linear function between reaction time and memory set size (N). By now, a slight correction has to be introduced. In order to respond 'no', the operator has to compare the encoded form with every item in the memory set. In order to respond 'yes', the operator does not need to compare the encoded form with every item in the memory set. When a 'yes' response can be given by the operator the comparison is terminated. By presenting a large amount of stimuli, the comparison is terminated on the average of the time needed to compare the result with half the memory set. Hence the average time of the comparison stage is c.N/2.

Keeping this correction in mind, it can be said that: If these three stages are really independent of each other, then the model will predict, as an example, the same slope but a higher situated RT-intercept when the presented stimuli are degraded.
In the latter case the encoding stage has more trouble in identifying the pattern, hence the term \( e \) will be increased as depicted in Fig. 3.1. Many results in the psychological literature confirmed this model prediction. As it was defined by Sternberg (1969):

- A stage is one of a series of successive processes that operates on an input to produce an output, and contributes an additive component to the RT.

- Additivity entails a property of independence for mean stage durations: The mean duration of a stage depends only on its input and levels of factors that influence it, and not directly on the mean duration of other stages.

![Figure 3.1: Postulated intercept due to stimulus degradation (after Sternberg, 1969)](image)

Hence, well-defined task variables are supposed to influence only particular outputs of the different model parts, while keeping the other outputs unchanged. To illustrate the additivity, different levels of the task variables, factors, therefore have to be applied. Sternberg's additive factor method is comparable with the conceptual framework of the superposition principle in linear system theory (Zadeh and Desoer, 1963). When applying the additive factor method, one searches in fact for the superposability of causes (factors) and effects (time contributions). Thus if a cause \( u_1 \) produces the effect \( y_1 \) and if cause \( u_2 \) produces the effect \( y_2 \), then the superposability of causes and effects implies that \( u_1 + u_2 \) would produce the effect \( y_1 + y_2 \). The Sternberg paradigm can be considered as the application of the separation principle to a static system.

In the case of the OCDM, an observer and a controller part are, analogously to the optimal control model, thought to be independent. In verifying this postulation, two plausible ways
are at hand. The first method is to identify all model parameters at the same time for different levels of the task variables. The final result then will be compared with the postulated effects. This method seems a rather time consuming alternative.

The second method is to measure human operator observation and control output quantities in different supervisory control situations. In these situations, the task variables, as mentioned in Table 2.1 will then be varied systematically. If these observation and control quantities can be regarded as independent of each other, thus if they are additive, then the different parts from which these quantities are originating can also be regarded as independent. The parameters of these independent parts will then be regarded as separately identifiable, in conformity with the separation principle. The quantities, selected as important indicators for this postulated handling are:

- The number of observation actions per experimental session,
- the number of control actions per experimental session,
- the mean amplitude of the control actions.

These indicators are chosen because they are the direct outputs of the decision mechanisms and controller mechanism of the model.

Besides the quantities mentioned another quantity is considered i.e. the distribution of the sample intervals, that are the intervals in time between the subsequent samples. A comparison between the sample distributions of operator and model is regarded as a sensible expansion of the other quantities. About the distribution form no hypotheses were formulated. To investigate the practical use of such a distribution, preliminary studies were made. The distribution of the control decisions intervals are kept beyond the scope of the investigation.

3.2 SEPARATION PRINCIPLE RELATED HYPOTHESES

The observer, as model component, is responsible for the generation of the state estimation of the supervised system, it plays an important role in the observation activities. The observation decision mechanism is also important. Therefore it is postulated that:

- Variations in the display structure will only cause an effect in the number of observation actions; the display structure task variable will neither influence the number of control actions, nor the mean amplitude of these control actions.

The system disturbances are influencing the observation activities and aspects of the control activities i.e. the control instants. The control magnitude is thought, in the cybernetic modeling, to be determined solely by the controller part. Consequently, no effect in control magnitude is expected under influence of the system disturbance task variable. Therefore it is postulated that:
Variations of the system disturbance task variable causes an effect in the number of observation actions as well in the number of control actions. No effect will, however, be caused in the magnitude of the control corrections.

Whereas the controller part is responsible for the magnitude of the set-point correction and the controller decision mechanism is responsible for the moments of control corrections, these parts are consequently thought to play an important role in the control activities. Therefore it is postulated that:

- Variations of the task requirement task variable cause an effect in the number of control actions executed and are also causing an effect in the magnitude of the control corrections; no effect in the number of observation actions, however, will be caused.

The system dynamics have an influence on all model parts functioning in the cybernetic modeling. Therefore it is postulated that:

- Variations of the system dynamics task variable cause an effect in the number of observation actions taken, the number of control actions executed, and cause an effect in the average magnitude of the control corrections.

In order not to complicate the experimental set-up considerably, it must be mentioned that, for the present, the task variable system dynamics will fall beyond the scope of investigation.

In table 3.1, the postulated relations between task variables and the directly measurable quantities are represented.

**Table 3.1: Postulated relations between task variables and directly measurable quantities.**

<table>
<thead>
<tr>
<th>Task variables:</th>
<th>Directly measurable quantities:</th>
<th>Number of observations</th>
<th>Number of control act.</th>
<th>Mean amplitude of control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Display structure</td>
<td></td>
<td>+</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>System disturbances</td>
<td></td>
<td>+</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>Task requirements</td>
<td></td>
<td>0</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>System dynamics</td>
<td></td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Whether the analogy of aspects from static modeling, such as in the Sternberg paradigm, to dynamic modeling, such as in the case of the OCDM is valid, is an important part of this investigation.

Chapter IV : THE EXPERIMENTAL DESIGN

4.1 THE SUPERVISORY CONTROL SITUATION

In a typical steady state control situation, the human operator is confronted with an automatically controlled multi-variable slowly responding and complex system. As a consequence of the limitations of human information processing, a large amount of different output variables cannot be observed at the same time. So, the operator must then be selective in which outputs he wants to observe at a certain moment.

In such cases, the automatic controllers serve for the continuous control of the supervised system, whereas the operator intervenes only when, for instance due to limitations inherent to automatic feedback control, one or more outputs are close to or are already exceeding specified boundaries. In order to be able to interfere in situations such as mentioned, the operator can influence the supervised process variables by means of changing set-points of the automatic controllers. Reasons from a methodological point of view kept us from starting a supervisory control investigation in the process industry itself. Reasons to build a computer simulation instead were better controllability of the experiments in different task conditions, economic considerations, and safety aspects. This first aspect can be explained as follows: Many of the disturbances and system failures in real life processes are occurring on unpredetermined moments. On such occasions, the interference of an investigator, at any level, is not wanted. An aspect such as mentioned above does not count in laboratory experiments. In such cases, disturbances and failures can be introduced at any time and of any kind.

4.2 CHOOSING AN APPROPRIATE PROCESS

In their investigation, Kok and Van Wijk (1978) used a one-input, two-output system to be supervised. One output was a very noisy and permanently displayed system output, whereas the other output gave, only on request, a time delayed nondisturbed information presentation of the same output variable. As they remarked in their thesis, the results from these experiments showed only the potential value of the application of the OCDM. They indicated therefore that direct extrapolation of these results to complex situations could not be made.

In the investigation reported here, their suggestion to apply a more complex system for the OCDM verification is followed. A computer simulation of an existing hydranon distillation column at the Dutch State Mines (DSM) at Geleen in the Netherlands was chosen as laboratory process. This choice was mainly based on the possibility to use the model as developed at the Eindhoven University of Technology (Haffmans (1974) and Vrins (1975)). Eight digital display units, six control units and eight recording pens in two trend recorder units were sufficient to build up an appropriate MMIf. Although at first sight the column fitted our wishes, three essential problems showed up. In order to obtain insight in the operator control behavior, all system output information needed by the operator was thought to be essential. The trend recording of the different output variables could be observed in sets of

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four at the same time. Therefore it was hard, if not totally impossible, to determine which output variable or variables the operator was looking at. This first problem could easily be solved by implementing a sample facility to the used computer simulation, in such a way, that the operator has to request for each output variable. The requested output presentation then could be realized by the application of a Visual Display Unit, VDU. There was, however, no possible way to have the VDU facility to be available within an acceptable time limit. The second problem was, that the system state vector of the distillation column is considerably larger than the original one-input and two-output system. As an indication, the state vector had grown to sixty eight elements. Therefore state estimation would become very time consuming. Moreover, the column contained several non-linearities; hence a linearization had to be executed. In addition to the second argument, the supervision task of the entire distillation column seemed too complex to start yet with the human operator modeling. The expectancy of extensive operator training before actually data collecting could be started kept us from using the entire column simulation. Either sub-tasks had to be defined, or a new supervision task had to be defined. In such a case, important aspects such as the urge of a linear description of the supervised system, the complexity of the process and of the task to be executed had to be taken into account. Due to the reasons mentioned before, it was decided to look for an alternative.

4.3 DESCRIPTION OF THE PROCESS USED

The process that finally has been chosen is called a Utility Plant or utilities. Such type of plants is often found in the process industries in order to generate different kinds of energy: Steam, high and low pressure and electrical power. The process was chosen because a model of such a plant was available for research (Campbell and Shirley, 1979). The model, described by a substantial set of linear equations, was implemented on a computer system and partly modified by Schneider, V.d.Veldt and Stassen to their purpose (1982). As this process was still found to be too complex, only a part of the modified version was used. The finally built process simulation consists of only three functional parts, i.e. a boiler, a back pressure turbine and a condensing turbine (Fig. 4.1).

The functioning of the process can be described as follows. The boiler is supplied with water and fuel. Due to the fuel combustion, high pressure steam is produced. A certain quantity of the high pressure steam production is used by the two turbines. Most of the high pressure steam, however, is supplied to other steam consuming processes which are not supervised by the operator. One turbine, a back pressure turbine, generates low pressure steam and electrical power. This power production is realized by means of a mechanical coupling between the turbine and a generator. The other turbine, a condensing turbine, is also coupled to a generator. A function of the condensing turbine to yield steam under vacuum, which is condensed and eventually returned to the boiler, is not taken into account in this simulation.
Figure 4.1: Schematic structure of the setpoint-controlled and computer-simulated utility plant.

The boiler is modeled by means of a first order system flow. The input is the fuel flow, the output is high pressure steam. The input of both turbines is high pressure steam flow. As two functions can be distinguished in the back pressure turbine, this part of the process was modeled by two first order systems. One first order system gives the relation between high pressure steam and electrical power. The second first order system gives the relation between high pressure steam to low pressure steam. The condensing turbine finally is modeled by means of a first order system. The input is the flow of the high pressure steam, whereas the output consists of the quantity of electrical power, as produced by the generator. A block diagram of the modeled process is given in Fig. 4.2, including the values of the different components.

Figure 4.2: Block diagram of the utility plant computer simulation.
The process is automatically controlled. The boiler is pressure controlled by applying a Proportional plus Derivative (PD) controller. The high pressure steam is controlled by increasing or decreasing the fuel consumption. Both turbines are Proportional plus Integral (PI) controlled. The flow of the low pressure steam \( y_2 \) is controlled by adjusting the input flow of the high pressure steam of the back pressure turbine. The total amount of electrical power \( y_3 \) is controlled by adjusting the input flow of the high pressure steam of the condensing turbine. The complexity, in this case, has two aspects. In the first place the more complex the simulated process becomes, the longer it takes to train the operator. In the second place, the number of measured data will increase drastically when the complexity becomes higher.

As it is often the case in technical systems, also in this process some interaction occurs. The amount of high pressure steam for other installations, for instance, is the total amount produced minus the amount consumed by both the turbines. The total amount of electrical power is the summation of the back pressure and condensing turbine power production. The interaction between the different output variables is graphically displayed in Fig. 4.3, where responses on discrete set-point changes are shown.

![Figure 4.3: Interaction in the utility plant process based on step responses of the tree outputs.](image)

Three output variables are displayed on the MMI: i.e. the pressure of the high pressure steam, the flow of the low pressure steam, and the total amount of electrical power. Three input variables can be used i.e. the fuel flow to the boiler and the flow of high pressure steam to each of the turbines. In a practical situation, many minor deviations from the nominal value take place. Such kind of variations cannot always be predicted exactly, although they do not occur completely unforeseen. In terms of signals, one can speak about noises acting on the supervised output variables. From these noises, some of the statistical properties are thought to be known by the operator. Hence, in order to have a realistic supervisory
control situation in the utility plant simulation, the following disturbances have been introduced. The first disturbance is acting on the high pressure steam flow, the second disturbance is acting on the low pressure steam flow; both disturbances simulate variations in the demand of different forms of steam. The third disturbance is acting on the electrical power production and models the variations in the demand for electricity. All disturbances are filtered white noises; filtered in such a way that only the low frequency components are applied as system disturbances. The effect of the disturbances on the deviations from the nominal value is mainly determined by the place where the disturbances act on the process, the time constants of the different first-order filters, and the intensity of the disturbances. In Figure 4.4 an example is shown a noise realization on the three set-point controlled outputs in the case that they are not supervised by the operator.

![Graphs](image)

Figure 4.4 Realization of output fluctuation due to the chosen disturbances acting on the different system components.

4.4 THE TASK SPECIFICATION.

The task of the human operator is to keep the three output variables within their specified boundaries. In order to accomplish this task, the operator is thought to make use of the output variables, the setpoint correction facility; he should be aware of the task specifications, the system dynamics and the statistical properties of the system disturbances.

Not all output variables are presented continuously. The pressure of the high pressure steam can be observed all the time, while the flow of the low pressure steam and the electrical power production have to be sampled. When a sample is wanted by the operator, this can be achieved by pushing the correct jump switch. Within a second, the output variable is displayed digitally. During a five second period, the actual output value is displayed and visually updated with a frequency of one second. When the operator wants to change a setpoint, he can do so by means of pushing on a tumble switch for a certain period. The longer the operator pushes that switch, the larger the setpoint change will be. The value of the setpoint can be
observed on a digital display right above the tumble switch. The newly chosen setpoint value then can be initiated by pushing the jump switch next to the thumble switch device, see Fig. 4.5.

| LB = Lower Boundary | S1 = Tumble Switch. |
| UB = Upper Boundary | S2 = Control Initiation Switch. |
| S3 = Sample Request Switch. |
| S4 = Sample switch for trend information |

Figure 4.5: Process interface modules; the display device (left), and the control device (right).

Any time an output variable exceeds one of its specified limits, the operator is alarmed visually, either locally or centrally. In the local alarm situation, the operator obtains information about which output exceeds a specified limit and whether the deviation is on the upper limit or on the lower limit side. A Light Emitting Diode (LED) on the left side of the display module is flashing when the lower boundary is threspassed, whereas a LED on the right side of the display module is flashing when the output variable passes the upper limit. In the central alarm situation, the operator is warned about the deviation of one or more of the output variables. The sampling devices have to be used to find out which output is out of boundaries, in what direction the deviation takes place and whether only one or more outputs are involved.

In order to apply an error score as a performance quality indicator, during the experiments it was determined whether the outputs were deviating from the specified limits. For each output the absolute value of the deviation integral, with respect to the boundaries, was computed. In formula, the error-score \( D \) of the output \( y \), is depicted in Fig. 4.6, and defined as:

\[
D = \sum_{k=k_{\min}}^{k_{\max}} |y(k) - y| + \sum_{k=k_{\min}}^{k_{\max}} |y(k) - y| + \sum_{k=k_{\min}}^{k_{\max}} |y(k) - y| + \ldots
\]
When the operator performs his supervisory task, the number of samples should be as low as possible. The same holds for the number of setpoint corrections. Apart from keeping the number of control actions low, the amplitude of the control actions should not be very large. The stress to minimize the action frequency was explained to the operator as an economic necessity. In fact, performance optimization was the actual reason to emphasis on the importance of minimization. The trade-off between number of actions made and accuracy of the control is completely determined by the operator himself. Any suggestion of the experimenter would lead to manipulation while not much experience was available about the number of actions. If there are several output variables outside of boundaries, the operator is instructed to give the pressure of the high pressure steam highest priority, followed by the flow of the low pressure steam.

4.5 THE FIRST EXPERIMENTAL CONDITIONS.

For the validation of the model and, for the subsequent verification of the model parameters, different experimental conditions have been chosen. Three task variables, out of the four mentioned in section 2.1, are manipulated. Each task variable is applied at two levels:

- The display structure task variable consists of a local alarm level or a central alarm presentation.
- The system disturbance consists of noise having a low intensity or a high intensity.
- The task requirement is manipulated by specifying a wide boundary or a narrow boundary.

Hence, there are eight possible experimental conditions to be tested. Recalling the hypotheses postulated with regard to the task variables involved and the directly measurable quantities, it follows that the effect of the different task variables can be represented as indicated in Fig. 4.7.
For the first set of experiments, the boundary level was fixed for two reasons:

The experimental conditions were randomly appointed. The subjects, however, had great difficulty to switch from a wide boundary control to narrow boundary control and visa versa. Quite often it took the main part of the next experiment, before they were adapted to the new condition. Frequently, the operators accepted, in the wide boundary conditions, the narrow boundary specification and consequently they had a more difficult task. This resulted therefore in a problem of how to indicate the postulated difference between the narrow and the wide task specification.

The second reason is that training the operator to an acceptable level takes far more time than what could have been expected from other investigations such as Landeweerd (1978). The narrow boundary control specification has therefore only been tested in two cases. The question whether a non randomized order of succession in the tasks requirement will finally effect the results, can be answered as follows: When first the wide boundary control situation was investigated, it could be argued that still some learning took place. Although checked for, this learning could effect a decrease of the number of actions; it could extend in the narrow boundary situation. When then the two task situations were compared with each other, the statistics will show less difference between both means of actions. If then still the statistics show a significant difference between narrow and broad boundary tasks, the result can be accepted without any doubt; a randomized set-up would have shown a larger difference between the two task situations. As such, this experimental design, as chosen here, can be regarded as a very conservative manner of hypotheses testing. The duration of each experiment took 45 minutes. The time has been chosen in consideration of two aspects.

From the psychological point of view, long experimental runs are fast becoming tiresome for the subjects. The subject's motivation to do their utmost disappears, especially at the end of the experiments. Because training requires a lot of time
investment, only the strictly needed number of experiments are are therefore been run.

From system theoretical point of view, somewhere 5 times the largest time constant is at least desirable to measure the effect of a control action with acceptable accuracy. As an indication, the largest time constant involved in the supervised system is 245 seconds.

4.6 SUPPLEMENTORY CONDITIONS

As display structure task variable the local alarm will be compared with the central alarm. In terms of Sternbergs reaction time experiment, based on visual stimulus presentation, the central alarm condition is a degraded form of the local alarm condition. This degradation will finally end when no alarm presentation at all is given to the operator. When it was already postulated that the separation principle would yield for local and central alarm task conditions, the extreme form of no alarm presentation might probably be situated outside the range of the valid application of the separation principle. Therefore it will be tested whether the no-alarm presentation task condition will still effect only the rate of sampling or that also the control activities are involved. However, it has been decided not to included this task situation in the experimental design but to test this task situation just tentatively. The task will be performed after the experiments belonging to the experimental design have been executed. Possible intervening effects are in this way sufficiently prevented.

In the preceding set of experiments, the output information will be presented to the operator by digital displays. In the five-seconds presentation period of a requested sample, the operator is thought to be able to determine the difference between the output variable and the nominal value, and the direction in which the output variable is heading. The operator might even determine the velocity component. In order to obtain that last kind of information, the operator has to be rather active and alert. When the trend of the output variables is displayed, instead, this determination activity takes less effort, i.e. the present value as well as the historical information is presented while the slope of the trend represents the velocity component.

On the classical trend recorders, most of the time more outputs together are presented. In such a case, it is hard to determine for an experimentator which of the output variable has been observed by the operator. Moreover, combinations of trend information can principally be made by the operator. When the trend is presented on a VDU, different combinations can still be observed; then the sample request can then also be recorded for later analyses.

Analog to the original set up with the digital displays, the trend of the boiler output will be presented permanently on the VDU, whereas the other outputs are still to be sampled. Because the digital output presentation could be regarded as an degraded form of trend information (actual information versus the combination of actual, historical and trend information), the ideas underlying the hypotheses such as stated in Table 3.1 are still regarded to be valid. Therefore, it is postulated, that:
The effect of information presentation, digitally or trend, will be mainly expressed by the amount of samples taken during the sessions, whereas no increase in the number of control actions will be found.

The number of samples taken, having trend information, will be the same or less than when digitally displayed information is applied; due to the trend information the performance will remain the same or will become somewhat better.

After introducing trend information it is interesting to know what the transfer on the operator's behavior will be when not assisted by trend information. In the supplementary conditions, the operators will first deal with local and central alarm conditions. In these conditions the information is displayed digitally or by means of trend information according to the applied randomization of the experimental conditions. Conditions without trend presentation do not differ from conditions discussed in section 4.5.; they are regarded as check. After these experiments the operator will be confronted again with conditions having digitally displayed output information. Permanency of transfer on the operator's supervising behavior induced by trend presentation can then, if present, better be understood.

Finally the results obtained from the measured data will be complemented with results from interviewing the operators. The diversity of aspects discussed makes an overview of experiments desirable. The experimental set-up is represented in Table 4.1, whereas the table 4.2 shows in which experiments the different subjects have been participating.

Table 4.1: Summary of task levels of the four taskvariables, where a '+' denotes involved and an 'o' denotes not involved.
An aspect which has been mentioned in section 3.1 is the determination of the distribution of the sample intervals. Because of the fact that negative time intervals will not occur, the probability density function is certainly not gaussian; it will be an asymmetric probability density function.

The importance of the determination of the probability density function is, that more insight in human sampling behavior can be obtained. Probably, it even will be possible to model a sampling strategy.

Results on the probability density function of model and operator intervals will be discussed in section 7.3.2

Table 4.2: Schematic presentation of participating subjects in the different experiments.

<table>
<thead>
<tr>
<th>Participating subjects:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp I</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Exp II</td>
<td>+</td>
<td>+</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>Exp III</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>Exp IV</td>
<td>o</td>
<td>o</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Exp V</td>
<td>o</td>
<td>o</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

legend:
+ participating
o non-participating

4.7 HYPOTHESES TESTING REQUIREMENTS

In collecting data for testing the postulations of Table 2.1, two requirements are thought to be essential. In the first place, the number of actions, control actions as well as sample actions, must have been leveled off to a constant value for each experimental condition. As the Internal Model concept yields perfect system knowledge including knowledge about the system disturbance statistics; the operator in consideration should be at least stationary in his supervisory behavior. In the second place, the deviation scores obtained during the experiments must as mentioned previously, be rather constant and of a low value. This second requirement is used as an indicator of the actual control quality. As it was indicated that only well-trained operator behavior should be considered in the hypotheses testing, no effects of learning should be present in the obtained data. As a consequence of this requirement, it took more than 150 hours of instructing, training and letting the operator to become experienced with the process. The drastic effect of learning on the operator's sample and control behavior is clearly shown in Fig. 4.8. The figure shows 86 sessions. Only the last nine in each condition were actually applied in the hypotheses testing. The eightysix
sessions were already preceeded by numerous training sessions in which the operator results of supervising the system were indicating clearly non-experienced operator behavior.

![Diagram](https://via.placeholder.com/150)

* low noise-local alarm  
* low noise-central alarm  
* high noise local alarm  
* high noise central alarm

Figure 4.8: Representation in four conditions of the decrease in sample in and control action due to learning (data from subject 2)

When a 95% confidence interval of a Student t-distribution is chosen to represent the important aspects in the data obtained, a two dimensional figure can be constructed. The control action distribution of the different trials in each condition is shown along the horizontal axis. Along the vertical axis, the sample action distribution is presented. An ellipsoide, connecting the ends of the distributions, can then be drawn to represent the combined distribution surface. For the sake of convenience, the ellipsoide will be represented in a form of a rectangle. For the first set of experiments, four of those rectangles can be constructed. The four rectangles in Fig. 4.9. which are crossing each other are composed of data from the learning phase of subject two. The four rectangles not crossing each other is composed on the basis of data of subject two, after it could be indicated that no learning effects were found in the data.

In the case that one or more rectangles are crossing each other, the Student's t statistic considers these sets of data as not different. The question if one can accept the application of the Student's t statistic on these data is completely dependent on the distribution characteristics of the data. For the application of t-test statistics a normal distribution of the data is thereby required. With the exception of one subject in only one experimental, discussed in Chapter VI, all distribution could be accepted for t-test statistics.

As an effect of the extended training it is clear that the amount of experiments needed for testing has to be chosen as economically as possible. The possible decrease in the amount of experiments is however limited; less than seven experiments per condition would become troublesome to indicate normality of the obtained distribution.
4.7.1 Requirements for the interpretation of the found results.

The postulated increase in sample actions due to the display structure task variable can rather easily be determined in the experimental scores. The additional increase in the number of sample actions and in the number of control actions postulated to be originating from the introduction of the different levels of the system disturbance task variable is however somewhat more complex. Therefore, the increment in the number of the samples and the increment in the number of control actions contributed by the system disturbance task variable need some extra attention.

The procedure which is applied can be described as follows. The centers of the two local alarm condition rectangles are connected with each other by a straight line, Fig. 4.10. Similarly, the two centers of the central alarm rectangles are connected. Each center represents the mean number of sample actions and the mean number of control actions. Analogously to the additive factor method, the lines are tested on parallelism. In the case that the connection line between the local alarm rectangles is found to be parallel to the central alarm line, additivity in sampling, due to the display structure task variable, is accepted.

In reaction time experiments such as Sternberg's, this testing would be sufficient. Here the Y-axis is only used whereas the X-axis is reserved to indicate the different experimental conditions.

In the underlying experiments however, the Y-axis as well as the X-axis is needed in the testing procedures, i.e. two
measured quantities are involved here. To indicate only parallelism will thus not be sufficient. When the display structure hypothesis is to be accepted, the centers of the low noise rectangles are to be statistically equal with respect to the X-coordinates whereas the Y-coordinates are to be statistically not equal. This combination of demands has also to be found in the case that the centers of the high noise rectangles are tested. This means that besides parallelism also the length of the two lines should be equal. Besides, the X-coordinates of the begin of the two lines is should be statistically equal. When the lines are regarded as the hypotenuses of two rectangle triangles, additivity in this case can be tested by showing that the two sides of each triangle are equal to the sides of the other triangle. These sides represent occasionally the increment in sample actions and control actions. Subtraction of the number of sample actions contribution by the alarm presentation i.e. the display structure task variable is admissable be it that it is a linear operation. When the sample increments are statistically equal and the increments of control actions are also found to be equal, the two demands are valid and thus independent action contribution of that specific task variable can be accepted.

![Graph](image.png)

Figure 4.10: Testing additivity by testing parallelism.

-BIBLIOGRAPHY-


Chapter V: THE STATISTICAL PROCEDURES

5.1 CHOICE OF THE STATISTICS.

In order to be able to test the hypotheses represented in Table 2.1, some kind of criterion has to be defined. The criterion mostly used in statistics is the level of significance. Four scales of measurements are identified having their own statistical procedures (see for instance Siegel, 1980). These levels are: the nominal scale, the ordinal scale, the interval scale and the ratio scale.

The kind of statistical procedures which can be used depends completely on the level of measurement. A classification of all the tests applicable to each level can be found in the many handbooks for experimental design and analyses such as Winer (1971), Kerlinger (1973), Keppel (1973) and Hinkle (1979). A classification of the types of statistical tests that can be used in the analyses of experimental data is as follows:

- The classical parametric tests,
- the non parametric tests, and
- the sequential tests for twofold qualifications.

In this investigation, it is tried to use the parametric tests as much as possible. The parametric tests have been chosen because their discrimination is mostly larger and therefore more powerful than that of the non-parametric tests. Because, only selected data, originating from well-trained operators will be used in the analyses, the data can be regarded as appropriate material. Extreme scores, a reason to choose immediately for non parametric tests, are not expected in these data. The data selection takes place taking into account the learning curve. Only the flat part of the curve representing the number of samples and/or the number of control actions for the successive trials in the different conditions, will be applied for hypotheses testing.

5.2 PARAMETER OPTIMIZATION PROCEDURES.

In modeling techniques besides a model structure parameters are involved. Some of the parameters are already to be known before any model verification takes place. These parameters will therefore be treated as fixed quantities. Other parameters however are still to be estimated. With the identification of these parameters the model behavior is evaluated according to a certain criterion. When the model structure is accepted, then the search for an 'best' fit according to the criterion has to be executed. By utilizing a parameter adjustment method the still unknown values of the non-fixed parameters can be determined.

When the effect of a parameter is not linearly related to the parameter value, the adjustment can become rather complex. Moreover, when the model parameters cannot be regarded as independent of each other, again the complexity in the optimization increases. Often iterative procedures are then
applied. A parameter vector is to be defined, which includes all parameters to be determined. The initial value of such a vector will be identified by \( \theta^1 \), after the \( i \)-th iteration the value of the parameter vector is described by \( \theta^i \). At each iteration, the outputs of the model are generated. The remaining difference between model output and operator data is expressed in terms of an error criterion \( J \). The value of the criterion \( J^i \) after the \( i \)-th iteration is compared with the value \( J^{i-1} \), whereas the applied optimization procedure determines the next value of the parameter vector \( \theta^{i+1} \). This procedure is terminated when the 'best' match has been found. Two questions remain:

- When can one decide whether the best match has been obtained?
- What kind of optimization procedure has to be applied?

Starting with the first question, one primarily needs a definition of optimality of the parameter set. When a set of \( N \) parameters is supposed to be needed to describe the model, then

\[
\theta = [\theta_1, \ldots, \theta_N]^T, \theta \in \Omega \text{ where } \Omega \text{ represents the set of all possible parameter vectors. Furthermore, it is assumed that the vector valued criterion } J \text{ has } M \text{ elements, thus }
\]

\[
J(\theta) = [J_1(\theta), \ldots, J_M(\theta)]^T.
\]

Optimality of a parameter set is now defined in terms of the so-called Pareto-optimality. The parameter vector \( \theta \) is an optimal solution if: \( \theta_o \in \Omega \) and, if there exists no other \( \theta \in \Omega \) such that:

\[
\begin{align*}
1) \quad &J_i(\theta) < J_i(\theta_o) \quad \text{for } i=1,2,\ldots,M, \\
2) \quad &J_j(\theta) < J_j(\theta_o) \quad \text{for at least one } j.
\end{align*}
\]

The multiple objective problem is solved when a vector \( \theta \in \Omega \) is found that minimizes all \( M \) elements of the criterion \( J \) simultaneously as a function of \( \theta \). It should be mentioned, however, that a Pareto-optimal solution \( \theta_o \) is not unique (Lin, 1976), and according to the definition, it is as good as any other Pareto-optimal solution. From the practical point of view, it is impossible, starting with different initial values, to determine all Pareto-optimal solutions and therefore only a partial solution of the problem has to be accepted. By utilizing an optimization procedure, the decision whether an improvement of the vector \( J \) has been obtained is according to the overall objective, thus defined as:

A parameter vector \( \theta \in \Omega \) is better than the vector \( \theta' \in \Omega \) when:

\[
\begin{align*}
1) \quad &J_i(\theta) < J_i(\theta') \quad \text{for } i=1,2,\ldots,M, \\
2) \quad &J_j(\theta) < J_j(\theta') \quad \text{for at least one } j.
\end{align*}
\]

- 50 -
The procedure is terminated at the value $\Theta_f^*$, the final value, if no improvement can be obtained. The final value $\Theta_f^*$, the Pareto-optimal solution, is generally depending on the initial value $\Theta_i^*$ and the procedure utilized. This leads to the second question: Which procedure should be used?

One of the well-known parameter adjustment procedures in literature is called the adaptive random search algorithm (Karnopp, 1963; Steward et al, 1968). Arguments, as to prefer the adaptive random search algorithm over methods such as a gradient type algorithm are mentioned in Karnopp (1963):

- Independency of the relation between criterion function and model structure.
- Ease of implementation.
- Efficiency of computation time.
- Flexibility of search strategy.
- Relatively fast convergence for high dimensional parameter spaces.
- Insensitivity for surface properties.

These arguments are so in favor to apply the adaptive random search method that therefore the method has been chosen as a starting point in this investigation.

---BIBLIOGRAPHY---

Chapter VI: RESULTS

6.1 INTRODUCTION

In this chapter the results of the experiments will be presented, together with a preliminary conclusion on the results of each group of experiments. In the next subsections some aspects of particular importance will be elucidated. Two sets of results will be distinguished: The outcome of the statistical hypotheses testing and the results of parameter optimization by means of different adjustment procedures. In this chapter, first the results of one human subject will be presented. These results are then compared with the results of the other subjects. Because subjects differed rather impressingly in their supervising behavior, the normalized quantities of each operator are presented for direct comparison. Thereafter, the results of each of the six subjects are discussed more or less separately. Comments about the acceptance of the separation principle belong to the final part of the hypotheses testing sections. In the next chapter the model parameters are identified and are being discussed.

6.2 HYPOTHESES TESTING

In the first stage of testing the hypotheses, it was examined whether the raw output data of the six subjects could be regarded as samples having a normal distribution. The data consisted of the number of samples and the number of control actions made in the different experimental conditions. Moreover, it was tested whether the operator action rate and his performance score had leveled off to a constant value. When testing both aspects, it was found that only in one set of results normality could not be indicated explicitly. In one experimental condition subject 2 sampled so rarely, only four times in nine sessions, that a skewed distribution was obtained. This inconvenience was accepted, being the only exception; the other data of this subject, and all data from the other subjects, gave enough confidence to apply parametric statistics. The experimental data of subject number four were chosen to illustrate all postulated effects in a rather condensed way. The other subjects differed with respect to one or more of these aspects.

Fig. 6.1. shows the 95% confidence interval limits of a Student's t- distribution of sample and control actions of subject four in four experimental conditions. Visually seen, the effect of the alarm presentation can be found only in the number of sample actions; no effect is found on the number of control actions. The noise intensity of the system disturbance task variable has obviously an effect on both the number of observation actions and the number of control actions.

The t-test results as given in Table 6.1 are in full agreement with the postulated effects of the alarm presentation of the display structure task variable and the noise intensity of the system disturbance task variable. In the Analysis of Variance (see Table 6.2), a significant part of the variance found in the rate of observations could be explained by the alarm presentation and the noise intensity. No variance could be explained by a indications of a decrease in actions due to a continuation in learning. Besides, a
significant part of the variance found in the rate of control actions could be explained by the noise intensity. No variance could be explained by the alarm presentation and remained learning effect.

Figure 6.1: Results of the 95% confidence interval of Student's t on experimental data of subject four.

Table 6.1: t-test on data of subject four.

<table>
<thead>
<tr>
<th>Condition:</th>
<th>number of cases</th>
<th>Observation actions</th>
<th>Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>number of cases</td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>low noise intensity</td>
<td>local alarm</td>
<td>6</td>
<td>21.67</td>
</tr>
<tr>
<td></td>
<td>central alarm</td>
<td>9</td>
<td>28.00</td>
</tr>
<tr>
<td>high noise intensity</td>
<td>local alarm</td>
<td>9</td>
<td>34.67</td>
</tr>
<tr>
<td></td>
<td>central alarm</td>
<td>10</td>
<td>42.80</td>
</tr>
<tr>
<td>local alarm</td>
<td>low noise</td>
<td>6</td>
<td>21.67</td>
</tr>
<tr>
<td></td>
<td>high noise</td>
<td>9</td>
<td>34.67</td>
</tr>
<tr>
<td>central alarm</td>
<td>low noise</td>
<td>9</td>
<td>28.00</td>
</tr>
<tr>
<td></td>
<td>high noise</td>
<td>10</td>
<td>42.80</td>
</tr>
</tbody>
</table>
Table 6.2.: Results of the Analyses of Variance on data of subject four, with F-ratio, degrees of freedom, and significance of F.

<table>
<thead>
<tr>
<th>Source</th>
<th>Observation actions</th>
<th>Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>df</td>
</tr>
<tr>
<td>Noise intensity</td>
<td>103.772</td>
<td>1</td>
</tr>
<tr>
<td>Alarm presentation</td>
<td>30.116</td>
<td>1</td>
</tr>
</tbody>
</table>

The only aspect that remained to be demonstrated is that the noise intensity has an additive contribution to the number of actions made. Based on the results depicted in Table 6.3 the increment of sample actions and the increment of control actions in the local alarm condition and in the central alarm condition can be interpreted statistically as equal. This effect can, according to the postulations, be regarded as in agreement with the acceptance of the application of the superposition principle.

Table 6.3.: t-test on the increments in number of actions in the data of subject four to indicate additivity.

<table>
<thead>
<tr>
<th>Subject: Noise intensity contribution in:</th>
<th>Number of cases</th>
<th>Increment of observation acts.</th>
<th>Increment of control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>p</td>
</tr>
<tr>
<td>local alarm conditions</td>
<td>6</td>
<td>13.83</td>
<td>6.37</td>
</tr>
<tr>
<td>central alarm conditions</td>
<td>9</td>
<td>14.22</td>
<td>4.47</td>
</tr>
</tbody>
</table>

The results can be summarized as follows:

When additivity is an appropriate indicator to accept the separation principle and the operator behavior can be regarded as typical, then this principle can be accepted in conditions where alarm presentation and noise intensity are involved as task variables.

To decide whether these results are of a more general character, the operator data of the other subjects have to be taken into account too. The first thing that can be said is that the operators differed substantially in the number of actions made and in their applied strategy. Although this does not immediately harm the hypotheses testing, it complicates however a direct comparison and it excludes the possibility to average the scores over the different subjects.

When one digs into the matter of hypotheses testing, for each of the subjects individually, the scores of subject six have to be used with great care. It was found that, when accepting a significance level $p < .05$ for the Analysis of
Variance, only subject six still showed learning effects in his sampling behavior \((p < .04)\). Besides learning effects as source of explaining variance in the measured quantities, the noise intensity and alarm presentation are also taken into consideration as sources; they are summarized in Table 6.4.

Table 6.4: Summary of Analyses of Variance on the data of six subjects, with F-ratio, degrees of freedom, and significance of F.

<table>
<thead>
<tr>
<th>Subject:</th>
<th>Source:</th>
<th>Observation actions.</th>
<th>Control actions.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>df</td>
<td>p</td>
</tr>
<tr>
<td>1</td>
<td>Learning effects</td>
<td>4.67 6 .056</td>
<td>4.38 6 .063</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>86.05 1 .000</td>
<td>39.58 1 .001</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>80.16 1 .000</td>
<td>.98 1 .368</td>
</tr>
<tr>
<td>2</td>
<td>Learning effects</td>
<td>2.45 8 .127</td>
<td>.65 8 .723</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>101.99 1 .000</td>
<td>108.77 1 .000</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>154.10 1 .000</td>
<td>.12 1 .735</td>
</tr>
<tr>
<td>3</td>
<td>Learning effects</td>
<td>.84 11 .612</td>
<td>.67 11 .740</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>19.29 1 .002</td>
<td>58.79 1 .000</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>3.92 1 .097</td>
<td>.01 1 .913</td>
</tr>
<tr>
<td>4</td>
<td>Learning effects</td>
<td>1.63 9 .167</td>
<td>1.57 9 .187</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>103.77 1 .000</td>
<td>277.70 1 .000</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>30.12 1 .000</td>
<td>.03 1 .847</td>
</tr>
<tr>
<td>5</td>
<td>Learning effects</td>
<td>.24 9 .985</td>
<td>.51 9 .851</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>21.95 1 .000</td>
<td>56.40 1 .000</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>4.84 1 .038</td>
<td>.55 1 .468</td>
</tr>
<tr>
<td>6</td>
<td>Learning effects</td>
<td>4.85 7 .036</td>
<td>3.65 7 .068</td>
</tr>
<tr>
<td></td>
<td>Noise intensity</td>
<td>148.20 1 .000</td>
<td>156.57 1 .000</td>
</tr>
<tr>
<td></td>
<td>Alarm presentation</td>
<td>1.34 1 .292</td>
<td>1.91 1 .216</td>
</tr>
</tbody>
</table>

Because the noise intensity results can be regarded to explain a substantial part of variance for each of the subjects, the additivity test will finally be executed to confirm or reject the hypotheses under consideration. A t-test on the observation and a t-test on the control increments showed no significant difference for each subject except for subject two, and then only in the case of the observation increment (Table 6.5).

As it will be discussed later, subject two showed a very peculiar observation strategy. Because this strategy could not be found in other operator data it is accepted as the exception that proves the rule. It will therefore be concluded that the separation principle can be accepted in these cases where the noise intensity is involved as task variable.

Based on the Analysis of Variance, it can be stated that the alarm presentation as source does not explain any of the variance found in the control action quantity. The alarm presentation as source does not always explain a substantial part of the variance. Because learning effects were found in the data of subject six (Table 6.4), this aspect of learning might contribute to the non-significancy found in the Analysis of Variance for the alarm presentation. For subject three such an argument cannot possibly be given. However, a value close to the conventional limit of significance can be shown in the data. The obtained results can be summarized as follows:
In all cases the effect of the alarm presentation on the control activity is precisely as postulated, i.e. no effect on the number of control actions is found.

In two thirds of the cases the effect of the alarm presentation on the sample activity is as postulated, i.e. a definite effect on the number of sample actions is found. The expected effect of the alarm presentation on the sample activity could always be indicated but the effect could not always be supported by statistical analyses.

Table 6.5: Summary of the additivity-testing by means of a t-test on the increments in number of actions.

<table>
<thead>
<tr>
<th>Subject:</th>
<th>Noise intensity contribution in:</th>
<th>Number of cases</th>
<th>Increment of observation acts.</th>
<th>Increment of control acts.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean (S.D.)</td>
<td>Mean (S.D.)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>6</td>
<td>10.50 (8.07)</td>
<td>21.17 (6.15)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>7</td>
<td>14.14 (5.24)</td>
<td>20.14 (11.55)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>9</td>
<td>14.11 (6.33)</td>
<td>38.67 (18.00)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>9</td>
<td>25.33 (8.87)</td>
<td>29.67 (7.81)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>12</td>
<td>29.25 (23.77)</td>
<td>22.67 (14.87)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>10</td>
<td>14.60 (10.20)</td>
<td>29.20 (17.00)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>6</td>
<td>13.83 (6.37)</td>
<td>42.17 (16.79)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>9</td>
<td>14.22 (4.47)</td>
<td>45.11 (10.25)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>9</td>
<td>20.11 (10.67)</td>
<td>29.11 (11.34)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>7</td>
<td>30.14 (20.01)</td>
<td>37.29 (21.57)</td>
</tr>
<tr>
<td></td>
<td>local alarm conditions</td>
<td>8</td>
<td>33.13 (11.23)</td>
<td>42.75 (14.79)</td>
</tr>
<tr>
<td></td>
<td>central alarm conditions</td>
<td>7</td>
<td>29.00 (10.61)</td>
<td>42.43 (15.13)</td>
</tr>
</tbody>
</table>

Before a final conclusion is drawn, one remark has to be made. In accepting the application of the separation principle it is important that the control activities are strictly not initiated by any display structure task variable. It is thereby thought to be much more essential than the fact that sometimes a non-significant effect of such a task variable on the sample activity has been found. The first aspect can be regarded as definitely effecting; the second aspect as presumably effecting.

Considering the results, it will be concluded that the postulated effect of the alarm presentation as task variable can be accepted provisionally. This means that, with regard to the display task variable, until the contrary has been shown the separation principle will be accepted.

About the noise intensity task variable the following can be said. The noise intensity task variable does have an effect on the operator sample and control behavior. The Analysis of Variance (Table 6.4) as well as the additivity test (Table 6.5)
are confirming the postulations, hence the results can be summarized as follows:

The effect of the noise intensity task variable is considered as in agreement with the acceptance of the existence of the separation principle. In those conditions however where noise intensity is substantially different, no garanties can yet be given.

In Chapter IV, it has been stated that the narrow boundary condition would be investigated (Experiment II). The hypothesis related to the task requirement task variable will hereby be discussed. It should be mentioned beforehand that only two subjects participated in this particular investigation. Conclusions therefore are to be regarded as of a preliminary kind.

As the postulated effect would be found only in the number of control actions, results of subject one contradict this postulation in all aspects (Table 6.6). Not only a significant increase in sampling has been found, also non-significant results are found when dealing with the control actions.

Table 6.6: Results of the t-test statistics on data of Exp I and Exp II with respect to narrow and broad boundary control of subject one.

<table>
<thead>
<tr>
<th>Condition:</th>
<th>Observation actions</th>
<th>Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n. of cases</td>
<td>Mean</td>
</tr>
<tr>
<td>Low noise intensity;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>local alarm</td>
<td>6</td>
<td>121.67</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>143.33</td>
</tr>
<tr>
<td>central alarm</td>
<td>7</td>
<td>134.71</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>152.11</td>
</tr>
<tr>
<td>High noise intensity;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>local alarm</td>
<td>7</td>
<td>115.14</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>151.22</td>
</tr>
<tr>
<td>central alarm</td>
<td>7</td>
<td>148.86</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>166.44</td>
</tr>
</tbody>
</table>

The results of subject two are more according to the stated hypothesis (Table 6.7). The experimental conditions in consideration show a significant increase in control actions. Moreover, two experimental conditions show also a non-significance increase in sample actions. The found results can be summarized as follows:

Based on these results such as mentioned, it is hard to conclude whether or not the task specification task variable should be considered as task variable for which
the existence of the separation principle can validly be accepted.

The first results here indicate strongly a rejection of the postulated relation. When the results of the next section, dealing with the atypical sample behavior of subject two are also taken into account, the indications become even stronger.

Table 6.7: Results of the t-test statistics on data of Exp I and Exp II with respect to narrow and broad boundary control of subject two.

<table>
<thead>
<tr>
<th>Condition:</th>
<th>Observation actions</th>
<th>Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low noise intensity:</td>
<td>n. of cases</td>
<td>Mean</td>
</tr>
<tr>
<td>local alarm</td>
<td>broad boundary</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>narrow boundary</td>
<td>8</td>
</tr>
<tr>
<td>central alarm</td>
<td>broad boundary</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>narrow boundary</td>
<td>9</td>
</tr>
<tr>
<td>High noise intensity:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>local alarm</td>
<td>broad boundary</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>narrow boundary</td>
<td>9</td>
</tr>
<tr>
<td>central alarm</td>
<td>broad boundary</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>narrow boundary</td>
<td>7</td>
</tr>
</tbody>
</table>

6.3 DISCUSSION OF THE DISPLAY STRUCTURE TASK VARIABLE ON THE HUMAN OPERATOR'S SAMPLING BEHAVIOR

6.3.1 Sampling strategy.

The display structure task variable has been varied by means of alarming the operator locally or warning him by means of a central alarm. This means, however, that only when output signals are deviating from the specified boundaries, and thus when the signals are not in agreement with the task specification, a distinction is made in the way of information presentation. When the sampling strategy of subject two would be a typical example, results as found and conclusions as made should be doubted under these task conditions. The sample strategy of the operator in consideration is predominantly based on sampling when an output has passed one of the specified boundaries, i.e. sampling when an alarm occurs. This is shown graphically in Fig. 6.2. Moreover, the figure shows that the sample strategy in a central alarm condition is predominantly based on sampling both output variables at the same time. The first figure (a) represents the absolute value of the deviation of the third output variable of the plant, the amount of produced electrical power, at the moment that the
output is sampled. The second figure (b) represents the absolute value of the deviation of the third output variable at the moment that the second output variable, the flow of the low pressure steam, is sampled. The dotted line represents the absolute value of the specified limits.

![Figure 6.2: Representation of the absolute value of the third output variable on the instant of sampling of the third output (a) and on the instant of sampling of the second output (b), in a central alarm condition.](image)

The sample strategy in a local alarm condition is predominantly based on sampling, as soon as an alarm occurs, of the other output variable, i.e. the variable which is not in alarm (see Fig. 6.3.)

A sampling strategy like the one just discussed, leads to accepting the postulated characteristics as induced by the display structure task variable. The sampling actions are, however, almost all initiated when the boundaries specified are passed; sampling is thus induced by the task requirement task variable. This clearcut strategy could not be retraced in the other subjects sampling behavior; it can thus be regarded as an atypical example. Otherwise the choice of alarm presentation as display structure task variable would have been wrongly chosen. Although one has to be somewhat careful with the found results, the conclusions made earlier are still thought to be valid.

The question should be posed why this strategy was not detected in a early stage. Large error scores would be expected as a consequence of sampling predominantly when the outputs are already deviating from the specified boundaries. The error score of subject two was, in fact, lower than the error scores of any of the other subjects. Results of other subjects required, however, during experimentation more specific attention. Because of the fact that the results of that subject were much better than the results of the other subjects and
because a lot of investment had been put in training, some explanation has to be found for the indicated strategy. Therefore a few additional experimental trials would serve that purpose. In the next section, the results of the additional trials are discussed.

![Figure 6.3: Absolute value of the third output when sampling the second output (a) and the absolute value of the second output when sampling the third output (b) in a local alarm condition.](image)

6.3.2 No alarm presentation (Experiment III).

The a-typical way of sampling of operator number two raised some questions. One of these questions concerns the effect of the alarm presentation on his overall performance. Therefore it was thought sensible to exclude the operator of any form of alarm information.

The consequence of excluding alarm presentation, for the operator is that he has to generate a new sample strategy. Although this realization of the display structure task variable is an extreme form the effect of no alarm presentation is only expected in human sampling behavior. As it has been remarked, the operator made so few errors in comparison with the other subjects, that one can easily say that his control strategy had reached a high performance level. Therefore it seems rather plausible to find no effects in control behavior after excluding the operator from any alarm. This would then be in accordance with the model hypotheses. In the rate of sampling, due to the urge to adopt a new sample strategy, an increase in actions is likely to occur. The change in sampling rate might be then conform the model. Both aspects just described will be regarded as a hypothesis and will therefore be experimentally tested.

6.3.3 Results of experiments with no alarm indication.

As postulated, the effect of not alarming the operator at all was a considerable increase in sample actions. Contrary to the hypothesis, also an increase in control actions was found
Besides, the error score was lower. In hindsight, this last result could have been expected because, in the alarm presentation conditions, the operator waited almost always until an alarm indication occurred before he sampled and before he changed setpoints. In the no alarm conditions he did not wait at all for an alarm. Therefore his control strategy could be initialized before an output actually reached the deviation zone. The effect of initiating a control action in an earlier stage than in the original experiments, may point the direction of a change in also control strategy. If this aspect could be accepted as plausible, then the increase found in control actions can be credited to the new control strategy. Although the strategy aspect has not been analysed to a great extent, the control magnitudes of the set point corrections were found to be smaller when compared with the magnitude in the original experiments.

Table 6.8: t-test on experimental data from subject 2 in different alarm presentation situations all dealing with narrow limits.

<table>
<thead>
<tr>
<th>Condition: small limits</th>
<th>Observation actions</th>
<th>Control actions</th>
<th>Deviation score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>number of cases</td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>low noise-local alarm</td>
<td>8</td>
<td>0.50</td>
<td>0.76</td>
</tr>
<tr>
<td>low noise-no alarm</td>
<td>9</td>
<td>166.67</td>
<td>6.71</td>
</tr>
<tr>
<td>low noise-central alarm</td>
<td>9</td>
<td>39.78</td>
<td>3.96</td>
</tr>
<tr>
<td>high noise-local alarm</td>
<td>9</td>
<td>22.78</td>
<td>3.56</td>
</tr>
<tr>
<td>high noise-no alarm</td>
<td>10</td>
<td>164.90</td>
<td>5.17</td>
</tr>
<tr>
<td>high noise-central alarm</td>
<td>7</td>
<td>54.00</td>
<td>6.09</td>
</tr>
</tbody>
</table>

The no-alarm conditions have also been investigated on the effect of the noise intensity task variable. In accordance with the postulations in Table 3.1, the effect of the noise intensity task variable should be found by an increase in sampling and controlling. As a result, a significant increase in the number of control actions was found, but no effect was found in the number of sample actions.

Overseeing all these results and realizing that only one subject was involved in this part of the investigation, only a very preliminary conclusion can be made.

Based on the results found, it is doubtful to regard the no alarm presentation in combination with a low level noise intensity as well in combination with a high noise intensity, as experimental conditions for which the separation principle can be validly accepted.
6.4 EFFECTS OF TREND INFORMATION ON HUMAN OPERATOR PERFORMANCE

6.4.1 Introduction

As was indicated by Rijnsdorp (1982), investigations showed that process operators regularly pay attention to the process state of the system. He continues that it is very probable that the perceived state is not only based on the actual values of the process quantities, but also based on the rate of change, i.e. the trend. Very probably for this reason, trend recorders are still required in many central control rooms (Rijnsdorp 1982). As a consequence, operators are forced to look alternately at VDU's and conventional trend recorders. Especially when operators are becoming older, fast eye correction to focus on interfaces located at different distances, become troublesome. As it was also remarked, it will not be easy to introduce many trends in the restricted area of one or a small number of VDU's; investigations on this subject are, however, very needed. Among others, it was therefore decided to incorporate some aspects of the problem of trend representation in the investigation.

Due to the fact that the display information, at the moment of experimentation, could only be realized by digital display presentation, the effect of trend recording had to be kept outside the investigation. However at the moment the realization of trend presentation became available, this form of presentation form was incorporated directly in the experimentation.

One important question has to be made; i.e. can trend presentation be regarded as a representative of the display structure task variable? The question as whether or not trend presentation is needed by operators might even be answered.

6.4.2 Description of the information presentation

Many questions such as, how to represent the output variables, which color should be used, how the information should be updated, which time interval of historical information should be presented etc., had to be answered. The ergonomical literature was searched for support of the generated ideas. Not much usable information was however found. It was therefore that colleagues, students and visitors of the lab. were encouraged to give critical remarks about the obtained trend presentation on the newly implemented VDU-device. Their remarks gave rise to a refinement of the trend representation.

It was decided that each output variable would be presented having a horizontal time axis and that every output variable had a fixed region on the screen.

The continuously presented trend of the boiler output was situated in the left upper part of the screen. The flow of the low pressure steam was presented in the right upper part, and the amount of electrical power was presented in the left lower part of the screen; both output variables were only available on request. A requested output variable could be observed for a period of 5-seconds. All output variables were updated on the right hand side of the time axis. Thereby the update frequency was 5-seconds. Every minute of historical information required twelve pixels on the screen. A minimum of nine minutes of trend information was shown. This information could increase to a
maximum of ten minutes. Then a one minute period of trend information was skipped and the remaining nine minutes shifted to the left side of the time axis. This skipping and shifting phenomenon repeated itself till the end of the experimental run.

The nominal value of the output variable in each trend recording was represented by a straight line segment having a cyan color whereas the background was black. The upper and lower limits consisted of a dotted red line. The output variables were represented by a string of plus characters, colored green. When an output variable crossed one of the limits a red bar appeared instead of the dotted limits. The output variable outside the limits turned on to yellow. When the variable returned within the tolerances again, the red bar disappeared and the deviation from the limit of the variable turns to red. The appearance of the red bar was chosen as an attention function. The deviation from the boundary having a red color had been chosen as a memory function. After the signal has returned within the limits, the plus characters are green again as they were before.

Above each trend the output characteristic was printed. Moreover, each trend had the subscription '10 min.' enclosed within two arrow points (See Fig. 6.4).

Figure 6.4: Layout of trend presentation and an illustrated example.

6.4.3 The effect of trend information on human operator performance; Experiment IV.

In a set of experiments the difference between trend information and digitally displayed output information on human performance was investigated. In table 3.1. it was postulated that the effect of the different display configurations will be reflected in the number of observation actions and not in the number of control actions. The difference between digital and trend information can be tentatively summarized as: Digital information is quantitative status information, whereas trend information is quantitative historical and status information plus qualitative predictive information.

When a sample is taken in the case the digital display is
used, the actual output variable is presented during a period of five seconds. When a sample is taken in the case the trend display is used, actual as well as historical information is being presented. From that information, the first derivative can be determined rather easily. This derived information is thought to be a tool for the prediction of the future state of the observed output variable.

Based on the difference in information presentation, it is postulated that the amount of samples in the case of digital display information will be higher. This is motivated by the fact that, with a digital display, only more than one sample will in principle be needed to obtain sufficient information to determine the trend of an output signal. In the case of trend display, the same information can be obtained with only just one sample.

It has been demonstrated, that dealing with digitally displayed output information, a local alarm presentation requires less sampling than a central alarm presentation. Because this has not been shown in the case of trend presentation, the alarm presentation hypotheses will be investigated anew. In the experiments, local alarm and central alarm indication will then be combined with either trend information or digitally displayed status information. Consequently a 2 by 2 design has been applied in this part of the investigation.

Hence, in the experimental design, only attention will be paid the display configuration; all other task variables, i.e. the intensity of the system disturbance, the task requirements, and the system dynamics, are kept constant.

The noise intensity will be at a high level whereas the specified limits of the task requirements will be broad.

The last four subjects of Experiment I were the supervisors in Experiment IV. Two of the major reasons for this choice were that those subjects were already extensively trained and could therefore be regarded as sufficiently skilled subjects; furthermore, the newly obtained results of these subjects could also be easily compared with previous results of the same subjects.

The quantities used for the comparison between trend and digital display are the quantities as used before i.e.:

- The number of observation actions,
- the number of control actions,
- the error score, i.e. the absolute deviation integral.

Although the operators were well-trained, four to six sessions for each condition were introduced as a refreshment course. The course was necessary because the subjects had not supervised the system during the summer period.

Similar to previous experiments, every experimental session lasted 45 minutes. Three sessions were held in the morning and three sessions were held in the afternoon. Two subjects controlled always in the morning, the other two subjects controlled in the afternoon. Two identical Utility Plant simulations could be used. One interface contained digital displays, the other contained identical displays but had also the additional VDU trend display.
6.5 RESULTS ON TREND PRESENTATION

6.5.1 Introduction

Firstly, the results of the originally planned conditions will be discussed (Experiment IV). As these results could not be easily interpreted, results from the digital display conditions will then be compared with results from Experiment I, dealing with the same subjects. This comparison required further experimentation. The results from these experiments (Experiment V) are thereby compared with the already obtained results from Experiment IV, and with the results from Experiment I. In the final comments, the suggestions are integrated with results derived from interviews with several operators.

6.5.2 Results of trend presentation, Experiment IV

Experimental scores were obtained in Experiment IV. The number of sample and control actions and the error scores were analyzed by means of an Analyses of Variance. It resulted that hardly any variance could be explained by both sources, i.e. the alarm presentation and trend or digital displayed information. Besides, no variance could be explained by a two way interaction between both sources.

The obtained results are represented in Table 6.9 and can be summarized by the following statement:

The postulated effects were not clearly demonstrated by the results. Only the data of subject number 4 are partially in accordance with the postulations. Due to the fact that a significant difference in the error score of subject 3 and subject 6 is found, conclusions on data of these subjects are hard to make.

Table 6.9: Results of an Analysis of Variance on data of four subjects obtained in Experiment IV

<table>
<thead>
<tr>
<th>Subject</th>
<th>Source</th>
<th>Sample</th>
<th>Control</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>F</td>
<td>df</td>
<td>p</td>
</tr>
<tr>
<td>3</td>
<td>Alarm</td>
<td>0.036</td>
<td>1</td>
<td>.852</td>
</tr>
<tr>
<td></td>
<td>Display</td>
<td>2.828</td>
<td>1</td>
<td>.106</td>
</tr>
<tr>
<td></td>
<td>2-way</td>
<td>1.120</td>
<td>1</td>
<td>.301</td>
</tr>
<tr>
<td>4</td>
<td>Alarm</td>
<td>2.567</td>
<td>1</td>
<td>.118</td>
</tr>
<tr>
<td></td>
<td>Display</td>
<td>6.396</td>
<td>1</td>
<td>.016</td>
</tr>
<tr>
<td></td>
<td>2-way</td>
<td>0.191</td>
<td>1</td>
<td>.655</td>
</tr>
<tr>
<td>5</td>
<td>Alarm</td>
<td>0.123</td>
<td>1</td>
<td>.728</td>
</tr>
<tr>
<td></td>
<td>Display</td>
<td>1.147</td>
<td>1</td>
<td>.294</td>
</tr>
<tr>
<td></td>
<td>2-way</td>
<td>0.010</td>
<td>1</td>
<td>.920</td>
</tr>
<tr>
<td>6</td>
<td>Alarm</td>
<td>0.380</td>
<td>1</td>
<td>.543</td>
</tr>
<tr>
<td></td>
<td>Display</td>
<td>21.205</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>2-way</td>
<td>0.705</td>
<td>1</td>
<td>.409</td>
</tr>
</tbody>
</table>
Because comparable data of Experiment I showed to a great extent an agreement with the postulations, in Experiment IV something had to be definitely different. Therefore the data of both experiments were statistically tested. When the scores of each subject of both experiments were used in a t-test, significant differences found. In the local alarm and digital display conditions of Experiment IV, the number of samples has significantly higher than in Experiment I. This was found to be true for each subject when accepting the significance level of p=.01. A similar effect was found in the central alarm digital display condition with the significance level of p=.05. In the local alarm digital display conditions, also the number of control actions in Experiment IV was significantly higher in comparison with Experiment I. This result was found in three out of the four cases accepting a significance level of p=.05. In the central alarm digital display condition this effect was shown in the data of two subjects with p=.05. The results are all summarized in Table 6.10.

That the effect of trend information presentation would be found in an increase in actions was completely unexpected. Moreover, it is absurd that now there is even an increase in actions with only digitally displayed output information. But, to believe that the found results were originated from the introduction of trend presentation could be the only explanation, because all other aspects were completely identical in both the task conditions.

Table 6.10: Results of a t-test on data before the trends were introduced (Exp I) and on data after the trends were introduced (Exp IV).

<table>
<thead>
<tr>
<th>Subj</th>
<th>Local Alarm and Digital Display</th>
<th>n. of cases</th>
<th>Number of Observation acts</th>
<th>Number of Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>3</td>
<td>before trend intro.</td>
<td>8</td>
<td>128.</td>
<td>18.0</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>7</td>
<td>160.</td>
<td>21.1</td>
</tr>
<tr>
<td>4</td>
<td>before trend intro.</td>
<td>8</td>
<td>35.</td>
<td>5.8</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>10</td>
<td>113.</td>
<td>16.8</td>
</tr>
<tr>
<td>5</td>
<td>before trend intro.</td>
<td>10</td>
<td>120.</td>
<td>9.8</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>8</td>
<td>192.</td>
<td>29.1</td>
</tr>
<tr>
<td>6</td>
<td>before trend intro.</td>
<td>8</td>
<td>141.</td>
<td>13.2</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>8</td>
<td>178.</td>
<td>19.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Subj</th>
<th>Central Alarm and Digital Display</th>
<th>n. of cases</th>
<th>Number of Observation acts</th>
<th>Number of Control actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>3</td>
<td>before trend intro.</td>
<td>9</td>
<td>128.</td>
<td>5.4</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>6</td>
<td>170.</td>
<td>35.9</td>
</tr>
<tr>
<td>4</td>
<td>before trend intro.</td>
<td>8</td>
<td>43.</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>9</td>
<td>121.</td>
<td>10.2</td>
</tr>
<tr>
<td>5</td>
<td>before trend intro.</td>
<td>10</td>
<td>136.</td>
<td>11.3</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>8</td>
<td>189.</td>
<td>18.5</td>
</tr>
<tr>
<td>6</td>
<td>before trend intro.</td>
<td>8</td>
<td>141.</td>
<td>12.4</td>
</tr>
<tr>
<td></td>
<td>after trend intro.</td>
<td>8</td>
<td>190.</td>
<td>25.1</td>
</tr>
</tbody>
</table>
6.5.3 Effects of skipping trend presentation (Exp V); description and results.

Results from the previous section gave rise to questions. In such a case one can either speculate about as possible cause or one can further investigate the matter by means of goal directed experimentation. The latter possibility was chosen. In Experiment V, trend information was totally skipped from the experimental set-up; only digitally displayed output information conditions were involved (see Table 4.1).

If the introduction of trend information had been debit to the unexpected increase in action, the exclusion of trend information could probably induce the reverse. In such a case trend information could be earmarked as the cause of the unexpected results. By excluding trend information conditions, the hypothesis was tested that:

When the introduction of trend information had caused an increase in sample taking, the exclusion of trend information would show a decrease in sampling.

When data obtained from Experiment V and data obtained from Experiment VI were analysed by t-test statistic, the following results were found:

In the local alarm and digital display conditions of Experiment V a decrease in the numbers of sample and control actions is found in comparison with data in similar conditions in Experiment IV.

The decrease in numbers of actions is significant for three subjects when accepting a significance level of $p=0.05$. When compared with data of Experiment IV, the central alarm and digital display conditions of Experiment V show a decrease in sample actions for three subjects, accepting $p=0.05$. A similar effect was found for the decrease in the number of control actions. These results can be interpreted as follows:

Introducing a trend display configuration in the experimental design will increase the number of actions made in the digital display condition.

Excluding the trend display again from the experimental design will decrease once again the number of actions made in the digital display conditions.

These results are shown in Fig. 6.5 where the mean of sample and control actions in the two digital display conditions are represented of all four subjects. Results of the t-test are summarized in Table 6.11.

When finally data of Experiment I are compared with data of Experiment V, some subjects showed less actions in the latter case. This effect is sometimes combined with a somewhat larger error score. Even though this effect occurred, still some of the operators decreased their number of actions considerably (see Table 6.12).

If this aspect can be explained by the trade-off between number of actions taken and the acceptance of slight boundary deviations cannot be answered properly. After about hundred additional hours of supervising the system some control non-
Chalance can be imagined to occur. It could however, also be the case that during the prolonged experiments a slight continuation of learning have been taken place. By the application of trend information in the set-up irreversible aspects could be thought of to have been introduced.

Fig. 6.5: The effect of trend recording on operator behavior exposed to digital information.

Table 6.11: Results of t-test statistics on digital display condition data, after trend were introduced (Exp IV) and after excluding trend presentation (Exp V).

<table>
<thead>
<tr>
<th>Subj.</th>
<th>Local Alarm and Digital Display</th>
<th>n. of cases</th>
<th>Number of Observation acts.</th>
<th>Number of Control actions</th>
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<tbody>
<tr>
<td></td>
<td></td>
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<td>Mean</td>
<td>S.D.</td>
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<td>3</td>
<td>after trend intro.</td>
<td>7</td>
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<td>excluding trend</td>
<td>9</td>
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<td>4</td>
<td>after trend intro.</td>
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<td>excluding trend</td>
<td>8</td>
<td>137.</td>
<td>9.4</td>
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<td>5</td>
<td>after trend intro.</td>
<td>8</td>
<td>192.</td>
<td>29.1</td>
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<td></td>
<td>excluding trend</td>
<td>4</td>
<td>123.</td>
<td>35.1</td>
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<td>6</td>
<td>after trend intro.</td>
<td>8</td>
<td>178.</td>
<td>19.4</td>
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<td></td>
<td>excluding trend</td>
<td>7</td>
<td>120.</td>
<td>11.4</td>
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<td></td>
<td>Central Alarm and Digital Display</td>
<td>n. of cases</td>
<td>Mean</td>
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<td>after trend intro.</td>
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<td>excluding trend</td>
<td>7</td>
<td>135.</td>
<td>11.4</td>
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Table 6.12: Results of t-test statistics on data, before trends were presented and after trends were excluded again.

<table>
<thead>
<tr>
<th>Subj.</th>
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<td>128.</td>
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<td>35.</td>
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<td>141.</td>
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<td>5</td>
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6.5.4 Post experimental interviews

After the experiments, the operators were interviewed. In these interviews several topics were discussed regarding all experiments. The main question here to be answered was focussed around the topic whether the initial increase in actions and subsequent the decrease in actions could be understood. Some of the operators answered that they did not realize the irregularity of the output signals until confronted with the information by means of trend information. The newly achieved knowledge made the operator more careful, and thus also more careful in the conditions with only digital displayed information. Evidently taught trend presentation the operators something about system behavior of what they were unaware in the previous experiments. A very possible transfer from trend to non-trend experiments can then be imagined. When following this thought, it now becomes plausible why operator four, whose supervision behavior has been used as paragon for the investigation of the separation principle, increased his sample and control actions so considerably. This operator might have a totally different mental model of the two to be sampled output variables for what they really are. It could therefore be possible that the operator sampled at those instants that the
output variable has almost equal values. Then the output signal might be interpreted as tame whereas, on the contrary, wild fluctuations took place between the sampled intervals. The effect of sampling so rarely might encourage him to sample even less frequently.

6.5.5 Concluding remarks

Anticipating on Chapter VII, practical supervision control behavior is always better than the best achieved with all kind of control models, optimal or non-optimal. Although there are indications that operator four does not have a perfect system knowledge, he is however very well capable to control the system with less information than most of his colleagues in non-trend conditions. His control behavior becomes comparable with respect to sample and control actions of the other subjects when trends are introduced. For this subject, the advantage of trend presentation was absent, interns of sample and control activity.

As a general effect, in all cases an increase in sampling and control actions are demonstrated. A decrease in actions is found after taking away trend presentation in the experiments.

It is therefore that the positive effect of trend recordings, as resulting in better supervision performance, has not been found in these experiments.

The question about regarding trend information as representative of the display structure task variable have not been answered yet.

The results as obtained and the analyses such as used give however not much support to accept the application of the separation principle under trend presentation conditions.

-BIBLIOGRAPHY-

Chapter VII: PARAMETER ESTIMATION PROCEDURES AND RESULTS.

7.1 INTRODUCTION.

Based on the results, as discussed in Chapter VI, there are arguments in favour of accepting the application of the separation principle in several conditions. Whether the estimation of the different parameters separately in those conditions can be extrapolated to non-observed task situations remains to be further investigated. As it was discussed, there are already task conditions known in which the application of the separation principle can be regarded as not valid.

For those task conditions where the application of the separation principle can be accepted, the parameters of the different model parts are identified separately. Logical sets of parameters will then be estimated concurrently.

The parameters determining sampling are optimized in such a way, that the sample instants of the model are fitted as close as possible to the actual sample instants of the operator. The next step will be the examination of the operator control instants. The pertaining parameters are then optimized in order to fit model control actions to those executed by the operator. After the control instants have been paid attention to, the control amplitudes needs to be considered. Suggestions to modify the applied control law are then given.

In this chapter the methods, in order to estimate the parameters, will be tested and briefly discussed. The different estimation procedures used will be discussed either in this chapter or in one of the appendices. Results found by the application of the different parameter adjustment procedures are finally discussed in this chapter.

7.2 THE APPLICATION OF THE ADAPTIVE RANDOM SEARCH METHOD.

In the investigations performed to estimate the model parameters, the adaptive random search method has been applied for reasons such as indicated in section 5.2. In this case an optimal parameter vector \( \theta \) was searched for by means of an iterative selection of a parameter vector \( \theta \). Then, from this vector the associated criterion vector was computed. The mechanism selected a new parameter from a gaussian distribution of which the mean and variance were functions of all preceding parameter and criterion vectors. This adaptive random search method has led to considerable computation time problems on the IBM 370/158 system. These problems arise since, on the one hand, each iteration step requires a long computation time and, on the other hand, a considerable amount of iterations is necessary. One iteration consists of the selection of a parameter vector, the computation of the process and model responses and finally the determination of the criterion vector. When we return to the one input-two output system of Kok and Van Wijk, the required CPU time for one iteration was three seconds, whereas 40 iterations for each parameter turned out to be sufficient. In the case of the Utility Plant simulation, with a discretization time of 5 seconds, the required CPU-time was 45 seconds. Moreover, one has to estimate at least 8 of the 14 parameters, which requires some thousands
of iterations.

After having experienced the full extent of the computation time problem, two solutions could be given. In the first place, one can limit the number of iterations. In such a case, optimality is naturally not guaranteed; even to trial one time with an exhaustive search, to get some more idea about the extent of the search length, it could not be fully accomplished on the Utility Plant data. In the second place, one can search for other parameter adjustment procedures. In that case, no a-priori guarantee can be given to find an appropriate optimization method. As the most practical approach that could be thought of is to estimate small groups of parameters with a fair amount of iterations and to search for the most promising alternative optimization procedures to be applied. As the model consists of three parts, the parameters of the observer part will be kept constant, whereas the parameters of the two decision mechanisms in the decision making part and the controller part will be estimated independently.

7.3 THE GRAPHICAL METHOD AND ITS APPLICATION

7.3.1: The graphical method and the observation decision parameters

In the previous section it is shortly discussed that the search method requires much computation time. It was mentioned that alternative optimization procedures would be tested to be used in the investigation. It was therefore that two approaches, the method of Polak and Payne and the grid method were tested and put aside. The description of both methods as well as the results of the latter method are discussed in Appendix B. As indicated in the appendix, the estimation of the parameters \(C_p\) and \(S_y^{\text{min}}\) caused certain problems related to convergency of the optimal parameter vector and to the huge amount of computation time. The next method to be discussed does not make use of a parameter estimation procedure in a strict sense, however, insight in the optimal displacement of the parameter \(C_p\) and \(S_y^{\text{min}}\) of the observation decision mechanism can be obtained. It is supposed that the operator samples the \(k\)-th output on the instants: \(t_{k_1}, \ldots, t_{k_i}, \ldots, t_{k_n}\). At these instants, estimations of deviations of the \(k\)-th output variable and uncertainties about these estimations are generated by the observer,

\[
|\hat{y}_{k_1} - y_{\text{nom}}|, \ldots, |\hat{y}_{k_i} - y_{\text{nom}}|, \ldots, |\hat{y}_{k_n} - y_{\text{nom}}| \quad \text{and} \quad S_{\hat{y}_{k_1}}, \ldots, S_{\hat{y}_{k_i}}, \ldots, S_{\hat{y}_{k_n}}
\]

respectively.

The \(i\)-th sample of output \(k\) is then situated on the hyperbolic decision line which is specified by:

\[
|\hat{y}_{k_i} - y_{\text{nom}}| = \frac{C_p}{S_{\hat{y}_{k_i}}} - \frac{1}{S_{\hat{y}^{\text{min}}_{k_i}}}
\]

(7.3.1)
The form of the hyperbolic line is completely determined by the parameter \( C_p \), whereas the position of the hyperbolic function in the two-dimensional plane is determined by \( \bar{y}_{(\text{min})} \). Since the sample moment \( i \) determines the values \( \hat{y}_{ki} \) and \( s_\gamma \), and because \( y_{\text{nom}} \) is given, the relation between the two parameters belonging to the \( i \)-th sample is specified by means of a straight line in the \( C_p, S_{\bar{y} (\text{min})} \)-plane:

\[
C_{pi} = -|\hat{y}_{ki} - y_{\text{nom}}| S_{\bar{y} (\text{min})}, + |\hat{y}_{ki} - y_{\text{nom}}| S_{\gamma_k} (7.3.2)
\]

In the case that the model is directed to sample output \( k \) on exactly the same instants as the human operator, the model output estimates \( \hat{y}_k \) and its variance \( S_{\gamma_k} \) are known on the moments of operator sampling and can be represented by a straight line in Fig. 7.1. Then, for a set of observations we have a bundle of lines of which the envelopes are given in Fig. 7.1.

![Graphical representations of sample lines.](image)

For each sampled output, such a graphical form can be made. If outputs are considered to be independent, the optimal parameter set can be obtained for the situation that each output has been sampled only twice. The optimal parameter set for each sampled output is then given by the coordinates of the crossing of the two lines. Optimality for more than two samples is postulated to be found firstly inside the envelopes of the bundle of sample lines; secondly, optimality will be found in the region where the envelopes are closest to each other i.e. the fuzzy crossing area of all or at least the majority of the straight sample lines. At this moment, it has to be mentioned that the interaction of output two and three has been ignored. Many different examples of parameter combinations of \( C_p \) and \( S_{\bar{y} (\text{min})} \) confirmed that optimality can principally be found in the postulated region, Fig.7.2. The number of actions of model and supervisor are about equal and the sample intervals are comparable to a great extent. This method should not be considered as a definite optimization in the parameter
verification string, but only as a good starting point. The method can be used to obtain rather quickly a very reasonable set of parameter values and, as such, it narrows down the search area substantially. This method therefore saves many iterations.

![Figure 7.2: Indicators to support the postulated search area.](image)

### 7.3.2 Distribution of the sample decision intervals

In the experiments, human supervisory control behavior has been measured. Under similar task conditions model behavior has been generated. From model and operator supervisory data, distribution functions then have been determined. When an appropriate approximation for the model parameter values is obtained, it becomes sensible to test the statistical rate of conformity between operator and model distributions.

A criterion to be used here pertains to the statistical difference of sequences of discrete signals of the human operator and the supervisory model.

The series generated by the operator are called point processes and are well-known in statistical literature. When the sample instants of an output value are indicated by \( t_i \), the sample intervals \( x_i \) are equal to:

\[
x_i = t_{i+1} - t_i, \quad i=1,2,3,...
\]

(7.3.3)

The interval series, \( x_i \), then can be analysed by determining the probability density function, in terms of histograms. In achieving the probability density function, a class width has to be determined. When the probability density function of the operator sample intervals are observed with a class width of five seconds, a typical shape with two peaks is found. Indications are present to associate the long sample intervals with regular sampling for the updating of the state estimate, whereas the short intervals are associated to obtain information with regard to derivative information.

The first test concerns the question whether or not the model probability density function shows statistics similar to the measured operator probability density function.

In order to match model and operator data, a quadratic criterion was defined on the differences between the actual
operator probability density functions and those generated by
the model. The criterion was minimized with respect to the
parameters. For this purpose an iteration procedure was used
which is a combination of the Newton-method and the steepest-
descent method; the algorithm of Marquardt (1963). Penalty
functions were defined on the outside of the search area in
order to avoid divergence of the parameter values during the
search.
The combination of optimization method and applied criterion
resulted in a unique solution without effects of local minima.
The starting values of the parameter vector were chosen on the
basis of the outcomes of the graphical method, which confirmed
again the practical use of the method. Jointly due to the
graphical method, the number of iterations to achieve an
optimal parameter set was found to be reasonable. Two examples
of how well the model probability density function fit the
actual operator probability density function is shown in Fig
7.3a and b.

Figure 7.3a and b: Typical examples of both probability density
functions of model and operator sample
intervals. Data of operator two in no alarm
task conditions.

7.4 MODELING THE HUMAN OPERATOR SAMPLING DECISION BEHAVIOR.

As it was discussed, the graphical method to narrow down the
search area was accepted as a useful tool. However, a similar
amount of samples taken by the operator and the model, obtained
with this method, does not guarantee that those samples are also
taken at the same instants of process operation. Before much
effort is put in finding an appropriate optimization method,
optimality is simulated. The practical utility of the chosen
hyperbolic decision mechanism is then investigated firstly
before the search for an appropriate optimization procedure is
further extended. After all the increase in complexity of the
supervised system does not imply that the observation decisions
are still based on the hyperbolic decision mechanism.
Simulated optimality was created by determining for each experimental run the pair \([ \hat{y}_{ki}, S_{y_{ki}} ]\) on every operator sample instant \(i\) of output \(k\). In Fig. 7.4, a typical example is shown. From this figure, it is hard to deduce a rule or mechanism to fit the scattered displacement of the depicted quantities. When the scattered data points in Fig. 7.4 are compared with the data representation of the model sampling, see Fig. 7.5, the hyperbolic relation can only be recognized easily in the latter case.

Figure 7.4: Position of operator triggered observer quantities

Figure 7.5: Sample quantities obtained from model sampling.
This result indicates clearly that in this situation, the operator does not have a sample strategy according to the suggested sampling model. The hyperbolic character of the decision rule, although not applicable in its present form, was still felt to be a sensible approach. It was therefore that it was decided to modify the sampling mechanism slightly.

7.4.1 Output estimations based on predictions ahead; first alternative.

The obtained operator data don't fit the postulated hyperbolic relation as incorporated in the observation decision rule. Because it seems plausible that experienced operators have expectancies about future process situation, their sampling might be depending on these expectancies. It is therefore assumed that actual sample actions are initiated by a mechanism that makes use of an estimation of the future system state, instead of on the basis of the present state. The sample actions would then be actuated by the predicted value of a, still unknown, number of time steps ahead. The only question that matters then, given the assumption is valid, is how many steps ahead has been predicted by the mechanism. The output value will then be predicted p-steps ahead on the basis of the applied input signal and the actual state, having the following form:

$$\hat{y}_{\text{pred}}(k) = C[A^p x(k) + \sum_{i=0}^{p-1} A^i B u(k)]$$  \hspace{1cm} (7.4.1)

A typical set of results is shown in Fig. 7.6a, b, c and d, for $\hat{y}(k)$ predicted 0, 2, 4, and 16 time steps, respectively. A time step is equivalent with 5-seconds. Predictions of more than 128 time steps are not taken into consideration. The results can be summarized as follows:

No visible grouping of sample points indicates a possible decision rule based on the predicted output values and the actual estimation uncertainty.

Figure 7.6a, b, c and d: Results for $\hat{y}(k)$ predicted several time steps ahead.
7.4.2 Output estimations based on predictions ahead of output and uncertainty; second alternative.

Although not much success has been encountered with the first alternative, still a second possibility has been investigated. The human sample decisions are now based on the prediction of the output variable as well as on predictions of the uncertainty of that output estimation. This sampling principle can be easily fitted in a hyperbolic decision principle. A prediction of a small deviation of the output variable, $\hat{y}$, and a predicted large uncertainty can occur. Similarly, a predicted considerable output deviation from the nominal value and a predicted small uncertainty about the estimated output can also take place. The results depicted in Fig. 7.7, do not show much difference in comparison with the results of the first alternative.

Based on these results, the following conclusion can be drawn:

Not much structural insight in sampling strategies has been obtained, except that the operator's behavior could not be described by one of these decision mechanisms.

![Figure 7.7: Disposition of sample points based on the second alternative.](image)

7.4.3 Output estimation based on the actual output value and the first derivative; third alternative.

The sampling mechanism is considered a very important part in the entire supervising modelling. While the results mentioned above are so unmistakingly clear, still two more procedures to describe the operator's sampling behavior have been investigated.

The third possibility considers not only the estimated output value, but also the first derivative of that signal. It is supposed, that the operator does not only make use of the estimated actual value of the output, but also that the operator makes use of the velocity component of the signal. It
is very well possible that the rate of change in the direction of the limit triggers the operator to take action. Although it was known that the model does not supervise the system any better when the first derivative is given, the human operator probably might. Arguments are thought to be present to investigate the probable effect of the rate of change on the human sampling behavior. The effect of having the first derivative available on the disposition of the samples is found graphically in Fig.7.8. It has to be concluded that:

The sample points in the two-dimensional plane have been shifted somewhat in comparison with the situation of not having derivative information. A substantial reorganization of the sample-points with some sort of ordering, however, has not been found.

Figure 7.8: Effect of including the rate of change on sample instants positioning.

7.4.4 Quasi decoupling outputs; fourth alternative.

While the hyperbolic decision rule has been formulated in the case that the supervised variables did not have any interaction, a decoupling of the different outputs in the present situation can finally be applied. Therefore the human operator decision rule will not be analyzed by the actual output estimations and uncertainty about these estimations, but by analyzing the transformed decoupled outputs. This means that the system matrix has to be diagonalized, whereafter the transformed, decoupled, outputs are to be estimated next to the determination of the estimation of the uncertainty. Thereafter the estimations at the one side and the uncertainty at the other side are weighted and then summed. The meaning of this exercise is that it is thought that the subject takes the interactions between the supervised outputs into consideration, when deciding to take samples. It is also supposed that the operator has an overall uncertainty about the estimations. Tests has been performed in which the
estimations and estimated uncertainties are added before the actual decoupling takes place such as indicated below:

\[ S_{y_{tot}} = \sqrt{\frac{S_{y_1}^2}{\frac{1}{2}} + \frac{S_{y_2}^2}{\frac{1}{2}} + \frac{S_{y_3}^2}{\frac{1}{2}}} \]

(7.4.2)

and

\[ |\hat{y}_{-y_{nom}}|_{total} = \frac{1}{d_1} |\hat{y}_1 - y_{nom1}| + \frac{1}{d_2} |\hat{y}_2 - y_{nom2}| + \frac{1}{d_3} |\hat{y}_3 - y_{nom3}| \]

(7.4.3)

in which \( S_{y_{max}} \) represents the stationary value of the corresponding uncertainty and in which \( d_k = y_{upperlimit} - y_{nom k} \) minus \( y_{nom k} \) for \( k=1,2,3 \), i.e. half the tolerance.

The reason not to decouple but still to add both of the quantities, can be argued as follows.

It is reasonable to suppose that the operator knows all the output interactions of the utility plant. This aspect can be supported by the results of post experimental interviews with different subjects.

It is also reasonable to suppose that the interactions of all state vector elements are not kept into consideration by the operator. The results obtained with the described procedure are depicted in Fig.7.9.

Again, the hyperbolic line cannot be visually identified in the sample point positioning. As a conclusion it should be mentioned that:

The fourth alternative procedure to describe human operator sampling could not be supported by the obtained results. The results do not lead in the expected direction.

As a final conclusion, it can be said that:

No sampling mechanism has been conducted by the human operator which can be described either by the original decision rule or by one of the alternative sampling rules as mentioned above.

It was therefore that it has been decided not to investigate the effect of decoupling any further. It seems appropriate now to give some reasonable suggestions why the promising results of the Kok and Van Wijk investigation could not be replicated in a more complex situation.

The reason that those rules cannot appropriately be applied on the obtained sampling data can possibly be found in the next consideration.

In a practical situation the sampling often takes place in the following form:

A quantity which is of importance, when manufacturing certain products, is not explicitly at hand but can be
estimated on the basis of a number of different (related) quantities being permanently available. Such a task situation is not found in the supervision of the utility plant. On the basis of the permanently available information, the pressure of the high pressure steam, the operator is not able to make an appropriate prediction of the other, non-permanently available, output quantities. The sample taking supplies no extra, additional, information about an output quantity, the sample taking gives only the actual value of the output variable itself.

![Figure 7.9: Position of sample points after a weighted summation of the estimates and the estimation uncertainty.](image)

In the supervision investigation as described by Kok and Van Wijk (1978), however, additional information in the strict sense had been sampled. In order to test the sample mechanism on its applicability the experimental set-up of the utility plant has to be changed. The presently sampled outputs has to be presented permanently, whereas new additional information has to be defined. These new sampled outputs then can be, for instance:

- The derivative of the presented value of the high pressure steam of the boiler. Sampling of this quantity gives the subject more certainty about the trend of the supervised variable. This quantity does not contain any information about the other supervised quantities.

- The amount of remaining high pressure steam after the turbines have consumed part of the total of produced high pressure steam. The presentation of this quantity supplies again additional information.

- The electrical power contribution of the back pressure turbine. This quantity gives information whether the condensing turbine should produce more or less electrical
In general, when the output of a (sub)system is disturbed by noise, the input of such a (sub)system is an appropriate variable to be sampled. Samples of such an input will probably lead to more accurate estimations of the actual value of the output of such a (sub)system. The argumentation given above is felt as a strong consideration in explaining why the sampling mechanism failed in this supervision situation.

7.5 MODELLING THE CONTROL DECISION OF THE HUMAN OPERATOR.

The control decision rule, as discussed in section 2.3.2., has been applied to describe the number and the instants of the operator's control decisions. This control decision rule has been successfully used by Kok and Van Wijk (1978) in the following way:

When it was determined that a certain supervised variable exceeded the subjectively accepted tolerance, the control decision mechanism triggered the controller part to compute a new input signal.

In this case, one had to deal with one input quantity which was kept constant for at least p-time steps as dictated by the single step control law parameter. It was necessary to keep the input quantity constant for a certain period since otherwise the model would determine new input adjustments as long as that particular output was still outside the specified limits. The value p of time steps is determined by the smallest number of steps found in the operator data between two successive control actions. When the operator supervises the utility plant, it sometimes happens that within a period of 10 seconds, two set point changes are initiated. With a discretisation step of five seconds, this means that the model parameter p of the controller part should have the value of 2. The determination of the control adjustment of the control law in the model with p=2, then shows totally different results; the number of model control adjustments differs sometimes a factor 100-1000 in comparison with the operator adjustments. A fixation of the control adjustment for a certain period and the application of an upper limit for the p-value is only acceptable when the output response is due to the control adjustment more than due to the disturbances.

As a result of the chosen parameters of the noise realisation, the two problems mentioned above are the reason of unacceptable results. Perturbations of the output variables are predominantly determined by the disturbances. When a maximum p-value is maintained, a much too large amplitude has to be accepted to bring back all three output variables within the set period to the nominal value.

A plausible explanation why Kok and Van Wijk could apply the decision rule successfully lies in the fact that only one input signal had to be determined by the control law. In the utility plant situation, however, three input signals have to be determined and executed at the same time while sub-system interaction was fully neglected. Also the smallest number of steps in the operator handling was determined irrespectively of
which setpoint was changed. In the model a setpoint change was always accompanied by set-point changes of all the other set-points. As an additional consequence of having small p-values instability of the controlled system takes place.

To be able to attack this complex problem, it has been decided to investigate first the human operator's control decisions when supervising the utility plant; an open loop analyses has therefore been applied; see Fig.7.10. In this way it is possible to examine the relation between combinations $\hat{y}_{ki}$ and $S\hat{y}_{ki}$, derived of the k-th output at the instant of time $t_i$, and the control decision on instant $t_i$ for the k-th input. In Fig.7.11a, combinations of $\hat{y}_2$ and $S\hat{y}_2$-values are graphically represented.

![Diagram](image)

**Figure 7.10: Open loop analyses of the control decisions.**

The typical example shown in this figure can be summarized as follows:

It is impossible to indentify some sort of control decision rule or strategy, since the control decision points are, as far as it can be seen, completely scattered along the plane.

In order to describe human operator control decisions more appropriately, other control decision mechanisms have therefore to be generated and tested on their applicability.

7.5.1 **Control decisions based on predicted observer quantities.**

As already suggested in a previous section, it seems rather plausible to accept that subjects predict to supervise output variables several steps ahead. These predicted values might determine the human operator control decision mechanism. When the operator predicts that an output variable will reach one of the specified limits within a certain period, he might already anticipate by changing the appropriate set-point. Although the uncertainty quantity was assumed to have no influence on the
control decision mechanism, this might turn out to be a wrong
way of modeling. The subjectively accepted tolerance might
change as related to the uncertainty of the estimated output
value. The subjectively accepted tolerance will then probably
become smaller when the uncertainty increases.

The time of prediction ahead of output \( y_2 \) is varied. When
comparing these figures with each other and when comparing
these with Fig. 7.11a, b, c and d not much ordering in control
decision points can be noticed.

![Figure 7.11a, b, c and d: The ordering of control decision points.](image)

From these results it can be concluded in the findings that:

No better control mechanism can be obtained by modeling on
the basis of predictions rather than the actual outputs.

The main reason for these disappointing conclusions might be
found in the fact that the set point changes applied by the
operator, are meant to control a particular output only instead
of making a sensible use of the system interaction. Such a
branched decision structure was not needed when the mechanism
was modeled originally. As a preliminary suggestion, a branched
decision mechanism which takes into account the interaction
between the sub-system, seems to be needed here.

7.6 MODELING THE CONTROL AMPLITUDES OF THE HUMAN OPERATOR.

In section 2.3.2 the functioning of the single step control
law was indicated. Application of the control law in this way
has shown that results do not fit the data. This is presumably
caused by the fact that all three inputs are changed at the
same time by the model, whereas such kind of changes are not
initiated by the operator. Also the control action is kept
constant for \( p \)-time steps by the model irrespectively of the
controlled output. Again, the operator does not behave similarly. As a consequence of disturbances acting on the system, it is possible that a variable requires a new input correction only shortly after a set point change. The model can handle such a situation only by accepting a small value of the p-parameter. Consequently large control amplitudes are generated. Another consequence of a small p-value lies in the fact that below a certain p-value instability occurred. The lower limit p-value is determined by the time constant of the slowest subsystem in the utility plant, i.e. the boiler. If the p-value is chosen close to the lower limit for the boiler subsystem, the consequence of the disturbances for the other two subsystems will still have the effect as described above. The time constants of these subsystems are roughly speaking one third of the boiler subsystem. For the appropriate control of these outputs, the p-value is still too large. This problem required the introduction of three independent p-values adapted to the time constants of the different sub-systems. The already large computation time involved keeps us away from simply accepting three independent p-values; i.e. an extension of the parameter set. Therefore it was tried, in different ways, to model control behavior by application of only one p-parameter.

7.6.1 Application of the single step control law with quasi independent set point initiations.

In order to obtain an approximation of human set point corrections, the single step control law in the model has been modified, as follows: Whenever it is decided to execute a control action, a new control vector \( u \) is determined in such a way that the output vector \( y = y_{nom} \) will be reached in \( p \)-time steps. The function can be described as follows:

Whenever on the basis of one of the signals a control action is executed, the nominal values of the output variables which are within their specified limits, are taken equal to the actual value.

This means that the vector \( y_{nom} \) will now be substituted by \( y'_{nom} \) in the following cases:

\[
\begin{align*}
y'_{nom_i} &= y_{nom_i} \quad \text{when } |\dot{y}_i - y_{nom_i}| > q_i \\
y'_{nom_i} &= \dot{y}_i \quad \text{when } |\dot{y}_i - y_{nom_i}| \leq q_i
\end{align*}
\]

The underlying idea was that the signals \( u_i \), for the cases \( y'_{nom_i} = \dot{y}_i \), would not be changed by means of a control action. Although this could not be realized when applying such a model structure, it was possible however to initiate within \( p \)-time steps new set point changes for these outputs for which \( y'_{nom_i} = \dot{y}_i \) was valid.

A p-value of 43 turned out to be the lower limit before instability takes place in a closed loop situation, i.e. when the control actions of the model are actuated as control inputs. When a relation between recorded instant of control decision and output response is made, the largest set point
corrections are made when $y'_{nom,j} = y_i'$
i.e. the correction that is thought to have no influence on the system. In this situation the cure is worse than the pain. It is therefore understandable that this alternative is not taken into consideration any longer. Besides this aspect, the control quality of the model is very bad. This poor control quality is indicated in Table 7.2 in which the

Table 7.2: Control quality indicated by the error score.

<table>
<thead>
<tr>
<th>Application of:</th>
<th>Deviation score of:</th>
</tr>
</thead>
<tbody>
<tr>
<td>single step control law having quasi independent set-point initiations with $p=43$.</td>
<td>1175 1014 52</td>
</tr>
<tr>
<td>non model intervention; automatic controlled system.</td>
<td>400 106 50</td>
</tr>
</tbody>
</table>

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<td>400 106 50</td>
</tr>
</tbody>
</table>

error score of each output when having the modified single step control law is compared with the error score when having no set point control, i.e. the non supervised nominal value automatic control situation. From this table it can be concluded that the single step control law, in this form, actually discontrols the system more than that it controls the system.

7.6.2 Modification of the quasi independent set point control mechanism, the second alternative.

In order to obtain improvement of the control quality the following control strategy is implemented: After each control action $p$-time steps have to be waited before the next control action is accepted. The set point control actions are executed similar to the form discussed in the previous subsection. The waiting period is similar for each controller input. For different $p$-values, the system responses are determined. The pertaining error score is represented in Table 7.3 in which the deviation scores of each output are represented for different $p$-values.

Table 7.3: Error score when having the quasi independent set point control mechanism.

<table>
<thead>
<tr>
<th>Collective counting for the input signals with:</th>
<th>Deviation score of:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p = 43$</td>
<td>422 99 76</td>
</tr>
<tr>
<td>$p = 23$</td>
<td>408 91 65</td>
</tr>
<tr>
<td>$p = 17$</td>
<td>1038 100 35</td>
</tr>
<tr>
<td>$p = 12$</td>
<td>instable instable instable</td>
</tr>
<tr>
<td>$p = 6$</td>
<td>instable instable instable</td>
</tr>
</tbody>
</table>
It can be concluded that:

Although a considerable decrease in the error score was found, still the scores are very similar to the non-supervised control situation.

7.6.3 Single step control strategy in the original form, the third alternative.

Because the discussed alternatives did not result in a comparable error score found after human operator control, the original control law was reconsidered. This control strategy can be summarized as follows:

Whenever a signal exceeds one of the subjectively accepted limits, while a previous control action took place less than p-time steps ago, the intended action has to be postponed. As soon as an action is permitted, three new input signals are determined and carried out; the aim is to bring back the output signals to their nominal values.

The quasi independent set point correction has then been left out of consideration. With this original control strategy, a number of responses are computed and the corresponding error scores are determined, and are represented in Table 7.4.

Table 7.4: Error score of the original single step control law.

<table>
<thead>
<tr>
<th>Collective set-point corrections with:</th>
<th>Deviation score of:</th>
<th>output 1</th>
<th>output 2</th>
<th>output 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>p = 35</td>
<td>241</td>
<td>68</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>p = 27</td>
<td>172</td>
<td>67</td>
<td>61</td>
<td></td>
</tr>
<tr>
<td>p = 25</td>
<td>452</td>
<td>64</td>
<td>48</td>
<td></td>
</tr>
<tr>
<td>p = 22</td>
<td>137</td>
<td>73</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td>p = 20</td>
<td>instable</td>
<td>98</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>p = 18</td>
<td>instable</td>
<td>66</td>
<td>35</td>
<td></td>
</tr>
<tr>
<td>p = 15</td>
<td>instable</td>
<td>90</td>
<td>41</td>
<td></td>
</tr>
</tbody>
</table>

When using this control strategy, the phenomena that the boiler output, the pressure of the high pressure steam, becomes instable for decreasing p-values is counter effected by still some improvement of the other two output error scores. It can be concluded that:

A lower error score can be obtained with this control strategy in comparison with the other alternatives.

It also can be concluded that:

Three independent p-values for the three subsystems are still desirable in spite of the increase in the number of parameters.
7.7 A MULTI-PARAMETER CONTROL LAW.

In the previous sections, disadvantages of the single step control law have been discussed together with the alternatives in order to compensate for these negative effects. From the operator action pattern, it has become clear that the discussed control law cannot be regarded as an appropriate modelling of such action patterns. The operator control actions are generally characterized by a kind of decoupled control strategy. In the strategy found, the boiler input is simply used to control the boiler output. For both other parts of the controlled system a comparable structure might be found. Therefore a true decoupled single step control law has to be defined. The newly accepted control law is based on the structure that input i is used to control output i, where i=1,2,3. Each of the separate control laws is dependent on the number of control steps pi in which the nominal value yi must be reached. A consequence of these decoupled control laws is that the number of parameters will increase from one to three. Due to the fact that no proper control decision mechanism has been found throughout the investigation, it has been decided to use the operator control decisions such as measured during the experiments. Whenever the subject decides to make a control correction, the model has the opportunity to use the same controller to make also a control correction. The control actions of the human operator are then used to control the process; the control actions of the model are determined in order to estimate, later on, the parameters pi. To save a lot of computation time, it has been decided not to include the Kalman filter but to simulate the process only. The amplitude of the control actions is then based on the actual state of the system; the estimated state, as generated by the observer part is therefore no longer needed.

By means of a vectorial criterion such as described Appendix D, the differences between the operator control amplitudes for the different output quantities and the comparable model control amplitudes are determined. The adaptive random search method is applied to estimate the pi-parameters; i=1,2,3. In Table 7.5, the numerical results of the best parameter values pi found with their associated criterion values for amplitude differences are represented. Figure 7.12 shows how the control amplitude analysis was performed.

Table 7.5: Numerical results obtained with the 'best' p values, based on control data of subject two in the final phase of the experiments.

<table>
<thead>
<tr>
<th>parameter:</th>
<th>p1</th>
<th>p2</th>
<th>p3</th>
<th>J1</th>
<th>J2</th>
<th>J3</th>
</tr>
</thead>
<tbody>
<tr>
<td>trial n</td>
<td>29</td>
<td>44</td>
<td>30</td>
<td>519.6</td>
<td>91.2</td>
<td>62.8</td>
</tr>
<tr>
<td>trial n+1</td>
<td>26</td>
<td>44</td>
<td>30</td>
<td>395.9</td>
<td>51.5</td>
<td>35.2</td>
</tr>
<tr>
<td>trial n+2</td>
<td>31</td>
<td>43</td>
<td>27</td>
<td>268.9</td>
<td>66.9</td>
<td>43.3</td>
</tr>
</tbody>
</table>
Operator and model control amplitudes are graphically represented in Appendix D. When the data represented in these figures are observed, the following remarks can be made:

- The control amplitudes of the operator and the model when dealing with the boiler input are very well comparable. The application of a decoupled control law seems therefore sensible.

- The control amplitudes of the low pressure steam input of operator and model are reasonably comparable.

- The control amplitudes of the electrical power input of operator and model are not comparable.

Figure 7.12: Graphical representation of control amplitude analyses.

An indication to substructure this statement is the insensibility of the criterion value $J_3$ for parameter $p_3$. These remarks can be very well associated with the relationships between the different in- and output combinations. With input number one only the boiler part subsystem can be influenced. This aspect is fully in accordance with the application of the decoupled control law. The strategy to determine the other inputs, in which strategy the interaction between in- and outputs has to be taken into account, are only partially described by the chosen decoupled control law. In a human operator control decision mechanism, it is therefore likely that the state of more than one supervised variable is taken into account when a set-point is changed. It can therefore be concluded that whenever interaction between in- and outputs takes place, singular decisions are not likely to occur. One can rather speak in such cases about a decision structure in which a number of conditions are checked before finally an appropriate set-point control action is executed. A consequence of accepting a decision structure for the control actions is that the number of parameters of the control decision part of the model will increase. Before a new control decision mechanism can be seriously considered, however, the difficulties with the large computation time has to be solved.

Chapter VIII: CONCLUDING REMARKS AND FURTHER RESEARCH

8.1 CONCLUDING REMARKS.

The ultimate aim of modeling the human operator's supervisory behavior is to develop and design appropriate Man-Machine-Interfaces which are based on insight in men's capabilities and limitations. In modeling this behavior, the structure of the model should be chosen in such a way that normative predictions can be obtained about non-investigated supervisory control task situations. Whether extrapolations to those task situations are acceptable or not, depends on the validity of accepting the separation principle, discussed in detail in this thesis.

A number of task conditions have been created to test the validity of the principle. Four task variables were used, i.e. the display structure, the noise intensity of the system disturbances, the task requirements of the human operator and the system dynamics. Except for the system dynamics, each task variable was varied on at least two levels.

By the application of a utility plant simulation, human operator sample and control behavior could be studied. The numbers of sample and control actions were tested on the superposability or additivity from one task condition to other task conditions, see throughout chapter VI. Superposability thereby was postulated as indicator for the acceptability of the separation principle, see section 3.2. The following results were obtained:

The display structure task variable was found to have an additive effect on the number of samples taken when a local alarm or a central alarm presentation was applied. This result was only found when the output information was digitally presented. No effect could be detected in the number of control actions. On the basis of these results the application of the separation principle was accepted to be valid. When trend information was presented, no additive effects could be traced. Consequently, the principle cannot be applied under this task condition.

The system disturbance task variable was found to have an additive effect on the number of sample and control actions under the conditions low noise and high noise intensity. Here, the results show that the separation principle could be accepted.

Based on the result of two subjects, the task requirement task variable showed an additive effect on the number of control actions and the number of sample actions. Because only additivity in the control actions should be found, the separation principle was provisionally not accepted when this task variable was varied between a broad and a small boundary control requirement.

The effect of the system dynamic task variable on the sample and control behavior of the operator was not investigated.

Besides the predictive value of the model, a positive effect on the parameter estimation economy can be obtained in assuming that the separation principle can be applied. In those situations where additivity in the sample and control quantities was found, sets of parameters in the different model parts were estimated independently (chapter VII) according to the separation principle (subsection 1.4.4).
Without hesitation, it can be said that the identification of the different model parameters gave rise to more questions than answers.

In the parameter estimation procedure, the parameters of the observer model part were fixed. This fixation was suggested in literature, and resulted in positive results with the model. The parameters of the observation decision making element have been estimated with several optimization procedures, see section 7.2 and appendix B. Results indicate that the number of model samples rather easily became equal to the number of operator samples, see section 7.3.

Induced by the hyperbolic decision rule, a pair of quantities was generated by the observer on each instant of sampling. These quantities, a model output estimation and a deviation score of the corresponding estimation were subsequently plotted. When the plotted data were compared with data obtained on the instants of operator sampling, no similarities could be found. Plots of operator data did not result in a hyperbolic configuration. Several modifications were made to obtain a hyperbolic relation based on the operator sampling instants. None of these modifications showed any better performance. Hence, it is doubtful if human observation decisions can be described by a hyperbolic decision rule in situations such as investigated. The positive results obtained when a non-interacting quantity is sampled such as in previous experiments leads to a feeling that system interaction may be cause of the negative results.

For the control decision rule, see section 7.5, similar results are found as in the case of the observation decisions. Therefore it was doubted that a control decision mechanism as verified here can model the human control decisions, during the supervision of complex systems.

The modeling of the operator's determination of the control amplitude was based on a single step control mechanism with one parameter, see section 7.6. Only when a system part did not effect other parts, model control amplitudes were very well comparable with those of the human operator. In other cases a reasonable fit could not be obtained.

As one of the major results of this investigation, it could clearly be showed that a supervisory control model working nicely when dealing with a rather simple process and without system interaction, cannot be extrapolated directly to a somewhat more complex task situation. Although it is familiar that an increase in task complexity carries along an increase in unforeseen circumstances, the actual number of pitfalls and dead-end street approaches was not expected. Still the results such as obtained are regarded as a fruitful contribution to obtain more insight in the multi-objective problem of supervisory control modeling. Thereby, the cybernetic approach is thought to be a technique appropriate for tackling the multi-dimensional character of supervisory control behavior. Restrictions are found in the area of computation time which remains, of course, a very practical constraint. Methods to reduce computation time to some extent are given throughout the chapters.

The application of an error criterion defined on the outputs of the model as a function of time, the vector valued criterion, showed a lack of unimodality of the criterion function, see Appendix B. Moreover, a constraint related to the large computation times was encountered. A less demanding
criterion was introduced (subsection 7.3.2) for which only the statistical properties of the operator and model outputs were required. Not only unimodality was achieved, but also less computation time in comparison with the vector valued criterion. Preliminary but very promising results were obtained.

In section 6.4 the effect of trend recording on the operator behavior was discussed. Contrary to what might be expected, trend recording resulted in more sample and control activities in comparison with plain digital status output information found in the preceding experiments, in which the same subjects participated. Moreover, a remarkable side effect was detected. The introduction of trend presentation showed an increase in actions when trends were presented but also when trends were absent. However, no explanation could be given for these unexpected results. When finally the trend recording was skipped from the experiments, a significant decrease in the rate of sampling and control was found. Data from these experiments and from experiments before trend presentation was introduced could be accepted as equal to a reasonable extent.

The interviews held at the end of the experiments, indicated that trend recording showed the irregular form of the output in an explicit form. Output quantities presenting historical information differed substantially from their own feeling of these quantities based on the sampling the digitally presented outputs. The discrepancy resulted in an increase in the number of actions taken. It should be mentioned thereby that the results of the interviews contributed to a great extent to the explanation of the results found.

8.2 FURTHER RESEARCH.

In order to keep the number of parameters in the model low, as a condition for keeping computation time low, one can consider to skip the complete observer. The actual state will then be used. The variance of the estimation error can be modeled as an exponential function. This function has to increase in time after a sample has been taken. The parameters of this exponential function can be deduced, for instance, by a comparison between the results of the estimation error and results of some exponential functions. Preliminary studies showed that satisfying results can be obtained. As a consequence, results will hardly differ, but the required computation time will be become smaller than 20% of the present computation time.

Further, the presently used decision making elements need to be changed. Although a hyperbolic decision rule seems to carry similarity to our decisions, this does obviously apply only in those cases where supervised quantities are independent. A more distinctive working decision structure is apparently needed when interactive output quantities are to be supervised.

A similar argumentation seems valid for the control decision mechanism. The presently used control decision mechanism including the several modifications did not result in control decisions which correspond with the control decisions of the operators.

Also the control amplitude mechanism requires some structural modifications. The savings to be obtained by not considering an observer for state estimations but by directly using the state itself, gives one the opportunity to introduce a much more sophisticated controller mechanism. Although it is realized
that such a need can partially be coped with when more than one parameter is applied.

It is known that the modeling of relatively simple manual control tasks has required several years before these tasks could be described satisfactorily. Realizing the handicap of the task complexity and the much later on-set of systematic supervisory control investigation, it would be a complete underestimation of the topic to expect already general applications of supervisory control models. The model such as verified here gave a lot of negative results. As said before, system interaction could not be coped with. Therefore the model requires a substantial number of modifications before it can be applied to describe the operator's supervisory behavior in an acceptable way.

Whether overall system performance is better when operators are supervising totally decoupled processes, in comparison with processes which do have a high degree of system interaction, remains unanswered for the moment. However, when the decoupling show better overall system performance, the model might be a direct contribution to describe supervisory control behavior. Else, the model needs modifications such as suggested in this final section.
For the application of the Observer Controller and Decision model a discrete description of the system state is required:

\[ x(k+1) = Ax(k) + Bu(k) + Gw(k) \quad k = 1, 2, 3, \ldots \]
\[ y(k) = Cx(k) \]

The dimension of the system, including the noise filters, is 11.

The applied matrices for a discretion time of 1 second and for a discretion time of 5 seconds are represented below:

The C matrix is invariant with different discretion time steps. The matrix consists of a unit matrix of 3 by 3 and is complemented with zero elements on the right-hand side.

Transformed A-matrix for \( T = 1 \text{sec.} \)

<table>
<thead>
<tr>
<th></th>
<th>1.56E-2</th>
<th>1.11E-1</th>
<th>1.11E-2</th>
<th>0</th>
<th>0</th>
<th>-1.11E-2</th>
<th>-1.11E-2</th>
<th>1.11E-2</th>
<th>0</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>9.80E-1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8.30E-3</td>
<td>0</td>
<td>8.23E-3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>-7.84E-4</td>
<td>9.84E-1</td>
<td>0</td>
<td>-1.65E-3</td>
<td>1.65E-3</td>
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AN ALTERNATIVE FOR THE TIME CONSUMING ADAPTIVE RANDOM SEARCH.

1. Introduction.

One of the most promising methods, to replace the adaptive random search, was suggested and investigated by Frieling (1980). This method has received the name of algorithm of Polak and Payne, (1975). Applying this algorithm, one bases the determination of a Pareto optimal solution on a two dimensional criterion vector. This bi-criteria vector cannot possibly cope with the original 2m+n dimensional vector.

In section 5.2, it was defined that the criterion J has M elements. It is supposed now that there exist m control signals and n sampled outputs in the supervised Utility Plant. When from the original criterion vector, J, the first m elements are related to the amplitude aspects of the control signals, and the last m+n elements are related to the time aspects of the control signals as well as the time aspects of the sampled outputs according to the formula:

\[ J^T = [J_1 \ldots J_m J_{m+1} \ldots J_{2m} J_{2m+1} \ldots J_{2m+n}] \]

a two dimensional criterion vector J' can be defined as:

\[
\begin{bmatrix}
J'_1 \\
J'_2
\end{bmatrix}
= \begin{bmatrix}
m \\
2m+n
\end{bmatrix}
\sum_{i=1}^{m} k_i J_i \\
\sum_{i=m+1}^{2m+n} k_i J_i
\]

with \( k_i \) as potential weighting factor. Applying this new criterion vector J', the optimization method of Polak & Payne can be used. The algorithm was the only appropriate optimization method for vectorial criteria that was found in literature.

When this method was tested by Frieling, the method required, similar to the adaptive random search-method, a considerable amount of computation time. Due to his findings, (Frieling, 1980) it was decided not to use this method any longer but to look further for, and/or to invent oneself, an appropriate alternative instead.

2. gridding the parameter space.

Because no optimization procedures could be altered in such a way that it fitted more or less the subject of investigation, a so-called grid-method is suggested here.

When having a r-dimensional criterion vector, a subspace \( \Omega \) of \( \mathbb{R}^r \) can be chosen within which the optimal parameter vector is thought to be situated. The procedure is as follows: One selects \( 2^r \) parameter vectors within \( \Omega \), for which the criterion vectors are determined. Thereafter a \( \Omega^1 \subset \Omega \) is selected in which the 'best' of the \( 2^r \) parameter vectors, the pareto optimal parameter vector, is situated. In \( \Omega^1 \) again,
2^r parameter vectors are chosen. Based on the criterion values, \( Q^2 \) and \( Q^1 \) is chosen and so on, until an optimal parameter vector has been found. A method, as described above, has the advantage of a simple implementation and besides, the advantage of obtaining the optimal parameter vector with relatively few iterations and with a high accuracy. However, demands are put in the course of the criterion as a function of the parameters. In the case that local minima are met, the possibility exists that this method does not converge to a global minimum. This convergency problem happens to be very general problem for a great many optimization procedures.

Although the method serves our purpose, still a severe disadvantage has been found during the application. In the case of large parameter vector dimensions, many criterion values and therefore also many model responses have to be computed in each iteration. As in this case, there are still 14 parameters to be determined; the number of parameter vectors are already reaching \( 2^{14} = 16384 \) for each iteration. Therefore it seems also preferable here to keep the number of parameters, to be estimated concurrently, as few as possible; as it was shown already, this can only be realized by sequential parameter estimation.

3. The application of the grid method.

For a critical evaluation of the practical utility of the grid method, the parameters of the observation decision mechanism are dealt with. In this case, artificial operator data are used. A well-known parameter set is used to generate artificially, the operator behavior. Model behavior has then to be fitted with the 'operator' behavior to minimize the criterion. In this approach it is possible to evaluate whether the found minimum criterion values actually belong to the appropriate parameter values. Consequences of a non optimal retrieval can then be quantified easily.

As it was found during different kind of exercises with parameter estimation procedures, the parameter \( C_p \), the curve parameter, was rather insensitive, (Sastra, 1978, Van Oostveen, 1982). Therefore it is practical only to estimate the two remaining parameters, \( S_y^{(\text{min})} \) and \( S_y^{(\text{min})} \), as a try-out of the applicability of the grid method. The estimation procedure is indicated in Fig. C.1.

**Figure C.1:** The estimation of parameters in the model.
The new parameters are determined when the first grid consisting of $\theta^1, \theta^2, \theta^3, \theta^4$ are determined and the associated criterion values are computed (see Fig.C2).

![Figure C2: Application of the grid method in estimating the parameter $S_{\bar{y}}(\text{min})$.](image)

4. Results with the application of the grid method.

When the search area or subspace $\Omega$ has been determined, the location of $\theta^1, \theta^2, \theta^3$, and $\theta^4$ of the first grid is also determined.

In this test, the Optimal parameter set $\theta^0$ of our artificial operator is known; the values of $S_{\bar{y}}(\text{min})_2$ and $S_{\bar{y}}(\text{min})_3$ are respectively 1.88 and 0.106. The values are chosen such that they are situated slightly outside the middle of the search area $\Omega$. Therefore, the discrimination power of the method has been directly tested in the first trial. Two trials are executed to investigate whether or not the method converges to $\theta^0$, whereas computation costs are kept to a minimum. For the first test, $\Omega^1$ has been chosen as follows:

$$\Omega^1 = \{ S_{\bar{y}}(\text{min})_2 \mid 1.6 \leq S_{\bar{y}}(\text{min})_2 \leq 2.2 \text{ and } 0.07 \leq S_{\bar{y}}(\text{min})_3 \leq 0.13 \}$$

This choice of $\Omega$ is fully determined by results with different parameter values. Parameter values outside $\Omega$ show unrealistically many or few sample actions in comparison with the human operator when supervising in similar control situations.
The choice of this $\Omega$ search area implies that the chosen $\theta^0 = \begin{bmatrix} 1.88 \\ 0.106 \end{bmatrix}$ will be situated in rectangle $\theta^2$. The results after two trials, graphically represented in Fig. C3, are not very successful.

![Figure C3](image)

Figure C3: First result of the applied grid method.

The optimal parameter set is determined to be situated in $\theta^1$ rectangle. Irrespectively of how many trials may thereafter be tried, the method cannot possibly lead to reaching rectangle - $\theta^2$. When looking at the other criterion values, it appears that a local minimum has been met. A second run has therefore been initiated.

$$\Omega^2 = \begin{bmatrix} \begin{array}{c} S_y(\text{min})_2 \\ S_y(\text{min})_3 \end{array} \end{bmatrix} \begin{array}{c} 1.45 <= S_y(\text{min})_2 <= 2.45 \\ 0.05 <= S_y(\text{min})_3 <= 0.15 \end{array}$$

The search area $\Omega^2$ has been chosen such that the first grid will be situated outside the possible local minimum of the first experimental run. Results are given in Fig. C4. These results are, after two trials, converging in the appropriate direction. When the area close to the presumed local minimum is investigated more carefully, and when four sets of parameter values are additionally applied, the existence of local minima are found such as indicated in Fig. C5. It should be noted thereby, that the summation of the criterion values of the parameters is considered.
Figure C4: Results of two trials with a new defined search area.

Figure C5: The search for local minima.

In the same Fig. C5, investigation of the area close to the optimum is represented. The direction from which the grid method approaches the optimum yields the highest criterion value. Again this indicates local minima. The associated number of samples of the different parameter values such as made by the model are represented in Fig. C6.
When the criterion values in Fig. C5 are compared with the number of samples taken (Fig. C6) by identical parameter values, some remarkable aspects shows up. In the first place, the criterion values associated to identical number of samples are rather divers. A criterion value of zero represents a similar amount of samples in comparison with a criterion value of 695, viz. \( n=22 \). A criterion value of 695, shows in one case 22 samples, and the same criterion value shows in another case 26 samples.

Figure C6: Graphical representation of number of samples of the two outputs as result of some experimental trials.

The chosen computation method seems therefore not appropriate to differentiate the number of samples taken.

An illustrative example, it will be shown that under an equal criterion value one can have \( n \) as well as \( 2n \) samples taken in an experimental run.

As one takes a series of samples on the interval \([0,T]\), the compilation \( \sigma \) can be described by:

\[
\sigma = \{s_i \mid i=0, \ldots, K\} \text{ with } K=5 \text{ and } \tau = \{t_i \mid i=1, \ldots, L\} \text{ with } L=5.
\]

Based on the determination of reference intervals, the criterion \( J \) is given by the next equation:

\[
J_a = |t_1 - s_1| + |s_2 - t_2| + |t_3 - s_3| + |t_4 - s_4| + |t_5 - s_5|
\]

The criterion is computed by the summation of line pieces as given in Fig. C7a.

When it is supposed that \( \sigma \) remains unchanged but that the number of samples in \( \tau \) becomes twice the number, the computation of \( J \) will then have the following form:

\[
J_b = |s_1 - t_1| + |s_1 - t_2| + |s_2 - t_3| + |s_2 - t_4| + |s_3 - t_5| + |s_3 - t_6| + |s_4 - t_7| + \\
|s_4 - t_8| + |s_5 - t_9|.
\]
In this situation, $\tau^p$ is the compilation $\{t_j | j=1, \ldots, N\}$, $N=10$. Although the distances become shorter, the number of distances becomes larger. The final effect results in exact the same criterion.

It should be noted that $t^\tau$ conjunes with $s^5$ and that it consequently will not increase the criterion. $J^p$ consists then of the summation of the line pieces such as indicated in Fig. C7b. In this case, $J^p=J^p$.

It has been indicated that double the number of samples can be found while the criterion remains unchanged. It can also have totally different criterion values although the number of samples is equal or almost equal.

Observing the results of Fig. C5 and Fig. C6, it can be shown that a set of 22 samples has a criterion of zero. A 20-samples set can also induce a criterion of 290, whereas a sample set of 21, actually closer to the number to be obtained, has a criterion of 740.

Being aware of the fact that a small in or decrease in the number of samples can have a considerable effect on the criterion and visa versa, the phenomenon of local minima in this situation becomes better known.

The confrontation with the choice of the criterion, in its present form, makes further applications of the screen method rather senseless. Besides, the method still consumes a great quantity of computation time. The results can therefore be summarized as follows:

The method as suggested can be regarded as a fruitful contribution to the already existing search methods. The existence of a substantial amount of local minima however makes this method, at this stage of the investigation and in this form, not very useful. Due to the reasons such as mentioned, the optimization procedure will not be taken further into account when dealing with the other parameter.

![Diagram](image)

**Figure C7a and C7b:** Line intervals for the computation of the criterion based on a summation of the different reference intervals.


Computation method of the vector valued criterion, (with the permission of the authors Kok and van Wijk, 1978, pp 161-164).

The method deals with the computation of reference intervals expressed in a vector valued criterion. Both definition and application are here discussed.

7.2.3 Definition of a vector valued criterion for signals of a discrete character.

We now define a vector valued criterion for signals of a discrete character by assigning the sum of the absolute values of the differences in amplitudes of the two step functions x and y, \( x, y \in L([0,T]) \), to the first element of the vector \( J \), and the sum of the absolute values of the differences in time instants of the activations to the second element of \( J \).

Let the step function \( x \) be given by the set of number \( \{x_i, s_i ; i=0,1, \ldots, K\} \), where \( x_i \) are the amplitudes and \( s_i \) are the time instants, and let the step function \( y \) be given accordingly by \( \{y_j, t_j ; i=0,1, \ldots, L\} \). If we assume that the total number of activations of these signals are equal, thus \( K=L \), then the elements of \( J \) could be defined on the basis of the corresponding activations:

\[
J_1 = \sum_{i=1}^{K} |x_i - y_i|; \quad J_2 = \sum_{i=1}^{K} |s_i - t_i|.
\]  

(7.2.10)

Here, we have classified activation \( i \) of \( x \) as a deviation from activation \( i \) of \( y \). Hence, this classification is based on the corresponding activation numbers of both signals. This was possible since the total number of activations was equal, but this method of classification fails if \( K \neq L \). Therefore, since we would like to make use of the same basic ideas in the normal case that \( K \neq L \), we need a general and reasonable rule to classify the deviations encountered in the comparison of the step functions \( x \) and \( y \).

Consider an arbitrary interval \([t_j-1, t_j] \) between two successive activations of the step function \( y \). Now, every activation of \( x \) which occurs within the interval \([t_j-1, t_j] \) will be classified as a deviation of either \( y_{j-1} \) or \( y_j \) according to the following rules:

\[
\text{if } s_p \in [t_{j-1}, t_j] \text{ then activation } p \text{ of } x \text{ is classified as a deviation from } y_{j-1},
\]  

(7.2.11)

\[
\text{if } s_p \in [t_j, t_{j+1}] \text{ then activation } p \text{ of } x \text{ is classified as a deviation from } y_j.
\]  

(7.2.12)

We choose \( t_j^1 \) in the middle of the interval, \( t_j^1 = \frac{1}{2}(t_{j-1} + t_j) \). This means in fact that we accept it as more reasonable to classify activation \( p \) of \( x \) as a deviation from \( y_j \) if \( s_p \) lies more closely to \( t_j^1 \) than to \( t_{j-1} \).

It should be noted that the rules (7.2.11) and (7.2.12) assume that the interval \([t_{j-1}, t_j] \) is the reference interval of concern, to which the activations of \( x \) are classified. Since this interval belongs to the function \( y \), we
have tacitly assumed that y is the reference signal and that x is the signal which shows the deviations. This choice was made arbitrarily, so to avoid any ambiguity we must indicate beforehand which step function is to be considered as the reference signal. The simplest way to do this is to choose either x or y as the reference signal. However, this approach can lead to the problem that in certain intervals of the reference signal the other signal shows no deviations. Instead, we introduce reference intervals which are referred alternatively to x and y according to a scheme as described below.

We first make the comment that it has no use to designate a reference interval to either x or y if the interval considered contains no deviations. Now, the first reference interval is determined in the following way. We have to make a choice between \([0,s_1]\) and \([0,t_1]\) corresponding to x and y, respectively. Three possible cases can arise:

- if \(s_1 < t_1\) then choose \([0,t_1]\) as the first interval;  
  \[(7.2.13a)\]

- if \(s_1 > t_1\) then choose \([0,s_1]\) as the first interval;  
  \[(7.2.13b)\]

- if \(s_1 = t_1\) then the choice is determined by the next interval.  
  \[(7.2.13c)\]

Hence, the signal which shows a constant value over the longest first period is referred to as the reference signal. For instance, if \(s_1 < t_1\) then \(t_1 \not\in [0,s_1]\) and we are not able to classify \(t_1\) in \([0,s_1]\) according to the rules (7.2.11) and (7.2.12), thus \([0,s_1]\) cannot be considered as the first reference interval. If \(s_1 = t_1\) none of the intervals contain deviations and the first reference interval cannot be determined. By evaluation of the next intervals \([s_1,s_2]\) and \([t_1,t_2]\) we can come to a conclusion, unless \(s_2 = t_2\). In the last case the decision can be made arbitrarily, since then \(s_1 \in [t_1,t_2]\) and \(t_1 \in [s_1,s_2]\); both intervals contain one deviation, but the criterion value is independent of the particular choice, namely \(J_1 = |x_1 - y_1|\) and \(J_2 = 0\). This procedure is continued until a choice can be made according to the rules (7.2.13a) and (7.2.13b).

After the first reference interval is determined along the rules (7.2.13a) and (7.2.13b), the contiguous interval of the same signal is designated as the next reference interval, and so on for the following intervals, as long as each of these intervals shows at least one deviation by the other signal. In this way a chain of reference intervals will result, for instance the chain (assuming \([0,s_1]\) as the first reference interval):

\[ [0,s_1),[s_1,s_2), \ldots, [s_{p-1},s_p) \text{ with } 1 \leq p \leq K+1. \]  
\[(7.2.14)\]

This chain ends with the interval \([s_{p-1},s_p)\) when the next interval \([s_p,s_{p+1})\) contains no deviations, or when the end of the period is reached \((p=K+1, s_p = T)\). In the former case \((p<K)\) we have a transition of reference signals, and \([t_q,t_{q+1})\) is designated as the first interval of the next chain which is constructed in the same way as the chain (7.2.14):

\[ [t_q,t_{q+1}),[t_{q+1},t_{q+2}), \ldots, [t_{r-1},t_r) \text{ with } 1 \leq r \leq K+1. \]  
\[(7.2.15)\]

Here it is assumed that \(t_q\) is the "last" deviation contained in \([s_{p-1},s_p)\), i.e. \(t_q \in [s_{p-1},s_p)\) but \(t_{q+1} \not\in [s_p,s_{p+1})\), otherwise the first chain would not have ended with \([s_{p-1},s_p)\).

This procedure of constructing chains is continued until the total period \([0,T)\) is covered by the union of all chains of reference intervals. Though each chain is a union of disjoint intervals, in general the total chain covering the period \([0,T)\) will also show intervals which are not disjoint, due to the trans-
itions. For example, in the transition mentioned above we have an intersection of the intervals which is equal to \([s_{p-1}, s_p] \cap [t_q, t_{q+1}] = [t_1, s_p]\). The possibility exists that the boundaries of the intersection are evaluated twice; this occurs if \( t_q \in [\frac{1}{2}(s_{p-1}+s_p), s_p) \) and \( s_p \in [t_q, \frac{1}{2}(t_q+t_{q+1})) \), since in that case we first have a classification of activation \( q \) of \( y \) as a deviation of activation \( p \) of \( x \), and then we have the reverse. To avoid this inconsistency the rules (7.2.11) and (7.2.12) for the classification of the first deviation in each chain are modified such that deviation \( p \) is neglected and deviation \( p+1 \) is the first to be considered:

\[
\text{if } p < K \text{ then deviation } p+1 \text{ is the first deviation in the new chain;} \quad (7.2.16)
\]

\[
\text{if } p = K \text{ then the new chain contains no deviations and } [t_q, t_{q+1}] = [t_1, T] \quad (7.2.17)
\]

In the first case, \( p < K \), it can be verified that \( s_p \in [t_q, t_{q+1}) \), since \( [s_p, s_p+1] \subseteq [t_q, t_{q+1}) \) and \( s_p+1 < t_q+1 \), otherwise the preceding chain would have been ended. If \( p = K \) then \( s_p+1 = t_q+1 = T \) and we have \( s_p+1 \in [t_q, t_{q+1}) \), hence the chain consists of the interval \( [t_q, t_{q+1}) \) only and contains no deviations after \( p \) has been neglected.

To illustrate the procedure of designating the reference intervals we give an example in Fig. 7.2.3.

\[
\text{Fig. 7.2.3 The construction of chains of reference intervals.}
\]
Since $s_1 > t_1$, the first reference interval is $[0,s_1)$. The next contiguous interval is $[s_1,s_2)$, which contains $t_2$ and $t_3$. We proceed with $[s_2,s_3)$, but this interval contains no deviations. Therefore, the first chain is $c_0 = [s_1,s_2)$. The second chain is a union of intervals of $y$, namely $\bigcup_{j=4}^{7} \{ t_j \}$. Continuing this procedure we obtain the following reference intervals:

$2 \bigcup_{i=1}^{7} \{ t_i \} \bigcup \bigcup_{i=1}^{7} \{ t_i \} \bigcup \bigcup_{i=1}^{7} \{ t_i \} \bigcup \bigcup_{i=1}^{7} \{ t_i \}$

with $\{ t_1, t_2, t_3, s_3, s_4, s_5, t_6, t_7, t_8, s_8 \}$ as deviations. It should be noted that $\{ s_2, t_5, s_7, t_9 \}$ are neglected as first deviations in a chain.

For the classification of the deviations, we first evaluate $t_1 \in [0,s_1)$. With $s_1 = \{0,s_1\}$ we conclude that $t_1 \in [s_1,s_2)$ and classify $t_1$ as a deviation of $s_1$. Proceeding with $t_2 \in [s_1,s_2)$, and finding $t_2 \in [s_2,s_3)$, we classify $t_2$ as a deviation of $s_1$. Repeating this process, we arrive at the following deviations and corresponding references:

$\{ t_1 \to s_1, t_2 \to s_2, t_3 \to s_3, s_3 \to t_4, s_4 \to t_4, s_4 \to t_5, t_6 \to s_6, t_7 \to s_7, s_7 \to t_9 \}$

Once the classifications are determined the criterion values can be calculated accordingly. For the differences in amplitudes we find:

$$J_1 = |y_1 - x_1| + |y_2 - x_1| + |y_3 - x_2| + |x_3 - y_4| + |x_4 - y_4| + |x_5 - y_6| +$$
$$+ |y_6 - x_6| + |y_7 - x_6| + |y_8 - x_7| + |x_8 - y_9|,$$

and for the differences in time instants of activations we find:

$$J_2 = |t_1 - s_1| + |t_2 - s_1| + |t_3 - s_2| + |s_3 - t_4| + |s_4 - t_4| + |s_5 - t_5| +$$
$$+ |t_6 - s_6| + |t_7 - s_6| + |t_8 - s_7| + |s_8 - t_9|,$$

where $J_1$ and $J_2$ are the two elements of the vector valued criterion $J$.

Though the computation of the vector valued criterion seems to be rather complicated, the procedures can be easily implemented in a computer algorithm. Since the number of calculations and decisions is limited the computation of the criterion values is fast, making it a very suitable choice for a numerical optimization method such as a random search.

7.2.4 Definition of a scalar valued criterion for "decision signals".

A special case of the vector valued criterion of Sec. 7.2.3 is the application on "decision signals"; which are signals that do not contain amplitude information, but only time information. Such signals are frequently encountered in modeling the human supervisor. For instance, the sampling requests of the supervisor is a signal that only contains time information in the form of a sequence of time instants. Since these signals are measurable outputs of the operator as well as of the observer/controller/decision model, to verify the model we need a criterion to compare this class of signals. The approach of the previous section can be followed here as well.

It should be noted that, in the definition of the vector valued criterion for signals of a discrete character, the amplitudes of the signals only appeared in the computation of the element $J_1$ of $J$. However, the construction of reference intervals, the classification of deviations and the computation of $J_2$ was merely based on the time instants of activations. Therefore, in exactly the same way, a scalar valued criterion can be assigned to any two decision signals.
Operator and model control amplitudes of the boiler, the back pressure turbine and the condensing turbine sub-systems, i.e. control input 1, 2 and 3 respectively. Operator data are obtained from the control of subject one in three of the last experimental runs under identical conditions (indicated as trial n, n+1 and n+2 in Table 7.5).
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1) Hoewel in het algemeen een proefschrift als het begin van een wetenschappelijke carrière aan universiteit of hogeschool wordt gezien, wordt promovendi, onder de huidige omstandigheden, na voltooiing van hun proefschrift nog weinig tijd gegund zich daadwerkelijk aan wetenschappelijk onderzoek te wijden.

2) Hoewel veel psychologen de relatie tussen mens en omgeving als statisch modelleren bedenke men dat deze relatie overwegend als dynamisch moet worden beschouwd.

3) De mate van gebruikersvriendelijkheid van tekstverwerkers is in zijn meest elementaire vorm te onderzoeken door het apparaat kortstondig de netvoeding te onthouden. Indien dan geproduceerde teksten spoorloos zijn is het apparaat zeker niet als gebruikersvriendelijk te beschouwen.

4) Daar de voorwaardelijke financiering als uitgangspunt heeft dat er strikte afspraken worden gemaakt binnen de diverse vakgroepen en/of afdelingen, zal deze financieringsvorm een bepaald selectief effect hebben op de toch al schaarse interdisciplinaire samenwerking.

5) Het algemeen gebruik van gegevensbanken wordt mede beperkt doordat de daarvoor bestemde Query-talen hoofdzakelijk zijn gericht op informatici. Het dient derhalve aanbeveling deze talen ook eens te toetsen op de mate van vriendelijkheid voor de algemene gebruiker.

6) Juist omdat procesinformatiesystemen in principe een hoge mate van flexibiliteit dienen te bezitten, verplicht dit de producent en/of leverancier op ergonomische inzichten gebaseerde richtlijnen te verschaffen aan de gebruikers van dergelijke systemen.

7) De door de ontwerper vaak vermeende idee dat de invoering van procespresentatie op beeldschermen automatisch een verbetering van procesbeheersing tot gevolg heeft berust op een misvatting. Zonder gericht onderzoek zal eerder een taakverzwaring dan een taakverlichting het gevolg zijn.

8) Door het gebruik van rekenmachines kunnen complexe berekeningen sneller en betrouwbaarder worden uitgevoerd dan voorheen. De hoeveelheid routinematige bezigheden in het wetenschappelijk onderzoek wordt hierdoor echter nauwelijks beïnvloed, daar de zelf opgelegde onderzoeksbegrenzingen tegelijkertijd mede worden verruimd.

9) De associatie die gelegd zou kunnen worden tussen het gezegde 'een proefballonnetje oplaten' en de omslag van dit boekje is uiterlijke schijn. De inhoud wordt beschouwd meer te zijn dan 'zomaar iets proberen om reakties los te krijgen'.

-STELLINGEN-