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Understanding Perceived Complexity in Human Supervisory Control

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Abstract: Industrial processes are becoming more complex owing to technological developments and new opportunities. Technological developments, hardware and software, have become more reliable and system configurations more robust. However, the reliability of operator control actions has not improved at the same pace. Consequently human reliability has become the relatively weakest aspect of automated, operator-supervised systems. Hence, understanding how the human operator experiences increasing complexity may play an important role in task allocation and human–machine system design. In this paper the perceived complexity is studied within four typical operational environments in supervisory control. Mathematical formulations for these four operational environments are proposed, and their properties are analysed. A laboratory system is used to investigate the perceived complexity under various operational environments. The experimental results show a significantly different perceived complexity for the coupled and uncoupled operation environments. Extrapolation of the results revealed that the operator would have perceived the system as extremely complex if he/she would have to operate more than eight strongly interconnected subsystems extensively in 30 minutes. Implications of this study are also addressed.

Keywords: Human–machine system; Human supervisory control; Industrial process; Perceived complexity; Typical operational environment

1. INTRODUCTION

Systems are becoming more complex owing to the many new links and dependencies among various domains (e.g., Woods 1988; Scuricini 1988; Wieringa and Stassen 1993). Our society becomes automated in many ways and feelings exist that even the smallest error of a falling automatic control system may cause a disaster. The recent commotion about the 'Millennium Bug' is a good illustration.

Technological systems such as chemical processes and power systems show also an increasing number of interactions between different domains and between plants (Henneman and Rouse 1986; Johannsen et al 1994; Min and Chang 1991; Murray and Liu 1997; Rasmussen 1994; Rouse and Rouse 1979; Treu 1996).

Indeed, technological developments have made hardware and software more reliable and system configurations more robust, but the reliability of operator control actions has not improved at the same pace. Consequently human reliability has become the relatively weakest aspect of automated, operator-supervised systems. Hence, an understanding of how the human operator experiences the increasing complexity plays an important role in task allocation and human–machine system design for human supervisory control of complex processes (Li and Wieringa 1997).

In this paper, the authors investigate the relationship between, on the one hand, the number of subsystems and the strength of the interconnections, and on the other hand, the operator performance and perceived complexity. The paper is organised as follows. In section 2, a conceptual framework is proposed to describe the relations between various complexities in human supervisory control. The operational environment in supervisory control is classified into four general types, mathematical formulations for these operational environments are proposed and their properties are analysed. In section 3, the experimental set-up to test perceived complexities is described, and various sessions are then designed to test human perceived complexity in the four general operational environments, and how different shaping factors influence the perceived complexity. In section 4, conclusions are drawn from this research, and section 5 is the conclusion.

2. CONCEPTUAL FRAMEWORK OF COMPLEXITY AND CLASSIFICATION OF OPERATIONAL ENVIRONMENTS

2.1. Conceptual Framework for Complexity in Human Supervisory Control

Regarding the definition of human supervisory control, an accepted definition is that one or more human operators are intermittently programming and continuously receiving information from a computer that itself closes autonomous control loops (Sheridan 1992).

The main tasks in human supervisory control normally include planning the task, teaching the computer, monitoring the automation system, intervening when failures happen, and learning from practice.

Regarding the study on complexity, early in 1977 Simon pointed out that 'almost all complex systems that occur in nature exhibit an underlying hierarchic structure'. Scuricini (1988) defines a system as complex when it is built up of a plurality of interacting elements, of a variety of kinds, in such a way that in the holistic results no evidence can be traced of the characteristics of the single elements; and the complexity of large technological systems is strictly linked to the complexity of the artificial world, of the eco- and human systems. Goodstein (1981) outlines three dimensions of complexity that are used to classify systems for modelling purposes: structural complexity, functional complexity, and interface complexity. On the other hand, Rouse and Rouse (1979) believe that complexity is related to the human's understanding of the relationships within a problem as well as the strategy which the human uses to solve the problem. Kieras and Polson (1985) work on the cognitive complexity theory, which considers cognitive processes as computational processes that exhibit a complexity. A situation is considered as complex when it induces complex cognitive processes: the number of steps to perform for achieving a task, the amount of information to maintain in working memory, the amount of knowledge to extract from long-term memory, etc. In their paper, Henneman and Rouse (1986) discuss different types of complexity: non-behavioural perspectives including computational complexity, software complexity, complexity of physical systems and behavioural complexity including perceptual complexity, and problem-solving complexity.

In this paper, two types of complexity in human supervisory control and their relations are to be studied: *objective complexity* and *perceived complexity*.

Regarding objective complexity in supervisory control, the operator will experience two general categories of objective complexity: technical system complexity and task complexity.

Technical system complexity comes from the operational environment and the operator is involved in and that requires attention. The operational environment comprises human–machine interface (HMI) and support system, process system and control system, among which the HMI and support system have direct interaction with the operator, and the process system and control system have indirect interaction with the operator in general. Therefore, technical system complexity could be further classified into:

- process and control system complexity; and
- human–machine system complexity.

Regarding the shaping factors of complexity, according to Stassen et al (1990, 1993), number and interaction are the two major factors. Therefore the authors further identify the shaping factors for process and control system complexities and HMI complexity respectively.

For process and control system complexities, the shaping factors include:

- the variety of components (equipment), loops, variables, etc.;
- the number of components (equipment), loops, variables, etc.;
- the links among components (equipment), loops, variables, etc.

Similarly, for HMI complexity, the shaping factors include:

- the type of display (for example, 'direct manipulation interface' (DMI), virtual reality, or indirect visualisation-based interface);
- the number of menus, decision points, etc.;
- the links among menus, decision points, etc.

Task complexity originates from the supervisory tasks that are allocated to the operator. The following factors contribute to task complexity:

- the nature and diversity of the task;
- the number of tasks;
- the links and dependencies among tasks;
- uncertainty of arrival, rate of occurrence, and duration of tasks;
- physical and mental demand load of the tasks.

In the above lists, various objective complexities and their shaping factors are identified. Among the objective complexities, HMI complexity and task complexity have a direct impact on the perceived complexity of the operator. For example, through HMI, a technical system may appear to be more or less complex to the operator (Wieringa and Li 1997).

It is noted that the perceived complexity is not only the reflection of objective complexities, but there are also other factors that affect perceived complexity. For example, within the same operational environment, doing the same task, different operators may experience system complexity differently. Therefore, two factors contribute to the variation of the perceived complexity:

- *Personal factors*: these include intelligence, knowledge, job training, personality of the operator, cultural background, and the willingness to be involved in the operation.
- *The operation and management strategy that has been designed for the operator or developed by the operator himself*: operation and management strategy makes a significant contribution to human perceived complexity in super-

visory control. A well-scheduled operation and management strategy would reduce the perceived complexity of the real system, thus improving the operator's performance.

In conclusion, the perceived complexity is the reflection of:

- objective complexities including task complexity and technical system complexities and is affected by
- personal factors, including training, experience-related knowledge, creativity, degree of willingness to be involved, personal type, etc., and
- the operation strategy designed for the operator or developed by the operator himself through his experience.

A conceptual framework that relates objective complexities and perceived complexity is shown in Fig. 1.

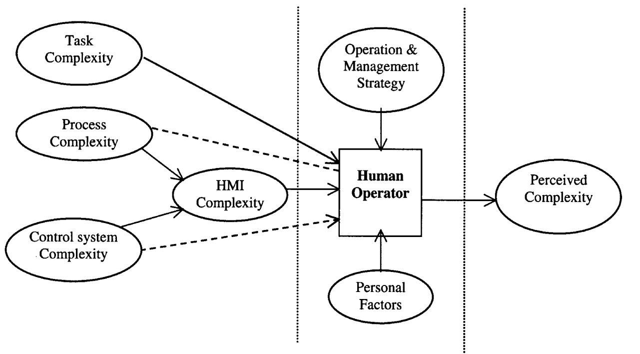

Fig. 1. Conceptual framework for perceived complexity in human supervisory control. Dashed lines suggest indirect impact of objective complexity on the human operator, whereas solid lines suggest a direct impact.

2.2. Classification of Operational Environments in Supervisory Control

Regarding the complexity measurement, Henneman and Rouse (1986) point out that complexity should manifest itself in some measurable way; i.e., a complex system should result in longer times for failure diagnosis, longer reaction times, etc. They used different measures for structural complexity and strategic complexity. Min and Chang (1991) used an information theoretic method to measure system complexity, and complexity may be assessed through functional entropy. McCabe (1976) proposed a cyclomatic measure for software complexity, and Murray and Liu (1997) used such a cyclomatic metric to assess task complexity in the supervision of networked systems. Javaux and De Keyser (1997) summarised four forms of measurement for cognitive complexity: variation of factors, ordinal comparison, ordinary comparison with nominal index, and metrical comparison.

In order to study the impact of complexity on operator performance in human supervisory control, Stassen et al (1993) designed an artificial system which was in fact a simulation program and consisted of 16 subsystems (in fact first-order systems) that were linked together in a cascade (the output of the nth subsystem ($1 \leqslant n \leqslant 16$) was connected via a gain 0.5 to the input of the subsystem $n + 1$). Each subsystem was given a set point value. The task of the operator was to manipulate the control inputs and bring the system outputs to their set points. The system performance and the operator rated mental load were recorded. The experiments by Stassen et al (1993) revealed that when the number of subsystems was four the operator's task was too easy and caused a too low mental load whereas a total of 16 subsystems would cause too much stress. Stassen et al (1990, 1993) further hypothesised that the performance of a human supervisor might be the same if systems had equal complexity, although these systems may differ in number of functions and degree of interaction. Thus 'isocomplexity curves' may be drawn as a function of number of functions and degree of interaction. In analogy to the well-known Richter scale, which classifies the force of an earthquake, the classification of complexity is also made between zero and seven (Fig. 2). It is recognised that this classification can be taken as a basis for developing a methodology to standardise evaluation and validation studies (Johannsen et al 1994). Only at the moment that different processes – different in terms of the number of functions to be supervised and of the degree of interaction – can be standardised by the isocomplexity curves could one develop a methodology to measure performance as a function of the isocomplexity curve value (Johannsen et al 1994).

Based on previous work, in order to examine and to measure perceived complexity in human supervisory control, three structured operational environments and

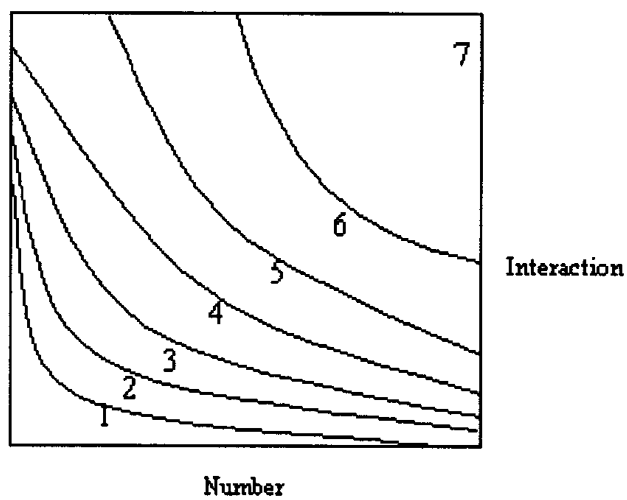

Fig. 2. Isocomplexity curves.

four typical operational environments in human supervisory control are proposed. These three structured environments are:

- fully uncoupled environments;
- cascade environments;
- fully coupled environments.

In order to illustrate the three structured operational environments, a digraph is employed as follows.

A digraph is an ordered pair G = (*V*, *E*), where *V* is a set of nodes v_i; *E* is a set of edges (v_i, v_j) directed from v_i to v_j. In the digraph, a node may represent a subsystem or a unit, a basic operational task, a menu in the operation interface, an alarm to be handled when the plant malfunctions, etc. An edge in the digraph is the link between two nodes.

The fully uncoupled environment, the cascade environment and the fully coupled environment are illustrated in Figs 3, 4 and 5 respectively, with examples.

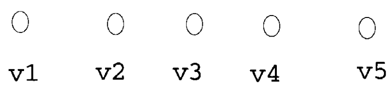

Fig. 3. An example of a fully uncoupled environment with five subsystems.

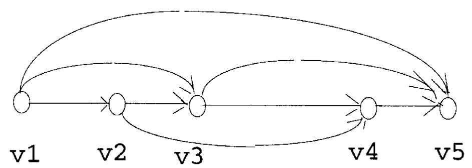

Fig. 4. An example of a cascade environment with five subsystems.

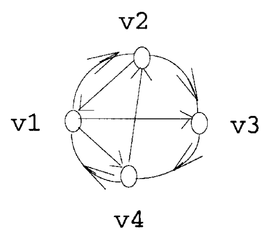

Fig. 5. An example of a fully coupled environment with four subsystems.

Remark 1. In Figs 4 and 5, the edges between two nodes only represent the links of these two subsystems; the actual inputs or outputs of the subsystems are not presented in the figures. For example, a node with two incoming edges does not necessarily mean that this node has two inputs – it may have only one input and all signals from other subsystem are first combined and then get in the subsystem through one input channel. For the same reason, a node with only one incoming edge does not mean that it has only one input.

These three structured environments could also be presented using adjacent structured matrices. A structured matrix is made up of free parameters (which may be individually modified) or of fixed zeros (Li et al 1996). Let all non-zero parameters be represented by $\times$. For example, M is a structured matrix as follows:

$$\mathrm{M} = \begin{pmatrix} \times & 0 & 0 \\ \times & \times & 0 \\ 0 & \times & 0 \end{pmatrix} \tag{1}$$

Thus the structured matrix representing the above-mentioned three structured environments in Figs 3, 4 and 5 are shown as follows:

$$\mathrm{M}_1 = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccccc} v_1 & v_2 & v_3 & v_4 & v_5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \tag{2}$$

$$\mathrm{M}_2 = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccccc} v_1 & v_2 & v_3 & v_4 & v_5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ \times & 0 & 0 & 0 & 0 \\ \times & \times & 0 & 0 & 0 \\ 0 & \times & \times & 0 & 0 \\ \times & 0 & \times & \times & 0 \end{bmatrix} \end{array} \tag{3}$$

$$\mathrm{M}_3 = \begin{array}{c} \\ v_1 \\ v_2 \\ v_3 \\ v_4 \end{array} \begin{array}{c} \begin{array}{cccc} v_1 & v_2 & v_3 & v_4 \end{array} \\ \begin{bmatrix} 0 & \times & 0 & \times \\ \times & 0 & 0 & \times \\ \times & \times & 0 & 0 \\ \times & 0 & \times & 0 \end{bmatrix} \end{array} \tag{4}$$

Above, three types of structured operational environments are proposed. When the strength of interconnections between dynamic subsystems is considered, four typical operational environments in the supervisory control of industrial plants could be further classified.

A real-world system with an operator in the loop can be generally described as follows:

$$\mathrm{S}: x(k+1) = f(x(k), u(k), d_1(k)) \tag{5}$$

$$y(k) = h(x(k) + d_2(k)) \tag{6}$$

where $x(k) \in R^n$ is the state vector of the plant at time instance k, $y(k) \in R^l$ is the information vector of the plant presented to the operator at time instance k, $u(k) \in R^m$ is the information input from the operator to the plant at time instance k, and $d_1(k) \in R^n$,$d_2(k) \in R^m$ are environmental noise and disturbance. $f(\cdot)$, $h(\cdot)$ are some functions or formats of relations. For example, if the operator is operating the system manually, $f(\cdot)$, $h(\cdot)$ are linear or nonlinear functions representing the plant dynamics. If the operator is monitoring the process, then $f(\cdot)$, $h(\cdot)$ could be descriptions, inference formulas, etc., that represent the monitoring system. Equation (6) combines the real-time, past and predicted information of a supervised system.

The operation input to the plant from the operator may be described as

$$u(k) = g(r(k), y(k), \mathrm{hf}(k)) \tag{7}$$

where r is the vector of goals for operators, hf is human factors and $g(\cdot)$ is some functions or formats of relations. For example, in manual control the human controller is assumed to behave like a servo controller, reacting to the difference between the desired state and the actual state. Consequently, such situations use fundamental control engineering principles such as those used in servo controllers, which means that an integrator function should be included in the loop in order to realise zero mean deviation. Therefore, $g(\cdot)$ in this case is a linear model with remnant (McRuer and Jex, 1967), i.e.

$$g(s) = K\frac{1 + s\tau_1}{1 + s\tau_2}\frac{1}{1 + s\tau_n}e^{-s\tau_v} \tag{8}$$

where $g(s)$ is the Laplace transform of the function, and among the five parameters in (8), two are attributed to neuromuscular properties: the neuromuscular time constant, τ_n, which is approximately 200 ms, and the reaction time, τ_v, which is between 120 and 200 ms. These parameters are time invariant and do not change when the operator controls systems with different dynamics. It is assumed that the other three parameters are adjusted during learning by the operator of the system dynamics, resulting in good servo behaviour. The value of K is between 1 and 100 and the time constants τ_1, τ_2 are adjusted to ensure stability; therefore, these three parameters are related to r and y in (7). In general, all these five parameters are the function of the human factors hf in (7).

In conclusion, Equation (7) describes the processing behaviour of operators in controlling, monitoring, guidance, command, coordinating, organising, etc.

It is well known that an industrial plant is generally composed of several interconnected subsystems, and subsystems in slowly responding processes are usually operated at some working points; therefore, the whole plant could be simply linearised. Equations (5) and (6) may be possibly further simplified as

$$\mathrm{S}: \begin{array}{l} x(k+1) = A(k)x(k) + B(k)u(k) + d_1(k) \\ y(k) = C(k)x(k) + d_2(k) \end{array} \tag{9}$$

where A, B and C are matrices with dimensions $n \times n$, $n \times m$ and $l \times n$ respectively. Matrix A represents the relation of the system's future state to the present state, matrix B represents the relation of the system's future state to the information input from the operator/controller, and matrix C represents the system's present output in the present state. Suppose that the plant S is composed of N subsystems S_i, $i = 1, 2, \ldots, N$ with system matrices $A_i(k)$, $B_i(k)$, $C_i(k)$, $i = 1, 2, \ldots, N$, then $A(k)$, $B(k)$ and $C(k)$ in (9) could be further decomposed as

$$A(k) = \begin{bmatrix} A_1(k) & & & \\ & \cdot & A^u{}_{ij}(k) & \\ & & \cdot & \\ & A^d{}_{ij}(k) & \cdot & \\ & & & A_N(k) \end{bmatrix} \tag{10}$$

$$B(k) = \begin{bmatrix} B_1(k) & & & \\ & \cdot & B^u{}_{ij}(k) & \\ & & \cdot & \\ & B^d{}_{ij}(k) & \cdot & \\ & & & B_N(k) \end{bmatrix} \tag{11}$$

$$C(k) = \begin{bmatrix} C_1(k) & & & \\ & \cdot & C^u{}_{ij}(k) & \\ & & \cdot & \\ & C^d{}_{ij}(k) & \cdot & \\ & & & C_N(k) \end{bmatrix} \tag{12}$$

and the N subsystems could be described as follows:

$$S_i : x_i(k+1) = A_i(k)x_i(k) + B_i(k)U_i(k) + \sum_{j \neq i} A_{ij}(k)x_j(k) + \sum_{j \prec i} B^d{}_{ij}(k)u_j(k) + \sum_{j \succ i} B^u{}_{ij}(k)u_j(k)y_i(k) = C_i(k)x_i(k) + \sum_{j \prec i} C^d(k)_{ij}x_j(k) + \sum_{j \prec i} C^u ij(k)x_j(k) \tag{13}$$

where $A_i(k)$, $B_i(k)$, $C_i(k)$ are systems matrices for these N subsystems with

$A_i(k) \in R^{n_i \times n_i}$, $B_i(k) \in R^{n_i \times m_i}$, $C_i(k) \in R^{l_i \times n_i}$, $i = 1, 2 \cdots N$, $\sum_{i=1}^{N} n_i = n$, $\sum_{i=1}^{N} m_i = m$, $\sum_{i=1}^{N} l_i = l$. $A_{ij}(k)$, $B^u_{ij}(k)$, B^d_{ij}, $C^u_{ij}(k)$, C^d_{ij} are interaction matrices among subsystems; the type and strength of links among these subsystems are determined by these interaction matrices.

In the following, the relative gain array (Seborg et al 1989) for plant described in (9), (10), (11), (12) and (13) will be studied. In industrial processes, the relative gain array is used to detect the degree of interaction among system loops or subsystems. It is an important index for examining the stability of the plant under control and also has been widely used to design the control structure in process control (Seborg et al 1989). Therefore, by deriving the relative gain, the operation environment under human control could be further analysed.

Suppose that the transfer function of plant S in (9) is denoted as $G = [g_{ij}]_{l \times m}$, and let $g_{ij}(\infty) = \lim_{k \to \infty} y_i(k)/u_i(k)$ for $u_j(k) \equiv 1$, then the gain matrix of linear system from (9) may be described as $G(\infty) = [g_{ij}(\infty)]_{l\times m}$, and the system in stable state is described as

$$y(\infty) = G(\infty)u(\infty) = \begin{bmatrix} G_1(\infty) & & & & \\ & \cdot & & G^u{}_{ij}(\infty) & \\ & & \cdot & & \\ & G^d{}_{ij}(\infty) & & \cdot & \\ & & & & G_N(\infty) \end{bmatrix} u(\infty) \tag{14}$$

where $G_i(\infty) \in R^{l_i\times m_i}$ is the static gain array for the ith subsystem in (10), (11), (12) and (13).

In industrial processes, the input number and output number for each subsystem are not necessarily the same as described above. However, in process control, each controlled variable will be allocated a manipulated variable, and engineers are generally more interested in the relations between the controlled variables and manipulated variables; therefore, it is reasonable to assume that $n = l$ in (9), $m_i = l_i$, $i = 1, 2, \ldots, N$ in (10), (11), (12) and (13). Based on this assumption, the relative gain array of the whole plant described in (9), (10), (11), (12), and (13) may be derived:

$$\mathrm{RGA} = G(\infty) \otimes (G^{\perp}(\infty))^T = \begin{bmatrix} \mathrm{RGA}_1 & & & & \\ & \cdot & & \mathrm{RGA^u}_{\mathrm{ij}} & \\ & & \cdot & & \\ & \mathrm{RGA^d}_{\mathrm{ij}} & & \cdot & \\ & & & & \mathrm{RGA_N} \end{bmatrix} = [\mathrm{Rga_{ij}}]_{\mathrm{m\times m}} \tag{15}$$

where $\mathrm{RGA}_i \in R^{m_i\times m_i}$ is the block relative gain array for the ith subsystem, $\otimes$ is the Kronecker product (i.e. element-by-element multiplication), and $G^{\perp}$ is the inverse of matrix G.

In the following, four typical operation environments will be introduced and their properties will be discussed.

Operation environment 1 (OE1). OE1 is an operation environment that, in plant S of (9), there exist no interactions among subsystems, that is, in (10), (11), (12) and (13):

$$A^u_{ij} = 0, A^d_{ij} = 0, B^u_{ij} = 0, B^d_{ij} = 0, C^u_{ij} = 0, C^d_{ij} = 0$$

The structural representation for OE1 is like that shown in Fig. 3.

Operation environment 2 (OE2). OE2 is an operation environment that, in plant S of (9), there exist no feedback interactions among subsystems, that is, in (10), (11), (12) and (13), either $A^u_{ij} = 0,\ B^u_{ij} = 0,\ C^u_{ij} = 0,\ or\ A^d_{ij} = 0,\ B^d_{ij} = 0,\ C^d_{ij} = 0$.

The structural representation for OE2 is as shown in Fig. 4.

Operation environment 3 (OE3). OE3 is an operation environment that, in plant S of (9), there exist both feedforward and feedback interactions among subsystems, and the relative gain array (15) of plant S satisfies that the summation of all elements of any row or any column of RGA_i, $\forall\, i = 1, 2, \ldots, N$ is a real positive number, i.e.

$$0 \le \sum_{j=1}^{m_i} \mathrm{RGA}_i(j,k),\ \forall i = 1, 2, \cdots, N$$

and

$$0 \le \sum_{k=1}^{m_i} \mathrm{RGA}_i(j,k),\ \forall i = 1, 2, \cdots, N$$

Operation environment 4 (OE4). OE4 is an operation environment that, in plant S of (9), there exist both feed-forward and feedback interactions among subsystems, and for the relative gain array (15) of plant S there exist at least one column or row in a bock relative gain array RGA_i $\exists i = 1, 2, \ldots, N$ in (15) such the summation of its elements is real negative number, i.e. $\exists \mathrm{RGA}_i$, $i = 1, 2, \ldots, N$, such that

$$\sum_{j=1}^{m_i} \mathrm{RGA}_i(j,k), <\ 0,\ \exists i = 1, 2, \cdots, N$$

or

$$\sum_{k=1}^{m_i} \mathrm{RGA}_i(j,k), <\ 0,\ \exists i = 1, 2, \cdots, N$$

The structural representation for OE3 and OE4 is as shown in Fig. 5.

Proposition 1. OE1, OE2 and OE3 are operational environments that the whole plant can generally be controlled and stabilised, if each subsystem is stable.

Proposition 2. OE4 is an operational environment that the whole plant may possibly not be controlled and stabilised under some control schemes, e.g. decentralised diagonal control scheme, even if each subsystem is stable.

Propositions 1 and 2 are generalisations of the relative gain array theory (Seborg et al 1989).

In the following, Propositions 1 and 2 will be illustrated by a plant with two interconnected subsystems, i.e. a 2×2 (two inputs and two outputs) plant. For such a plant, its corresponding relative gain array can be formulated as

$$\mathrm{RGA} = \begin{bmatrix} \mathrm{Rga}_{11} & \mathrm{Rga}_{12} \\ \mathrm{Rga}_{21} & \mathrm{Rga}_{22} \end{bmatrix} \tag{16}$$

and it has been proved that $\mathrm{Rga}_{11} = \mathrm{Rga}_{22}$, $\mathrm{Rga}_{21} = \mathrm{Rga}_{12} = 1 - \mathrm{Rga}_{11}$ (Bristol 1966). According to the relative gain array theory, one may have:

- If $0 \leqslant \mathrm{Rga}_{11} \leqslant 1$, the plant can be controlled and stabilised by a decentralised diagonal controller (a decentralised diagonal controller is a control scheme such that each controlled variable is controlled by a manipulation variable through a controller, and these controllers are not interconnected. The decentralised diagonal controller is illustrated in Fig. 6. Furthermore, when $Reg_{11} = 0.5$, the interaction between these two subsystems is strongest, and the system is most difficult to control by the decentralised diagonal controller.

- If $Reg_{11} < 0$ or $1 < Reg_{11}$, then the plant is uncontrollable by the decentralised diagonal controller, e.g., the plant is unstable under the decentralised feedback controller.

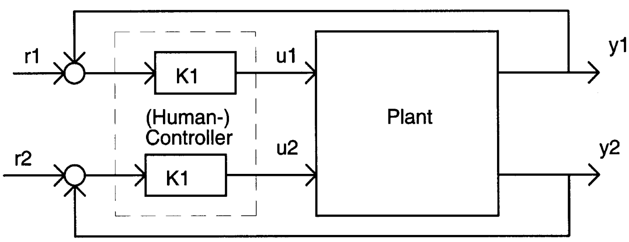

Fig. 6. Decentralised diagonal control scheme of a 2 × 2 plant.

It is well known that the decentralised diagonal control scheme is widely used in the process industry. Its characteristic is that each controlled objective is allocated one manipulated variable, and each manipulated variable is responsible for only one objective. In human supervisory control, the human operator generally functions as a human controller as illustrated in Fig. 6. Therefore, the human operator may face various operational environments like OE1, OE2, OE3 and OE4, defined above.

These four typical operational environments are also summarised in Table 1. These four typical operational environments are illustrated in greater detail in Table 2 by a process consisting of two subsystems as an example.

Table 1. Four typical operation environments

Type	Properties
OE1	There exists no interconnection among subsystems (fully uncoupled operational environment)
OE2	There exist feedforward interconnections among subsystems (cascade operational environment)
OE3	There exist feedforward and feedback interconnections among subsystems (fully coupled operational environment, and the operational environment is stable under decentralised diagonal control scheme)
OE4	There exist feedforward and feedback interconnections among subsystems (fully coupled operational environment, and the operational environment is unstable under decentralised diagonal control scheme)

Table 2. Four typical operational environments for a process consisting of two subsystems

Type no.	Graphical representation	Properties using two subsystems[a]
OE1	v1 ○ ○ v2	Fully uncoupled operational environment $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} G_1 & O \\ O & G_2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$
OE2	v1 ○→○ v2	Cascade operational environment $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} G_1 & O \\ K_{21}G_1 & G_2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$
OE3	v1 ⇄ v2	Fully coupled stable operational environment $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} G_1 & K_{12}G_2 \\ K_{21}G_1 & G_2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$
OE4	v1 ⇄ v2	Fully coupled operational environment (unstable operational environment under decentralised diagonal control scheme) $\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} G_1 & K_{12}G_2 \\ K_{21}G_1 & G_2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$

[a] K_{12}, K_{21} are interaction gains between subsystems. G_i ($i = 1, 2$) are transfer functions of subsystems; y_i, u_i ($i = 1, 2$) are outputs and inputs respectively.

3. EXPERIMENTAL SET-UP AND TEST SESSION DESIGN

3.1. Experimental Set-Up

In order to determine the limitation for mastering complexity, Stassen et al. (1993) developed a computer simulation of an artificial system. The subsystems of this system were connected in a cascade. The experimental results revealed that the human-perceived complexity is the highest for such kinds of plants when interaction gain is 0.5. The authors also found that, when the total number of subsystems for this artificial system was 16, the task was extremely complex and difficult and for most subjects impossible to perform.

The authors used an experimental system consisting of up to five heat exchange subsystems (because of the expense of building plant and the experimental space, as well as the availability of equipment, the authors were not able to use a larger-scale plant with more than five subsystems). The interconnections between the subsystems could be defined according to the desired experimental condition. The automation system (DCS system) in this experiment was provided by Honeywell Corp. This operation and control system has multiple functions, according to which the controller parameters can be designed, and various different system configurations can be built up. The heat exchange subsystem is illustrated in Fig. 7.

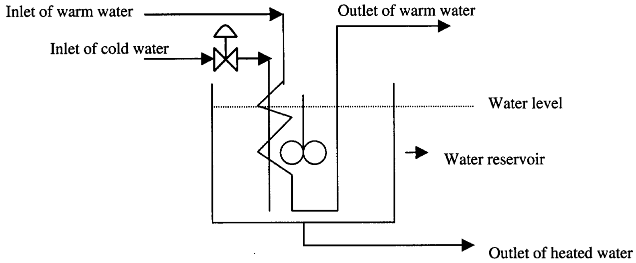

Fig. 7. A heat exchanger.

The control purpose for each subsystem is to heat cold water in the reservoir with warm water to a certain temperature, and maintain the water temperature in the reservoirs. The I/O point of the system were controllable valves for the cold water flow and thermometers to measure water temperature in the reservoirs. The temperature and flow rate of hot water for each subsystem are not controllable and also taken as disturbances. The control purpose for the whole plant is to keep the water temperature in every reservoir at its assigned set point. Each reservoir was connected to an automation system (Honeywell TDC 3000) and could be controlled independently.

In order to create the four operational environments, the subsystems are interconnected through electrical channels; that is, the physical configuration of these individual subsystems are not changed, but their input and output signals are subject to various changes. For example, suppose there are two subsystems with $G_1(s)$ and $G_2(s)$ as their transfer function. The configuration of the whole plant can be any desirable combination of $G_1(s)$ and $G_2(s)$ by using the interaction matrix $K(s) \in C^{2\times 2}$. The whole plant $P(s)$ could be described as follows:

$$P(s) = K(s)\begin{bmatrix} G_1(s) & 0 \\ 0 & G_2(s) \end{bmatrix} \tag{17}$$

where $K(s) \in R^{2\times 2}$.

Using appropriate choices of $K(s) \in C^{2\times 2}$ one could realise any of the four types of operational environments described above. The whole experimental plant is illustrated in Fig. 8.

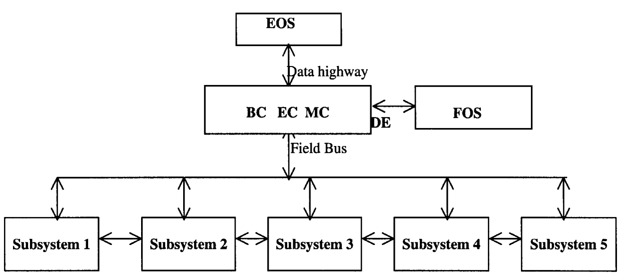

Fig. 8. Experimental set-up shown with the maximum number of subsystems (five) that was used. EOS, enhanced operation system; FOS, field operation system; BC, basic controller; EC, extended controller; MC, multi-function controller; DDE, direct data exchange.

The role of the student operator in the experiment can be incorporated into the whole system as illustrated in Fig. 6. The modelling of the manipulation from operators is also as described in section 2 when discussing Equation (7).

According to Fig. 8, there are two operation systems in this experimental set-up: the EOS and the FOS.

In EOS, a 21-inch monitor was used to display all process variables and control information. The data display is refreshed every 2 seconds. Numerical operation keys are provided to manually set the system parameters, to start and control the plant, and to give other instructions. These operation keys are integrated into a flat control board. An armchair is provided for the operator. The EOS creates a similar environment for the operator to that of someone working in an office today using a PC to deal with daily affairs. In EOS, two operation modes are provided:

- MAN – manual operation by the operator;
- AUTO – automation system is in charge.

In FOS, digital and analogue meters are lined up together to display the plant data and control information. A numerical keyboard can be used to set system parameters and to operate the system. The digital and analogue meters together with all operation keys are integrated into one board in the system console. The system console stands on the ground, and the operator has to stand in front of the control panel of the FOS for operation. A monitor was also provided in FOS, but was a bit far away from the control console. FOS has direct data exchange with the controllers, and the process information is refreshed in the sampling time of the basic controller (every 2 seconds). For FOS, three different operational modes are possible:

- MAN – manual operation, through which the operator may manipulate the control variables directly using 'increase' or 'decrease' digital keys;
- LM – loop manual operation, through which the operator may manipulate the control variables directly using 'increase' and 'decrease' analogue keys; in LM operation, the EOS has no influence to the controller system;
- AUTO – activate the automation system, in which case each subsystem is controlled by the automation system.

A decentralised diagonal controller is designed for the plant; i.e., each subsystem has its own controller, and there exists no coupling among the control loops of the subsystems. The purpose of introducing the decentralised PID controller is to make the whole system run automatically when the operator presses the 'AUTO' button in the operation station (either in EOS or FOS).

3.2. Test Design

Six students participated in the experimental test (all males, of average age 23 and with an engineering background). They received fixed fees for each experimental hour. Before the experiment, they were informed that those who achieved the best job performance would receive additional rewards.

The participants had to perform the following tasks:

- *Teaching*: The operator gives instructions to the computer, starts up the plant, manipulates system control input to bring the system output to the desired values, and brings the system into automation.
- *Monitoring and intervening*: If process variables exceed predefined limits, the operator should intervene, i.e., switch off the automatic operation and operate manually.

In this experiment, in total 21 sessions were designed to test how different factors influence perceived complexity. These 21 sessions are listed in the Appendix.

The first 17 sessions were designed to test how the number of subsystems affect perceived complexity for the four different structured operational environments.

In order to test how time constraints affect human perceived complexity, sessions 18, 19 and 20 were designed.

In order to examine how the shift of automation to manual control affects the perceived complexity, session 21 was designed. In this session, when an abnormal situation occurred, the participants were required to take over from the automation system, and bring the system back to the normal situation manually.

In order to examine the perceived complexity of the system under different operation environments, a scale similar scale to RSME (Zijlstra 1993) was used to obtain these measures. The rating scale ranged from 0 to 100.

The following types of experimental data were recorded:

- the perceived complexity rated by the operator;
- the operation time for each session;
- the keystroke rate of the operator for each session.

The rated perceived complexity is a subjective measure; operation time was used to examine the performance of the operator, the keystroke rate was used as a sort of index to reflect the mental load of the operator while performing various tasks in different operation environments. Meanwhile, the authors also designed questionnaires to evaluate operator experiences in more detail.

4. TEST RESULTS

4.1. Training

Before operation, all participants received sufficient training. Firstly, they were introduced to the system configuration, the subjective rating scales for perceived complexity, and other policies. The instructor demonstrated the operational procedures. They then performed one experiment (Session 1 in the Appendix), and kept practising until they were familiar with the procedures; i.e. their performance in the last few practices did not differ significantly, and they reached the end of the learning curve. During training, they used the rating scale to assess the perceived complexity of the system while performing the required task (regarding how to use the subjective rating scale, please refer to Zijlstra 1993). Their final rated perceived complexity for this session was used as a basis for the following sessions. Their learning results were recorded. The training normally lasted for more than 1 hour.

Table 3. Training results

Participant s	Results at start		Final training results	
	Compl	OT (minutes)	Compl	OT (minutes)
P1	6	17	6	6
P2	35	9	30	3
P3	20	12	20	3
P4	30	10	10	7
P5	15	9	10	7
P6	10	21	10	6

Table 3 lists the training results for the six participants (in this table, the authors only list the results at the start and the final records for Session 1). In the table, P1 to P6 are participants' codes. 'Compl' is the abbreviation for 'perceived complexity'; 'OT' is the abbreviation for 'operation time' (in minutes). Table 3 shows that training improves performance significantly (the operation time reduces significantly) and that the duration of training is sufficient to reach the end of the training curve. Meanwhile training is also able to reduce the perceived complexity, though not significantly.

4.2. Perceived Complexity as a Function of the Number of Subsystems for the Four Structured Operation Environments

First, Sessions 2–17 in the Appendix are performed. The first 17 sessions are designed to check how the number of subsystems affect the perceived complexity in the four different structured operational environments. The task for the human operator in these sessions is to manipulate the control input and bring the cold water in each reservoir to the set point, then bring the system into automation. The task is done in EOS.

Table 4 shows the experimental results for the first 17 sessions. In Table 4, 'Mean compl' stands for 'mean value of perceived complexity': 'Stdev compl' stands for 'standard deviation of perceived complexity'; 'Mean OT' stands for 'mean value of operation time' (in minutes); 'Stdev OT' stands for 'standard deviation of operation time'; 'Mean stroke rate' stands for 'mean value of keystroke rate (strokes

Table 4. Test results for session 1 to 17

Session no.	Operational environment type	Mean compl	SD compl	Mean OT	SD OT	Mean strike rate	SD stroke rate
One subsystem							
1	OE1	14.3	9.0	5.3	1.9	8.7	7.7
Two subsystems, four types of operational environment							
2	OE1	24.2	8.6	8.7	4.2	16.8	26.1
3	OE2	26.3	9.1	9.8	2.8	13.4	18.3
4	OE3	29.8	10.6	9.3	5.5	16.8	20.3
5	OE4	38.3	12.1	13.5	4.6	12.6	15.4
Three subsystems, four types of operational environment							
6	OE1	30.8	8.0	10.8	3.2	14.4	14.9
7	OE2	40.0	8.9	10.0	3.0	18.9	23.8
8	OE3	49.7	15.1	13.2	4.9	17.4	19.7
9	OE4	53.3	14.7	20.2	2.6	14.7	16.7
Four subsystems, four types of operational environment							
10	OE1	38.3	8.2	13.8	2.5	13.6	8.5
11	OE2	51.7	14.4	17.0	4.2	12.8	7.5
12	OE3	51.8	10.3	16.7	3.4	11.2	4.5
13	OE4	59.5	9.4	21.0	2.4	12.8	9.0
Five subsystems, four types of operational environment							
14	OE1	39.7	10.1	14.3	1.2	12.5	7.6
15	OE2	55.0	17.9	21.2	5.2	10.0	5.7
16	OE3	57.8	9.7	21.5	4.1	10.5	5.6
17	OE4	66.8	6.2	23.5	5.1	12.0	5.5

per minute)'; 'Stdev stroke rate' stands for 'standard deviation of keystroke rate'.

According to the experimental results in Table 4, it is easy to show the following.

Result 1. Perceived complexity increases with the number of subsystems; as the perceived complexity increases, human operation performance decreases correspondingly (operation time increases).

In order to explore Result 1 further, curve fitting was used to model human perceived complexity as a function of the number of subsystem in these four structured operation environments. It is shown that linear models are the most appropriate models for perceived complexity. The linear approximation models are formulated as follows:

$$\begin{aligned} C_1 &= 5.4n + 14.35 \\ C_2 &= 9.78n + 9.02 \\ C_3 &= 8.61n + 17.14 \\ C_4 &= 9.17n + 22.38 \end{aligned} \tag{18}$$

where C_i ($i = 1, 2, 3, 4$) is the perceived complexity in the four different operational environments and n ($2 \leqslant n \leqslant 5$) is the number of subsystems.

Result 2. Linear extrapolation on (18) shows that perceived complexity will exceed 100 (the assumed maximum for perceived complexity) if:

- for operational environment OE1, the number of subsystems is more than 15.
- for operational environments OE2 and OE3, the number of subsystems exceed nine;
- for operational environment OE4, the number of subsystems exceeds eight.

Curve fitting is also used to model operation time as a function of the number of subsystems. Linear models are also found to be the most appropriate models for operation time, and the linear approximation models are formulated as follows:

$$\begin{aligned} OT_1 &= 1.98n + 4.97 \\ OT_2 &= 4.12n + 0.08 \\ OT_3 &= 4.01n + 1.14 \\ OT_4 &= 3.08n + 8.77 \end{aligned} \tag{19}$$

where OTi ($i = 1, 2, 3, 4$) is the operation time in the four different operation environments and ($2 \leqslant n \leqslant 5$) is the number of subsystems.

Result 3. Linear extrapolation on (19) reveals that when 15 subsystems are controlled in operational environment OE1, when nine subsystems are controlled in OE2 and OE4, and when eight subsystems are controlled on OE4, the operation time will exceed 30 minutes. Therefore:

> the operator will generally perceive a much high degree of complexity if he is required to operate and control extensively about 10 subsystems in about 30 minutes (i.e., equivalent to 20 subsystems per hour).

Remark 2. The statement in Result 3 is very interesting. The maximum number acquired (15 subsystems with no interconnection, eight or nine subsystems with interconnection) is incidentally similar to that found in previous experiments conducted by different researchers and using different measures (Stassen et al 1993; Wei et al 1995). The maximum operation time (more than 30 minutes) is also incidentally similar to that found in previous experiments.

Above, the authors have examined how the number of subsystems contributes to the perceived complexity in the four structured operational environments. It is obvious that environment OE2 is more complex and more difficult to operate than environment OE1, and OE3 more complex than OE2, and so on. However, one may also be interested in whether there exist significant differences among the four structured environments. Our analysis shows the following.

Result 4. Regarding the four structured operational environments, Student's *t*-test revealed:

(1) For perceived complexity

- There exist distinct differences between OE1 and OE4. OE2 and OE3 do not show a significant difference (significance level, $\alpha = 0.05$, Sachs 1982).
- There exists a significant difference between the non-coupled operation environment (OE1) and coupled operation environments (OE3 and OE4) (significance level $\alpha = 0.05$).

(2) For the operation time

- There exists a significant difference between OE1 and OE4 (significance level $\alpha = 0.05$).
- When the number of subsystems is large enough (for example more than three or four), the OE2, OE3 and OE4 show a significant difference in terms of the operation time (significance level $\alpha = 0.05$).

(3) For the keystroke rate

- When significance level $\alpha = 0.05$, there is no significant difference among the four structured operational environments in terms of the keystroke rate.

Further analysis on individual records and performance has been carried out; participants also explained their operational strategy developed through training and experience. The authors find that personal factors contribute significantly to the difference in operational performance and the perceived complexity among these participants, which is reflected in the large standard deviation in the experimental results.

4.3. Contribution of the Time Constraint to the Perceived Complexity

Sessions 18–20 in the Appendix are designed to test whether the time constraint contributes to perceived complexity. In these sessions, the operator is allocated the same task, but is required to do the task within an assigned period of time.

Table 5. Comparison of sessions with or without time constraints

Session no.	Time constraint (minutes)	Mean compl	SD compl	Mean stroke rate	SD stroke rate	Task accomplishment
3	No constraint	26.3	9.1	13.4	18.3	
18	3.0	30.0	9.5	22.8	10.0	Not finished in time
19	6.0	28.3	9.8	16.4	14.4	Finished in time
11	No constraint	51.7	14.4	13.2	7.5	
20	6.0	51.2	10.8	26.0	14	Not finished in time

The experimental results for Sessions 18–20 are listed in Table 5. Results of Sessions 18–20 are shown with those of Sessions 3 and 11 for comparison. The reason is that the operational environments of Sessions 18 and19 are almost the same as in Session 3, and Session 20 is the same as Session 11. The only difference is that in sessions 18, 19 and 20 tasks are required to be done within an assigned period; however, there is no time constraint for Sessions 3 and 11.

According to Table 5, the following is found.

Result 5. The time constraint does not make a significant contribution to the perceived complexity according to Student's *t*-test.

Further investigation shows that participants have two distinct viewpoints on time constraint. Some argue that an appropriate time constraint may stimulate them to perform their task to their best ability. Others, however, complain that a strict time constraint makes them nervous and therefore affects their performance adversely. The large deviation in the keystroke rate in Table 5 reflects the influence of time constraints on operation reaction of participants.

4.4. How Does the Shift from Automation to Manual Control Affect Perceived Complexity?

One of the main tasks in supervisory control is to intervene and take over some jobs done by the automation system. It is useful to know whether the shift from automation to manual control affects perceived complexity. Session 21 in the Appendix is designed for such a purpose. In this session, when an abnormal situation happens the operator may choose to cut off the automation system and to control the whole plant manually, or only to regulate the abnormal subsystem, leaving the automation system in charge of the other subsystems. It is finally shown that all participants rely on the automation system and regulate only the abnormal subsystem manually. The operator is required to

Table 6. Comparison of Sessions 3 and 21

Session no.	Mean compl	SD compl	Mean OT	SD OT	Mean stroke rate	SD stroke rate
3	26.3	9.1	9.8	2.8	13.4	18.3
21	20.8	7.4	5.3	2.7	11	11.2

operate in FOS (field operation system). Table 6 lists the experimental results.

Considering that Sessions 3 and 21 have the same number of subsystems and the same type of links among subsystems, their results are put together for comparison.

Result 6. According to Table 6, the shift from automation to manual control has a significant impact on operator performance based on Student's *t*-test. It also has an impact on perceived complexity and keystroke rate, but not significantly (signficance level $\alpha = 0.05$).

For Session 21 the operation is performed in FOS, while for Session 3 the operation is performed in EOS. As has been described previously, in EOS the operator is provided with an armchair, whereas in FOS the operator has to stand . In addition, in EOS system information is displayed on one monitor, whereas in FOS different analogue or numerical meters are used to display the process information, and these meters are integrated on the control panel of the FOS. A monitor was also provided in FOS, but was a bit far away from the control console, but the authors found that all participants chose to look at the display screen in FOS, despite inconvenience.

Participants stated that FOS is more difficult for operation, but has little impact on the perceived complexity. Participants also said that a big screen used to display all process information would be very helpful in reducing task complexity.

Detailed discussions on the impact of the change of automation level on mental load and human performance may be found in the recent work of Wei and Wieringa (1998).

5. DISCUSSION AND CONCLUSIONS

In this paper, the human experience of complexity in supervisory control is examined. Firstly, a conceptual framework for perceived complexity is introduced, and the operational environments in human supervisory control are classified into four different types; mathematical formulation and properties of these environments are proposed. A laboratory test plant was used and 21 test sessions were designed to identify how different factors contribute to perceived complexity in supervisory control of complex industrial processes.

The experimental results revealed that human operators manipulating a plant with about eight strongly interconnected subsystems (refer to the fourth operational environment, OE4, in Table 1) within 30 minutes would experience much complexity. This research also revealed that operational environments for human operators are dynamically changing in supervisory control, depending on what the operator is performing, and when and where. Therefore, they can experience different perceived complexities at different times.

The implications of the above results are useful for understanding, for example, alarm handling. It is well known that operators sometimes have to handle more than 2000 alarms per person per 24 hours, with peaks that lie in the order of 35 alarms per minute (= 525 per hour per person). Our experiment reveals that the number of subsystems that can be operated upon should be restricted to about 15 per hour. How can this factor of 35 difference be explained?

There are a few factors that need to be taken into account when bridging the gap between these two numbers:

- Our operators are students and don't have a long training background and experience in operating the plant. Although our results show that the subjects were at the end of their learning curves the authors think it is plausible they may develop strategies when operating the simulated plants for a longer period of time.
- Stassen et al (1993) showed that, for the artificial system (as described earlier) they used, the workload caused by 360 set-point requests per hour from 16 subsystems was too high and induced stress. They found more consistent results among subjects when the number of subsystems was less, namely eight, while using the same set-point request rate. These results suggest that repetition of alarms causes fewer problems than the size of the system and the number of interconnections among the subsystems.
- Not all alarms mentioned above come from separate subsystems or different process variables. About 33% of the alarms are from the same alarm point. Often alarms have causal relations and are repetitive. Classification of the alarms into categories such as standing alarms, consequence alarms, repeating alarms, precursor alarms and redundant alarms reveals that the number of alarms that require operator reaction is considerably less. The example of 80% repetitive alarms and 15% causal alarms has been reported to us (personal communication by the second author). Only 5% are real alarms that require considerable work. In order to compare the theoretical and industrial finds only these 5% alarms should be considered. The rest serve as information and noise.

This analysis shows that the workload of professional operators, even after correction for effects mentioned, is probably much too high during periods of alarm flooding. It is necessary to reduce and/or restructure the alarms that require no serious attention and action from the operator. These findings have serious implications for the design of partly automated systems and alarm systems.

Furthermore, one may also be interested in the possible implications of this study to the overall process system and automation system design. Some possible suggestions are thus made as follows:

- In process flowsheet synthesis, subsystems are never isolated from others: interconnections of subsystems are essential. In this case, cascade interconnection (e.g., feedforward interconnection) of subsystems is encouraged because, according to the results, the second structured operational environment is less complex and less difficult to operators. However, because the difference between the second and the third is not significant, the introduction of feedback interconnections (such as a recycle in the process) does not cause much more difference than no introduction of feedback at all. If a recycle is introduced, the structural distance between these two interconnected parts should be as small as possible, so that the structured environment of the whole process may still be considered as a cascade.
- Strong coupling of subsystems, which may cause instability for decentralised controllers, should be avoided in general. Highly sensitive subsystems as well as strongly coupled subsystems that may cause instability for decentralised controllers will cause great increase of perceived complexity and difficulty to operators, once they are directly involved in the manual control of such a process (refer to the fourth operational environment in Table 1).
- The implications of automation system design are similar to those for process system design. When the subsystem number is not large (for example, no more than three), cascade control strategy is encouraged and multivariable control is also possible. In this case, one operator is generally enough for human supervisory control. However, in this case, a multivariable controller should be carefully designed such that if some part of this controller fails, the rest of the controller should be compatible with the human operator, once the operator decides to intervene and take over part of the control function. That is to say, the real-time human–machine system with the operator in loop should not cause instability.
- When the subsystem number is large enough (e.g., more than eight), assigning only one operator to supervise the whole plant isnot appropriate, especially in the abnormal state of the process. A team of operators in a hierarchical supervisory control structure is usually required. In this case, every low-level operator is in charge of a small number of subsystems (where the low-level controller is a cascade controller in most cases, and a few are multivariable controllers). High-level operators are in charge of a simple aggregated model of the whole plant. Thus, the whole automation system is a hierarchical multivariable controller.
- In normal operation, the operation procedure designed for the operator (e.g., the teaching and instruction function in Sheridan's (1992) five functions of supervisory control) is better designed in such a way that these procedures (or steps) are in time sequence and content independent. In an abnormal state, the operation procedure (e.g., the monitor and intervention function in Sheridan's (1992) five functions) should be designed such that the procedures are in time sequence, while the procedures or steps should not form cycles. If there is feedback interconnection, the cycle should be as small as possible.

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Appendix: Experimental Sessions to Perceived Complexity

Session 1: one subsystem
Session 2: OE1-2 (i.e., the first operational environment OE1 with two subsystems)
Session 3: OE2-2
Session 4: OE3-2
Session 5: OE4-2
Session 6: OE1-3
Session 7: OE2-3
Session 8: OE3-3
Session 9: OE4-3
Session 10: OE1-4
Session 11: OE2-4
Session 12: OE3-4
Session 13: OE4-4
Session 14: OE1-5
Session 15: OE2-5
Session 16: OE3-5
Session 17: OE4-5
Session 18: OE2-2 (time constraint: 3 minutes)
Session 19: OE3-2 (time constraint: 6 minutes)
Session 20: OE3-4 (time constraint: 6 minutes)
Session 21: OE2-2 (the operator was required to monitor and intervene when some control loops failed)