Chapter 12

# Decision making in dynamic task environments

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Two decades of process tracing studies have provided one robust conclusion: there is no generally used strategy for a particular choice problem, but the selected strategy is highly contingent upon various task and context factors, such as complexity or time pressure (see, for a review, Ford *et al.*, 1989). Recently, Payne *et al.* (1993) added a further dimension to this conclusion by suggesting that strategy selection is not only contingent but also highly adaptive. They based their conclusion on a comparison of the strategies that subjects selected in various task contexts and the outcomes of simulations in which both effort and accuracy were taken into account. Generally, subjects appeared to select a decision strategy that saves considerable effort at the expense of only a small decline in accuracy.

The conclusion that decision making is quite adaptive is based solely on static decision tasks. Many real-world decision tasks, however, are dynamic in nature, which means that the decision context changes over time. When fire-fighters are controlling a fire, when an operator is trying to find a fault in a production process, or when a physician is diagnosing a disease, decisions must be made in an inherently unstable environment. In such situations the system (the fire, the production process or the patient) changes over time, a factor the decision maker has to take into consideration.

How well do people perform in dynamic tasks? In order to provide a tentative answer to this question we will present an overview of the main findings in dynamic decision making research. First, however, we will describe the characteristics of dynamic task environments.

## CHARACTERISTICS OF DYNAMIC TASKS

The following characteristics of dynamic tasks, which are most often mentioned in studies on dynamic decision making, were provided by Edwards (1962: 60): 'The environment in which the decision is set may be changing, either as a function of the sequence of decisions, or independently of them, or both.' More recently, Brehmer (1992) included an additional aspect, namely that decisions need to be made in real time.

This factor added an extra dimension to dynamic decision making, as the decision maker has to consider the dimension of time explicitly. It is not enough to know *what* should be done but also *when* it should be done. Taken together, in dynamic tasks individuals typically control a changing system, they receive feedback about the state of the system and they need to make a sequence of decisions.

### Change over time

Dynamic decision situations change over time. A fire spreads and a patient's health deteriorates, but these developments may be corrected by the actions of the decision maker. The main effect of the changing nature of dynamic tasks is that the time dimension has to be taken into account explicitly. In continuously evolving situations, decision makers constantly have to decide when to intervene in the system under control, which also implies that time pressure can result when they wait too long before their intervention. In contrast to static tasks, time pressure in dynamic environments is defined by the changing situation itself (for a review of studies on time pressure in static tasks, see Edland and Svenson (1993), and this volume, Chapter 11). A process operator, for example, will experience more time pressure when the performance of the system under control deteriorates rapidly. Thus, decision makers need to relate system changes to the timing of their own actions.

### Availability of feedback

Feedback is one of the most crucial features of dynamic decision tasks. In general, the decision maker will have an overall indication of the state of the system, such as an alarm or the complaints of a patient. An overall performance decline provides the decision maker with a cue that something needs to be done. Furthermore, if actions have been applied, the overall system state can also be used to test whether the action was accurate, i.e., had the desired effect on system performance. In contrast with static tasks, decision makers can, therefore, use feedback to adjust system performance incrementally: they may take small steps at a time and select other actions as soon as the development of the system's performance is not in the required direction (Hogarth, 1981). In this regard, Kleinmuntz (1985) made a distinction between action-oriented strategies and judgement-oriented strategies. When action-oriented strategies are used, subjects just apply actions, observe their effect on the system under control and proceed depending on the observed effect. When judgement-oriented strategies are used, on the other hand, decision makers first try to reduce their uncertainty with regard to the cause underlying performance deterioration by requesting information.



### Need to make several (interdependent) decisions

Dynamic situations require multiple decisions, and these decisions affect the system under control. In predicting a future system state the decision maker therefore has to take both the autonomous system developments and the effects of his or her own actions into account. As noted by Huber (1990), one central factor in dealing with such a task is the quality of the mental representation of the system under control. The decision maker needs to have an accurate model of the relations between all system parameters and their temporal characteristics. This facilitates a mental simulation of the system's behaviour and consequently increases anticipation of future outcomes. In control theoretical terms, the possibility of predicting a future system state allows for feedforward control. Whereas feedforward control involves choosing actions on the basis of predictions of the future state of the system, feedback control involves choosing actions on the basis of information about the current system state.

### Experimental tasks

These abstract characteristics of dynamic tasks have been translated into a wide range of control environments such as simulated economies (Sterman, 1989), tribes or towns (Dörner, 1987), fire fighting (Brehmer, 1990, 1992) and medical diagnosis (Kleinmuntz and Thomas, 1987). Dependent on the specific research question, the dynamic task features mentioned above are more or less implemented in the experimental task. In most experiments, for example, time has been sliced up into discrete units, and the problems have been presented to the subjects in terms of a series of trials (for example, Dörner, 1987; Kleinmuntz and Thomas, 1987; Mackinnon and Wearing, 1985; Sterman, 1989). After subjects have chosen an action, they are presented with the next system state that reflects both the effect of their action and possible autonomous system developments. Brehmer (1990, 1992) and Kerstholt (1994a, 1995), on the other hand, used a real-time simulation. In such a situation the system changes continuously and there is only limited time to think about the most optimal actions. In Brehmer's task, for example, subjects had to extinguish a developing forest fire by sending out fire fighting units to specific locations in the forest. Whenever new events happened, such as when a fire spread in an unexpected direction or when a new fire started, the subjects had to redeploy their forces.

In addition to the specific task characteristics, dynamic laboratory tasks also differ with regard to their complexity. Most researchers have designed dynamic experimental tasks that are relatively complex. Participants have to take many system parameters into account, and the mutual dependencies between these variables and their dynamic developments are opaque. Because of this confounding between system dynamics and complexity it is indeed questionable to what extent the results of these studies increase our knowledge of dynamic decision making processes in general (Hunt, 1991). In the present chapter we will therefore limit ourselves to experimental studies that focused on dynamic decision making behaviour, rather than complexity as such.

## MAIN FINDINGS FROM DYNAMIC DECISION MAKING RESEARCH

In the previous section we mentioned three characteristics of dynamic decision tasks: change over time, availability of feedback and the need to make several (independent) decisions. With regard to change over time, it is important to know when to intervene with the system under control (*timing*), which is, in turn, related to the time that is reserved for diagnosis (*strategy selection*). With regard to the availability of feedback most research has focused on how well people deal with delays (*perception of feedback*). If several decisions need to be made it is important to maintain an accurate mental representation of the system under control. The main findings with regard to this aspect of dynamic decision tasks will be presented in the last section, *information selection over time*.

### Timing

One of the main requirements in evolving situations is to relate one's own timing of actions to system evolutions (De Keyser, 1990). Kerstholt (1994a, 1995) investigated the moment subjects started to intervene with the system under uncertain, changing system conditions as a function of the rate of system change. From normative models of the experimental task it could be deduced that the moment of intervention should be adjusted to the time left, that is, the higher the rate of change the earlier one should start with intervention. This is not what was observed. As a matter of fact, subjects based the moment of intervention only upon the current system state and did not take the rate of change into account. As a consequence less time remained for corrective actions if the system rapidly deteriorated, resulting in decreased performance. In another experiment it was found that subjects did adapt the moment of intervention to variations in false alarm rate (Kerstholt, 1995). When the probability increased that a system decline was due to a false alarm, subjects postponed intervention until a later time. In this situation, however, subjects should have intervened at the same system level, i.e., independent of the exact false alarm rate subjects should intervene at the latest point in time that still allowed for system recovery. Even though only a little research has been carried out, the results suggest that people are not very good at selecting the right time for intervention.



In order to time actions accurately it is necessary to have an understanding of the dynamics of the system in relation to one's own time use. In many situations people may have learned from experience when to start with a control action for a particular dynamic system. For example, river pilots know from experience when to start altering course, taking the response delay into account (Schraagen, 1994). By learning input–output relations they may anticipate a future system state. However, in many situations a person may not be able to learn these input–output relations simply because of the uniqueness of the situation he or she has to deal with. This is, for example, the case in modern technological environments where multiple systems have to be supervised and where intervention is only required in sporadically occurring, critical situations. Because of system dependencies, the fault may be propagated through the system while one is working on one particular disturbance. Research has indicated that people have a tendency to deal with multiple problems sequentially. This phenomenon was termed 'cognitive lockup' by Moray and Rotenberg (1989). From their experiment it was not clear, however, whether this tendency was also suboptimal; that is, would subjects have performed more accurately with a different problem solving strategy? In order to shed more light on this topic, Kerstholt *et al.* (1996) conducted an experiment in which subjects were required to supervise four dynamic subsystems and to deal with disturbances whenever they occurred. However, the task was designed in such a way that suboptimal performance would be attained if subjects were to deal with the problems sequentially. The results showed that there were rather large differences in performance. Some subjects performed very accurately, whereas others could not solve the problems within the time constraint. One factor that underlay this difference in performance supported the cognitive lockup phenomenon. Many subjects handled the disturbances strictly sequentially and they consistently ignored auditory alarms that signalled additional disturbances. Subjects who performed accurately, on the other hand, were aware of the dynamic developments of the system. They reacted to an auditory alarm by temporarily disrupting their diagnosis process to stabilise the additional disturbed system first, thereby acknowledging their understanding of the development of a disturbance over time. However, with a training curriculum that provided subjects with the opportunity to build up an accurate mental representation of the dependencies between the various systems, overall performance could be significantly improved (Kerstholt and Passenier, 1995).

Taken together, the results indicate that accurate timing behaviour requires extensive knowledge about the causal and temporal relations between system components. In addition to being able to anticipate dependent system reactions, it is important to relate system developments to one's own use of time.

**Strategy selection**

Studies that specifically investigated how time is divided between diagnosis and action indicated that individuals prefer a judgement-oriented strategy. Before applying an action, they first search for information that reduces their uncertainty concerning the cause underlying a decrease in system performance (Hogarth and Makridakis, 1981; Kerstholt, 1994a, 1995; Kleinmuntz and Thomas, 1987). In the studies by Kerstholt and by Kleinmuntz and Thomas the optimal decision strategy under various task conditions had been defined and subjects' strategies could therefore be compared to these optimal rules. It turned out that subjects also chose a judgement-oriented strategy in situations where an action-oriented strategy would have led to optimal performance, which suggests that subjects perform more poorly in selecting an appropriate strategy in dynamic tasks than in static tasks (e.g., Ford *et al.*, 1989; Payne *et al.*, 1993). They did not select the strategy that would lead to a better outcome *and* would avoid the effortful information processing phase.

How can we explain this tendency to select the suboptimal, judgement-oriented strategy? One necessary condition for adaptive behaviour is that people should have had the opportunity to learn the relations between strategy and outcome. Plausibly, subjects *a priori* believe that a judgement-oriented strategy (first think, then act) is a better strategy than an action-oriented strategy. If they do not have the opportunity to learn the relations between strategy use and outcome, it seems logical that they would select a judgement-oriented strategy. In order to explore this possibility Kerstholt (1994b) analysed strategy selection under two different practice conditions, a minimal and an extensive practice condition. It turned out that practice did not affect strategy selection. In both practice conditions judgement-oriented strategies were used in the same proportion of trials. In a related study, however, Kerstholt (1996) found that subjects could be induced to switch to an action-oriented strategy. When the costs of information were relatively low, subjects predominantly used a judgement-oriented strategy, but when the costs of information were relatively high, they predominantly used an action-oriented strategy. On the one hand, this shows that subjects were not obliviously engaged in information search and were capable of adjusting their strategy to changes in the cost structure. On the other hand, because their strategy was suboptimal in at least some task conditions, they were apparently not responsive to all relevant task variables.

In the context of her experimental task, Kerstholt (1996) mentioned two additional factors that might determine the superior outcome of action-oriented strategies and to which subjects may be less sensitive. The first one is the relation between the diagnostic value of information and its costs. The relative benefits of information decrease as the costs of information increase. Probably subjects were not aware of this relationship, and concentrated only on the explicit costs of the information and not on its diagnostic value. Surely this problem is not unique to dynamic tasks. Indeed, various studies with static tasks also indicate the difficulties people have in selecting information before making a choice (Connolly, 1988). The second factor is unique to dynamic tasks and concerns the time dimension. A judgement-oriented strategy implies that an action is preceded by an information search phase and, as requesting information takes time, one should start earlier with intervention. In systems that may spontaneously recover, however, this means that the proportion of unnecessary interventions also increases and, as a result, performance deteriorates. Subjects may not have realised that this temporal aspect of a judgement-oriented strategy can reduce its net effect. This last explanation was also put forward by Hogarth and Makridakis (1981). In their experiment, various teams were required to control a number of firms in a dynamic, competitive environment. It turned out that, even though the human teams were engaged in elaborate planning sessions, they were often outperformed by simulated teams that were just carrying out random actions. Because the environment was extremely dynamic and affected by numerous components, not under the influence of the subjects, the future could not easily be predicted. In other words, the time spent on the team's own strategic activities was not tuned to the dynamic development of the systems under control.

As far as strategy selection is concerned, the results therefore indicate that people are not sensitive to all task parameters in selecting the optimal strategy. Even though they do take more superficial factors such as the costs of information and actions into account, they may be less sensitive to the diagnostic value of the information and to the time dimension.



**Perception of feedback**

A major result from dynamic decision making research is that suboptimal performance often results from misperceptions of feedback (Brehmer, 1992; Diehl and Sterman, 1995; Kleinmuntz, 1993; Sterman, 1989). Performance is particularly affected when the decision maker receives delayed rather than immediate feedback. In Brehmer's fire fighting task, for example, it was found that a larger area of forest burned down when subjects had to take delays in reports from fire fighters into account (Brehmer, 1990). Recently, Diehl and Sterman (1995) varied feedback delay more systematically and they also concluded that subjects largely ignored time delays and were insensitive to feedback structure. Sterman (1989) tried to simulate the behaviour of his subjects in a stock management task in order to extract the main differences between subjects' decision behaviour and the structure of the environment. It appeared that subjects' behaviour could be well simulated by a simple 'hill-climbing' heuristic. According to such a rule the actions are based on only the locally available information. Taken together, the results suggest that people ignore delays in feedback, and react as if information informs them about the current state of affairs (Brehmer, 1990; Diehl and Sterman, 1995; Sterman, 1989). When they are faced with delays, subjects do not switch from feedback control to feedforward control, i.e., they do not base their actions on a prediction of a future system state. However, with feedback control, subjects are always too late with their actions as they base their actions upon an earlier system state.

Even though it has been consistently shown that individuals do not take feedback structures sufficiently into account, there is only limited understanding of the nature and the origin of these misperceptions of feedback (Kleinmuntz, 1993). Why is it so difficult to build up mental models that involve feedback delays?

One possibility is that subjects simply forget to take the delays into account, or are not aware of the presence of feedback delays. In Brehmer's fire fighting task, for example, subjects could infer a delay from the time information on their computer screen, but they were not explicitly informed about it (Brehmer, 1990). Another possibility is that people have not had enough opportunities to build up a representation of the temporal relations between system parameters. In order to interpret delayed feedback accurately, decision makers not only need to have a clear representation of the causal relations between system components but they also need a representation of the exact durations of the delays and to keep track of the temporal developments while controlling the system. The representation of time is not just a by-product of dealing with the task. Brown and West (1990), for example, found that increases in the number of relevant temporal stimuli led to a greater disruption of timing behaviour. In other words, processing temporal information is a controlled rather than an automatic process, requiring attentional resources (Michon and Jackson, 1984; Zakay, 1992). This means that subjects should at least be given sufficient training to acquire knowledge on both the causal and temporal relations between system parameters. Another possible explanation for the difficulty to take feedback delays into account is that subjects were aware of the delay but made miscalculations in relating the information to the actual system state. In this case poor performance does not result from incorrect time representations but from relating this knowledge to the evolving system state.

### Information selection over time

Of particular importance for dynamic system control is the ability to keep track of changing system states. Huber (1990, 1994) and Huber *et al.* (1990) investigated subjects' performance in a multistage betting task. In such a task the subjects' goal is to increase their capital by investing some part in a series of trials. It was found that subjects adapted their percentage stakes to the probability of winning but, in disagreement with the normative solution, not to the winning amount (Huber, 1994).

In a totally different domain Lusk and Hammond (1991) analysed how weather forecasters predicted microbursts (brief localised windstorms) while viewing radar data that were updated over time. They found that, even though the weather forecasters became more confident over time, most of them did not become more accurate. The same conclusion was drawn by Tolcott *et al.* (1989). In their experiment they found that army intelligence analysts became more confident after they had received updated information on an evolving situation. However, they interpreted this information in the light of the model they had constructed from early information and as a consequence they did not build up an improved model of the situation across time.

Most research on situation assessment has been carried out in the context of human factors research and has been related to the increased automation of systems in combination with manning reductions. In controlling aircraft or complex systems such as flexible manufacturing systems, refineries and nuclear power plant, operators need an up-to-date model of situational parameters to control the system effectively (Endsley, 1995). Especially in critical situations where active intervention is required of the operator it may be very difficult to build up an accurate model of the situation within a short time span. Not only are the systems under control extremely complex, but in the absence of history information at a lower control level it will take time to trace back the antecedents that led to the actual situation. A major challenge to interface design is to support the operators in maintaining an overview of the process evolution (Passenier and Kerstholt, 1996). Especially when a large number of functions are automated, the operator may not receive adequate feedback to keep track of changing system states. As mentioned by Norman (1990), reduced control possibilities may not be due to automation *per se* but more to an inadequate interface design that provides the operator with too little information on system changes.

To conclude, for efficient system control the operator needs an adequate mental model of both the structure of the system under control and the process evolution. This requires that sufficient feedback of control actions is provided. By giving history and preview information the operator can be further supported in maintaining an overview of the complete system.

## HOW ACCURATE IS DECISION MAKING IN DYNAMIC TASKS?

Payne *et al.* (1993) suggested that strategy selection in static tasks is highly adaptive: individuals select a strategy that strikes an efficient balance between effort and accuracy. Given that decision makers have two goals

– attaining accurate performance and investing minimal effort – they are able adaptively to incorporate these goals in their decision process, by taking the choice context into account. The fact that this effort–accuracy trade-off is also found in dynamic task environments (Kerstholt 1995, 1996) suggests that the minimisation of effort is an overall goal of the decision maker.

However, despite the fact that subjects seem to take effort into account, many results from dynamic decision making studies have shown that performance is far from optimal. As we have shown in the overview of research findings, people perform rather poorly on a number of dynamic task dimensions. For example, they neglect feedback delays and tend to use strategies that are both suboptimal *and* require a lot of effort. Does this mean that people cannot deal accurately with dynamic task environments?

One could distinguish three global reasons for suboptimal task performance. First, as is often suggested, poor performance may be explained by the limitations of the information processing system itself. Capacity limitations may force people to use heuristics or to deal with multiple disturbances sequentially, and it may be that the 'design' of our cognitive system is not suitable to represent or process time relations of the kind needed in process control. A second reason for poor task performance, however, is that the subjects do not possess the knowledge that is needed to deal with the decision problem. This knowledge may consist of input–output relations – the decision maker may have learned by experience which control action to take when a particular system state is observed – or it may consist of a model of the system under control, specifying the relations between system parameters and their temporal characteristics. Without this knowledge the subjects will simply not be able to relate the effects of their control actions to overall system performance. The third possible mechanism for poor performance is that the presentation of the problem does not match the mental representation of the decision maker. Mental representations and procedures have been developed in specific task contexts, and adaptive behaviour in a laboratory task can only be assessed when there is a correspondence between these mental knowledge structures and the structure of the problem (Anderson, 1990). Thus, the subjects have the knowledge of how to deal with, for example, temporal information, but their specific representation of this knowledge does not match the structure of the problem as it is presented to them (Gigerenzer *et al.*, 1988).

In trying to map the experimental findings on to these explanations one could tentatively conclude that people are not able to deal accurately with dynamic systems, as they ignore feedback delays and do not time their control actions to conform to normative solutions. Or, as Diehl and Sterman (1995: 214) put it: 'people's ability to infer correctly the behaviour of even simple feedback systems is poor [which is] a fundamental bound on human rationality – our cognitive capabilities do not include the ability to solve systems of high-order nonlinear differential equations intuitively'.



However, despite this conclusion from experimental research, it cannot be denied that experts can deal efficiently with highly complex dynamic systems in real life, such as, for example, manoeuvring a ship through restricted waterways. One difference between these real-life situations and experimental tasks is that people will have had numerous occasions in which knowledge could be acquired concerning the relation between input and actions. The expertise of river pilots, for example, seems to consist more of using specific references (e.g., pile moorings, buoys, leading lines) to check the ship's position and orientation in a particular area than in being able to predict accurately a ship's movements (Schraagen, 1994). In other words, even though people do not seem to build up a mental model of the system dynamics itself, they can accurately control the system after learning the relations between input and output signals (see also Dienes and Fahey, 1996).

Given that the efficient control of dynamic systems requires such extended knowledge and experience, it is rather peculiar that most research on dynamic decision making tends to use rather knowledge-intensive decision tasks, without lengthy practice sessions that give subjects the opportunity to build up their knowledge base. If the aim is to focus on performance measures, how well people perform in dynamic tasks, it seems more fruitful to look at experienced decision makers in a real-world context such as is done in the naturalistic decision making tradition (Klein *et al.*, 1993). On the other hand, if one aims at finding general aspects of dynamic decision making, generalisable to a wide range of task domains, then the experimental task should provide maximal control rather than the mere inclusion of all 'real-life' task parameters. At this level, the design of simple task environments is geared to measuring specific research questions, rather than to measuring performance in complex, dynamic tasks as such. Why, for example, are some people able to maintain an overview of the system under control whereas others fixate too much on a single, local, diagnosis problem (Kerstholt *et al.*, 1996)? Why do some decision makers make accurate use of real-time information whereas others use, less efficiently, predictive, planning information (Eisenhardt, 1989)? Instead of an additional study indicating how poorly subjects perform in dynamic tasks, it seems that the time is ripe for more detailed studies increasing our understanding of the way in which dynamic decision tasks are performed.

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