

Action variety of planners: Cognitive load and requisite variety

Jan C. Fransoo*, Vincent C.S. Wiers

*Technische Universiteit Eindhoven, Department of Technology Management,
P.O. Box 513, NL-5600 MB Eindhoven, Netherlands*

Received 1 May 2005; received in revised form 16 August 2005; accepted 18 September 2005

Available online 4 January 2006

Abstract

The complexity of planning tasks have increased over the past decade. There is relatively poor understanding what the implications are of increased task complexity in planning and scheduling operations. Previous work in the behavioral sciences have investigated the concept of cognitive load, addressing both task complexity and task workload or stress, and have concluded that decision makers tend to resort to routine action and reduce the variety in their actions with increasing complexity and workload. Alternatively, control theory suggests that a higher variety of actions is needed to deal with more complex problems. In this paper, we investigate the effects of task complexity in a chemical plant on the variety of actions deployed by the planners. The single work center resource structure and the availability of actual planning data from an MRP-application database allows us to both use field data and study a situation which is simple enough to measure the main effect. Our results suggest that increased task complexity without time pressure does indeed lead to increased action variety deployed by the planners.

© 2005 Elsevier B.V. All rights reserved.

Keywords: Cognitive load; Task complexity; Field study; Chemical industry; Requisite variety

1. Introduction

Production planning is determining what product to produce when on which resources. The process of production planning can be studied from various perspectives. The most common perspective taken in the operations management literature is the prescriptive axiomatic approach, in which the production planning problem is represented as a formal, usually mathematical, model and the interest of the researcher is to find an optimal decision or optimal decision policy (see, e.g., Lawler et al., 1993). The disciplinary background for most of these studies is operations research. A second approach is to study the production control decision from an empirical process perspective. In these studies, typically observation generates qualitative descriptions

of which the objective is to better understand the production planning process as production planners in real-life environments execute it. In many cases, the disciplinary background is in work psychology. While most work psychology studies of production planners are field studies, experimental studies are conducted in some occasions (see, e.g., Crawford and Wiers, 2001, for an overview). A third approach is to study the planning process from a cognitive perspective. The objective is to fully document the decision making process “within the mind” of the production planner. Most of these studies are experimental studies (in laboratories, with toy problems) but sometimes they are conducted in real-life environments or in microworlds or other simulated real-life environments, such as the fire-fighting task described in Dörner and Pfeifer (1993). A well-known disadvantage of studies that are not conducted in a real-life environment (such as experimental or axiomatic studies) is that the process from which the data is captured may insufficiently

* Corresponding author.

E-mail addresses: j.c.fransoo@tm.tue.nl (J.C. Fransoo),
v.c.s.wiers@tm.tue.nl (V.C.S. Wiers).

resemble the real-life process. A disadvantage of some field studies that are common in work psychology is the often qualitative nature of the results.

The behavior of planners can be seen as a series of planning actions that lead to a plan which is communicated to and executed on the shop floor. Planning actions can be to plan a new order, to change the order quantity, and the like. In this paper, we are interested in studying the variety of actions that planners demonstrate in their decision making outputs. We will test this hypothesis based on field data. We use the actual plans that production planners have produced for a period of three months. These were captured in the firm's MRP-application database. This helps us to further understand the planning processes in real life and investigate some of the results that have been found in more controlled environments. In addition, it challenges us to develop a methodology that is purely based on analyzing data captured in mainstream commercial planning software. In doing so, this study will not only help us to better understand the production planning process, but we will also be able to explicitly state the contribution and limitations of this new methodology and data source.

Our paper has been organized as follows. In the next section, we discuss the relevant empirical and experimental research work on the human factor in production planning and scheduling and develop our hypothesis. In Section 3, we discuss the methodology and the data collection process. In Section 4, we describe the planning environment that we have studied and within which we have collected our data. We present and analyze the results in Section 5 and conclude in Section 6.

2. Literature review and hypothesis

2.1. Planning and scheduling

Planning and scheduling tasks have been researched in laboratory settings and empirical studies. Sanderson (1989) reviewed both experimental and field studies on the human factor in planning and scheduling. She concludes her review with the comment that studies are very heterogeneous which makes it difficult to create an overall picture. Subsequently, she observes that “this is exacerbated by the fact that there is no underlying theory of how certain environmental parameters *should* affect human schedulers relative to scheduling rules. More systematic work needs to be done on what aspects of system configuration influence human scheduling abilities and how they exercise their influence” (Sanderson, 1989, p. 651).

In the 1980s, a renewed attention for the production scheduling task led to a range of field studies. The work of McKay (1992) focuses on various levels of decision making by human schedulers and how this fits the formal hierarchical production planning structure. Based on this empirical work, McKay presented a two-stage control model for production planning scheduling, where a distinction is made between the routine aspects of production scheduling and the exceptions that are dealt with. The distinction between routine and non-routine tasks in production scheduling is also proposed by Sanderson (1991) in setting up a Model Human Scheduler. This model is based on the decision ladder of Rasmussen (1986), which distinguishes between decisions that are made routinely and decisions that are new and require abstraction and the explicit design of a solution.

The work of Wiers (1997) focuses on the interaction between human schedulers and decision support systems. In line with Sanderson, he proposes a model where a distinction is made between mechanical scheduling decisions and decisions dealing with exceptions, which influences the way decision support systems should be setup. McKay and Buzacott (2000) describe the structure of the scheduling task using a seven-step model, which clearly identifies problem solving activities and “scheduling by rote”.

2.2. Action variety, cognitive load and requisite variety

We are interested in the variety of actions that planners deploy when making their planning decisions. In our study, we define an action as a change in the production plan measured at the end of the day, compared to the plan at the end of the previous day. More specifically, the relation between the number of actions and the variety in actions is the subject of the reported study.

The literature on production planning tasks suggests that there are routine elements that require relatively little attention, and problem solving activities that require the human to conceptualize and design more complex solutions. The routine elements are a stable factor in the planning task, in case a stationary workload needs to be processed on a daily basis, by planning the new orders (McKay and Buzacott, 2000). If the complexity of the task increases (more planning actions are needed), more ingenuity of the planner is required. The nature of the planning problem gradually changes from processing a series of routine actions to developing solutions to a more complex problem. Following this

line of thought, one would therefore expect to observe relatively low variety of actions if the total number of planning actions is limited (a steady stream of routine actions that are relatively monotonous), and that when the number of actions increases, the variety of these actions also increases. This means that when the planning complexity (indicated by the number of planning actions) is limited, a bottom-up decision strategy is followed, because the actions can be conducted with on a case-by-case basis, they do not completely upset the existing plan and therefore there is no need to zoom out and regard the plan as a whole.

Contrarily, when the number of necessary actions is high, the planner must go through a problem solving cycle to identify the problem, design and implement the solution (Hayes-Roth and Hayes-Roth, 1979). In such a case, it is not obvious for the planner what to do and a solution must be designed that consists of a number of different actions: moving orders, changing quantities, changing the sequence. The planner will be forced to ‘zoom out’, regard the plan as a whole, and define a strategy to come up with a solution. Hence, a top-down strategy will be more prevalent if the number of actions is higher (Hayes-Roth and Hayes-Roth, 1979). The use of top-down and bottom-up decision strategies has also been discussed by Payne and Bettman (2001). In the top-down approach, the decision maker evaluates the available actions in the context of the problem faced, and selects the best configuration of actions. In a bottom-up approach, the selection of actions is much more a learned response that has related specific actions to specific problem characteristics (Payne and Bettman, 2001). Because the bottom-up strategy in planning is associated with more routine decision making, it is expected that this strategy leads to more monotonous decision making than a top-down strategy.

In conclusion, our hypothesis is as follows:

H₀. if there are more planning actions, the variety of actions will increase.

Our hypothesis is in line with the (normative) law of requisite variety (Ashby, 1956), which postulates that more variety in control actions is needed to handle more variety in the controlled system. From this perspective, it is reasonable to assume that planners with at least some experience will exert a wider variety of actions when there is a need to conduct many actions.

However, the alternative perspective, which represents a large body of work in behavioral research studying the effects of cognitive load, suggests the contrary: if the magnitude of the problem is increased, decision makers will “fall back” to routine decisions

and use less variety in their actions. There is extensive literature on the effect of workload and task complexity on task performance (e.g., Campbell and Gingrich, 1986; Wood, 1986; Campbell, 1988; Ford et al., 1989). Bainbridge (1998) gives an overview of several processes underlying human performance, including mental workload and the response of individuals. She describes that different strategies may be used by operators to decrease the mental workload, by using actions that reduce the mental effort required. Dörner and Pfeifer (1993) report on a study in which subjects need to conduct a fire-fighting task in a computer game. The level of stress can be varied by a number of parameters including the speed by which the fire is spreading. Their conjecture is that under stress decision makers are less exact in observing the situation. Also, they will be less analytical in evaluating alternatives, concentrate on only a few aspects of the problem at hand, “feel helpless” and tend towards emergency decision making. Dörner and Pfeifer then observe this by measuring the variety of actions in the decisions. Their results indicate that the variety of actions is less under conditions of increased stress.

3. Method and data collection

Since MRP-application databases register all data that the planner uses as input and generates as output, they provide a potentially rich source of data for analysis of the behavior of planners. This data source does not only represent the results of actual decision making of production planners in real life, but it also captures this to a substantial level of detail. A disadvantage of these systems is that they do not keep track of the actual decision making process; only the results of the decision making process are captured. Also, these databases do not keep track of history, other than the financial history and possibly the actual production. Furthermore, systems do not maintain different versions of a production plan. Analyzing series of decisions by production planners thus requires a full download of the data at regular time intervals before they are overwritten or dumped.

3.1. Data collection

The planner is responsible for balancing the required capacity (planned orders) and available capacity (actual production) in time. The planner thus needs to ensure that inventory does not run out. He uses the planned orders proposed by the MRP system as basic information, and each day decides on a production plan, which

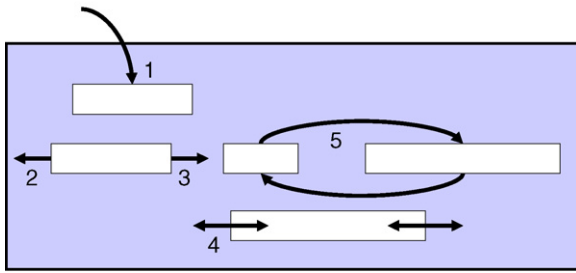


Fig. 1. Planning actions.

consists of production orders that will be released the next day. Fig. 1 shows a simplified graphical representation of the plan, where the bars represent orders planned on resources in time.

The planning actions that are derived from the plan are the following:

1. plan new order;
2. move order backward;
3. move order forward;
4. change the order duration;
5. swap orders.

The actions are carried out by the planners by modifying the start and end date/time of orders, and changing the duration of orders. This is done with a user interface that is text based.

Data have been collected for a period of three months. All data have been inserted into a relational database. This way, plans generated on consecutive days and pertaining to the same planning period could be compared. This enabled us to measure the changes that the planner makes in the plans, and enables us to compare how the planner relates the proposed plan

Table 1

Data downloaded from the MRP-application database on a daily basis

Field	Description
Plan date	The date that the plan was downloaded
Work center	The name of the work center on which the order is planned
Plant	A plant represents a geographical grouping of work centers
Start DT	The planned start date/time for the order
End DT	The planned end date/time for the order
Status	The status would be either 0 or 1; every order that is created gets status 0 until it is released by the planner
Order quantity	The planned quantity of the order
Product number	The product number that must be produced by the order
Product description	A description of the product, uniquely linked to the product number

(planned orders generated by MRP) with the actual plan (manufacturing orders released).

Every day, a download was made of the planned orders generated by the MRP system. Table 1 describes the data in each download.

Fig. 2 shows the availability of data during the measurement period. The presence of a bar for a specific date shows that a plan was downloaded at that date, and the height of the bar shows the number of orders in the plan.

The planners use the planned orders as created by MRP to generate production orders. In analyzing the planning actions, only orders were included that were both a planned and a production order. The question why only a manually specified selection of the planned orders became production orders has not been addressed in this research.

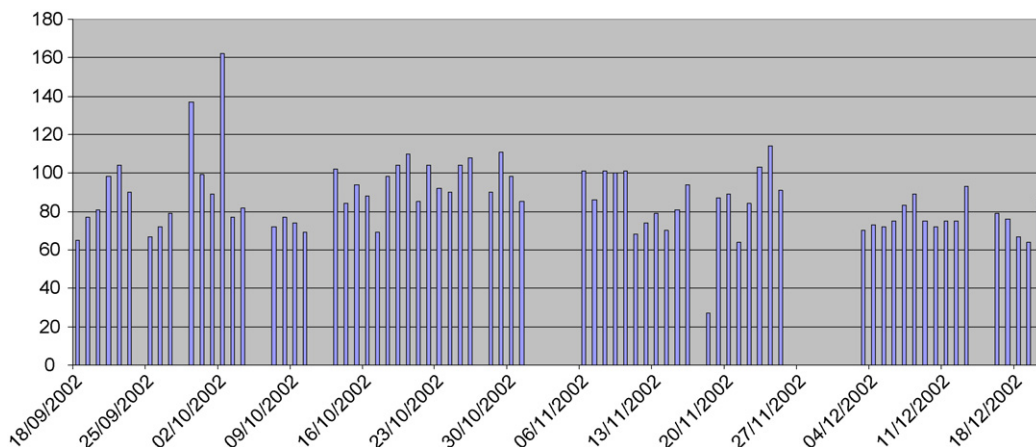


Fig. 2. Data availability.

A file was created that indicated the amount of realized production per production order number. Hence, for every order that was planned by the planner, it was known which amount was actually produced. However, no information was available about the real start and end date and time for the individual orders.

3.2. Measurement of planning actions

In this section, we will explain how we have extracted planning actions from the data files. Planning actions can also be referred to as judgments in the Social Judgment Theory terminology, which are extracted from the data as any change made in the plan. Note again that the planning actions recorded represent only the *final* decisions at the end of each day when the plan is downloaded from the system, and does not inform us about the *factual* decisions (Schneeweiss, 1999), which might be taken in between. For example, when moving an order forwards has been done in three steps throughout the day, we do not distinguish this from an order which has been moved forward in one step by the planner. We therefore do not claim to map the cognitive process of the planner, but only the actual decision making outcome patterns.

For every production order number, feedback information was available on how much of the order was actually produced. Using the order information from the plan, the *percentage of the order that was actually produced* was calculated. For every resource and plan date, an average percentage of realized to planned was calculated.

The *number of new orders* in the plan was determined by counting the production order numbers that existed in plan $t + 1$ and not in plan t .

To determine if orders had been *moved forward or backward* in the plan, a list was made of the occurrences of all production orders in all plans. This list was sorted on plan date and for each occurrence of a production order, it was checked if there had been a change with the previous occurrence of the production order. If the start date and the end date of the production order had both been moved forward (backward) in time, this would count as the production order being moved forward (backward) in time.

To calculate the *order duration (lotsize) changes*, the same list was used as for orders being moved forward or backward. For each occurrence of a production order, it was checked if there had been a change regarding duration with the previous occurrence of the production order.

A list was constructed from all plans that showed for each production order number its direct previous and next order. If another record would exist for the same production order number with a different previous or next order, the order would be marked ‘*swapped*’ for that production order on that plan date. The number of swapped orders has been summed up for each resource and plan date.

Other planning actions that are common in manufacturing companies such as splitting orders, moving orders to alternative resources do not apply to the planning task studied in this paper.

The *total number of actions* sums up the following actions: new orders, move order forwards, move order backwards, change order duration, swapped orders.

The variance was calculated for the action parameters for each case and this was used as an inverse measure for *variety*. Thus, the higher the statistical variance, the lower the action variety. Consider the following examples:

	Action type				
	1	2	3	4	5
Case 1	1	1	1	1	1
Case 2	0	8	0	0	0
Case 3	2	3	4	3	2

The first case has a very high variety because the actions are evenly spread across the action types. The statistical variance for this case is 0. The second case shows a very low variety as all actions are performed in one category. The variance for this case is 12.8. The third case is a middle way, where there is a spread of actions across the action types, but it is not perfectly divided, so there is some focus. The variance is .7.

The variety of the actions v has been calculated on normalized values x_i of the N actions y_i on every work center–plan date combination as follows:

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

$$x_i = \frac{y_i}{\sum_{i=1}^N y_i}$$

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

In other words, every action was divided by the total number of actions, and the resulting number was used in the calculation of the statistical variety. The actions were normalized to prevent an inherent correlation of

action variety with the total number of actions. A similar approach was used by Dörner and Pfeifer (1993).

4. Planning environment

In this study, we are considering one business unit of a large chemical company. The business unit operates seven plants across Europe. Each of the plants consists of a number of manufacturing units (reactors). The manufacturing units produce a variety of products. The manufacturing units that are part of our study produce a chemical product which is mostly delivered in bulk (trucks or containers) to industrial customers. Although theoretically the variety of products is extremely large (due to the possibility of blending in specific additions), in reality the number of products on each of the resources is fairly limited (typically around one dozen, with a few resources producing up to around three dozen products).

The planning of the reactors has been centralized in a European Central Planning Office. All customer orders are received at the European Customer Service Center that is located in the same building. The order handlers are located in the office adjacent to the office where the planners are located. There are four planners involved with planning the reactors, and one additional planner is responsible for planning the shipments from the plants to the customers. For each of the plants, one primary planner has been allocated. Also, for each of the plants, one of the other planners acts as a secondary planner, who can replace the primary planner in case of absence. Each of the planners has primary responsibility for one or two plants, and also carries secondary responsibility for one or two plants. Planners differ in their experience.

The production process and the role of the planner is depicted in Fig. 3. We consider the planning process to the extent to which the planner influences it. The planners use an MRP application that generates planned orders. Production planning as carried out by MRP is the process of converting customer orders with a specific due date and quantity into production orders with a specific manufacturing time and quantity. A

planned order can be viewed as an advise of the planning system which product to manufacture on which date and in which quantity. These planned orders are generated based on actual information regarding customer orders (actual orders placed by customers), demand forecasts (expectations of future orders made by someone else in the planning office), current inventory levels, required safety stock levels, and lotsizing rules. Customer orders and demand forecasts cannot be influenced by the planner and should be considered exogenous. Safety stock levels and lotsizing rules are system parameters that can be set by the planner. Hence, the planner is able to change the parameters that drive the generation of planned orders. However, the planner can also choose to change every planned order individually.

Every night, a new set of planned orders are generated by the system, based on the current inventory levels, the parameter settings for safety stocks and lotsizes, new customer orders that have arrived on the preceding day, and the available production capacity. New demand forecasts can be supplied every week, but in practice are only updated into the system once a month.

Each morning, when the planner arrives, he¹ sees a new list of planned orders, as well as all realized (produced) production orders on the previous day, and any manufacturing orders that have already been scheduled by him on previous days, but which have not yet been completed (either due to delay – which rarely happens – or due to the fact that the order is scheduled to be executed at a later date). The planner then needs to decide on the manufacturing orders. Using the planned orders as a suggestion, but using additional information such as inventory levels and available capacity, he needs to determine which orders actually to produce. All planning actions are considered as modifications to the originally suggested plan by the MRP algorithm.

In doing so, he can either:

- convert a planned order directly into a manufacturing order;
- modify the planned order, and then convert it into a manufacturing order;
- create a new manufacturing order without a planned order being present;
- delete a planned order.

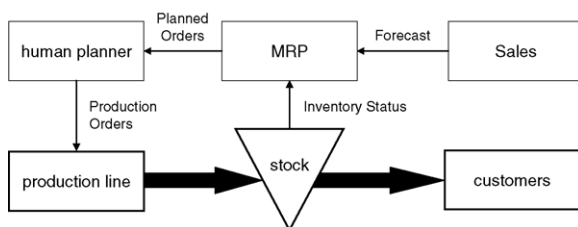


Fig. 3. Planning and production structure.

¹ The use of the term “he” is for convenience only and this does not imply that all planners were male.

The planner will work through the planned orders until he has processed all of them with a specific time horizon (which he can determine himself). When he has allocated all manufacturing orders to a specific time slot, his work for this specific plant is finished for the day. He may also modify any manufacturing orders that had been created on previous days. This may include moving the order backward in time (postponing the execution), bringing the order forward in time, changing the order duration (and hence the lotsize), and by changing production start times the planner may change the sequence of two or more orders.

For a number of days, varying between roughly 2 and 12, manufacturing orders have been assigned by the planner to a particular reactor for a particular period. This is called the manufacturing schedule. Overnight, all manufacturing orders that are scheduled for the following day only, are released to the specific plant. The people in the plant execute the schedule according to specification.

The information flow for the planner that is supported by information systems is depicted in Fig. 4. Both the input and results of the manual planning task are captured by the information system, making it possible to retrieve the data. Every day, the following information is available from the MRP-application's database:

- complete list of planned orders;
- complete manufacturing schedule (list of manufacturing orders assigned to a specific reactor in a specific time slot);
- complete list of production orders that have actually been executed.

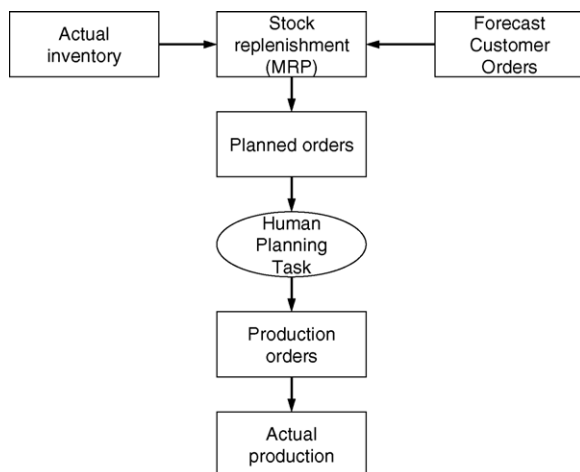


Fig. 4. Information flow MRP and human planner.

Table 2

Realized to planned production quantity

Work center	Between 90 and 110%		Average	Total no.
	No.	%		
A	214	89.1	100.5	240
B	450	94.5	102.5	476
C	299	74.9	101.2	399
D	108	71.1	97.2	152
E	139	73.1	106.3	190
F	236	92.2	98.0	256
G	212	62.5	105.7	339
H	229	78.9	97.0	290
I	338	78.2	97.0	432
J	210	91.3	102.9	230
K	253	83.4	101.6	303
L	185	77.4	99.6	239

In many real-life situations, there is a gap between the plan that is created by the planner, and the actual production activities. Typically, this gap is highest in discrete component manufacturing and lowest in process manufacturing. The case study described in this paper falls into the latter category.

Table 2 shows the average realized to planned production percentage for each work center during the study period, where the realized weight is calculated as percentage of the planned order weight. The cases that were averaged were all production orders for that work center, making no distinction between large and small orders. The table indicates that the gap between planned and realized production varies by work center. However, no relationship has been found between this measure and the constructs that are analyzed in this paper, i.e., number of actions and action variety. There are two possible explanations for this observation. The first one is that the actual difference between planned and actual quantities is relatively small, and within the bounds that would be covered by the safety stock. Second, a possible explanation is that the difference between planned and actual is random across all products, and this would mean that it is not possible for the planner to anticipate.

To conclude, it can be stated that the planning situation can be considered as relatively straightforward and has a small number of dimensions (single resource, limited number of products, very short horizon, limited uncertainty in plan execution). The limitation in storage capacity is not included in the MRP-application's logic, and needs to be taken into account by the planners manually. For most of the plants, this does not seem to be a problem.

Table 3

Spearman correlation coefficients for total number of actions and (normalized) variety of actions

Work center	Correlation	Significance	N
A	.630	.000	42
B	.686	.000	56
C	.687	.000	59
D	.547	.000	46
E	.768	.000	38
F	.718	.000	56
G	.812	.000	54
H	.769	.000	52
I	.577	.000	59
J	.706	.000	55
K	.728	.000	50
L	.771	.000	42
Combined	.723	.000	613

5. Analysis and results

Table 3 shows the correlation analysis between the total number of actions and the variety of actions.

The results show a significant relationship between the total number of actions and the variety of actions. Moreover, the strength of the relationship varies between .547 and .771.

The results suggest strong support for our hypothesis that when a planner is faced with an increased number of actions, the variety of actions increases. Under the assumption that the planners we have studied use a top-down strategy (Payne and Bettman, 2001) and that we are able to separate the effect of workload or stress from the effect of task complexity, this is in line with the theoretical background we have presented in Section 2. Results appear to be different from the results of studies such as conducted by Dörner and Pfeifer (1993), who argue that under situations of an increased workload under time constraints, the variety in actions decreases. There are several probable explanations for the difference in results between other studies and ours. The first one is that in other studies, the workload increases whereas there is a time constraint in solving the problem, thereby causing stress. Contrary, the planners described in this paper do not have tight time constraints in making the plan, even when there are many orders to take into account.

A second possible explanation of our results lies in the fact that much existing research on the relation between workload and action variety has been conducted using students as decision making subjects in laboratory setups. It is not unreasonable to assume that real planners in a practical situation demonstrate different behavior than students in an experimental

setting. More specifically, experience may play a role in the capability of a planner to deploy a larger variety of actions. It would be interesting to investigate this further in a controlled experimental setting.

A third possible explanation of the difference of other studies with our results is that the studied tasks, such as the fire-fighting task described by Dörner and Pfeifer (1993) has a number of characteristics that are different from a production planning task, the most prominent ones being the difference in uncertainty and perceived command over the situation.

6. Conclusions and discussion

In this paper, we have presented a study on the action variety used by planners in a chemical company based on the plan that is generated by the planner, and captured by an MRP-application database. Our results suggest strong support for our hypothesis that the variety of actions increases with the number of actions conducted. A theoretical basis for this hypothesis can be found in control theory's law of requisite variety and in the arguments put forward in the study by Payne and Bettman (2001). They argue that in situations where decisions need to be justified to others and accuracy is important, more alternatives are usually explored. The specific characteristics of the planning task thus lead to specific insights into the variety deployed by planners in their decision making process which may be different from earlier observations of deployed variety in other tasks, such as fire-fighting, in an experimental setting.

Apart from the objective to better understand the variety deployed by planners, a second objective of our study was to demonstrate and investigate the potential of data present in commonly used information systems in empirical research. In this study, we used readily available data that recorded the output of the planning task conducted at the company. The paper has demonstrated that such a study can be conducted and that the data source used is a useful source for conducting studies on human behavior. The paper also extends the methodologies developed in the past to a clear-cut methodology for analyzing data from commercially used information systems, using input–output analysis.

We would like to point out four important limitations of this study. The first is related to the number of planners involved. Only four planners were involved in this study. Since in reality usually a small number of planners conduct a similar task, it seems to be a natural limitation of a methodology based on real-life planning data. The second important limitation is that an input–output analysis that we have conducted does not provide us with

the ability to validate the process within the “black box”. The theories that explain the relationship between inputs and outputs thus need to have been well developed in either axiomatic or experimental studies. It would be interesting to explore the application of this methodology in planning information systems that capture a greater amount of detail, e.g., systems that work in an on-line mode rather than in an off-line daily updating mode. Third, our study has been conducted in a simple manufacturing environment in the chemical industry (single resource, sequencing problem). It is reasonable to assume that similar results may be found across flow process industries, but results may be different if the capacity structure is more complicated. Fourth, it should be noted that theory in operations management is underdeveloped (Amundsen, 1998). Therefore, while our analysis does provide us with an insight into the decision making behavior at the input–output level, we are not able to make normative statements about human planning behavior. Furthermore, it should be noted that the performance of planning actions in reality is very difficult to assess (Gary et al., 1995) and this has been excluded from our study.

Research into the actual decision making behavior of human planners has a potentially significant managerial implications. A better understanding of human planners is needed to develop better training programs for planners and schedulers. Current training for planners and schedulers typically consists of a “press this button now” course, which fails to recognize the variety in decisions to be made. Making the variety in possible decisions more explicit and dealing with them in a planner training could potentially enhance the performance of the planners.

Acknowledgements

The authors would like to thank participants of the workshop on human factors in planning, scheduling and control in manufacturing in 2002 in Eindhoven and 2004 in Jönköping for providing valuable feedback. In particular, the authors would like to thank Julien Cegarra, Ken McKay and Toni Wäfler for providing in-depth feedback to this work. Furthermore, the anonymous associate editor and several anonymous reviewers have helped to considerably increase the quality of the paper.

References

Amundsen, S.D., 1998. Relationships between theory-driven empirical research in operations management and other disciplines. *Journal of Operations Management* 16 (4), 341–359.

- Ashby, W.R., 1956. *An Introduction to Cybernetics*. John Wiley and Sons, New York.
- Bainbridge, L., 1998. Human capabilities and performance. In: Garland, D.J., Wise, J.A., Hopkin, V.D. (Eds.), *Handbook of Aviation Human Factors*. Lawrence Erlbaum Associates, Hillsdale, pp. 107–171.
- Campbell, D.J., 1988. Task complexity: a review and analysis. *Academy of Management Review* 13 (1), 40–52.
- Campbell, D.J., Gingrich, K.F., 1986. The interactive effects of task complexity and participation on task performance: a field experiment. *Organizational Behavior and Human Decision Processes* 38 (2), 162–180.
- Crawford, S., Wiers, V.C.S., 2001. From anecdotes to theory: reviewing the knowledge of the human factors in planning and scheduling. In: McCarthy, B.L., Wilson, J.R. (Eds.), *Human Performance in Planning and Scheduling*. Taylor and Francis, London, pp. 15–43.
- Dörner, D., Pfeifer, E., 1993. Strategic thinking and stress. *Ergonomics* 36 (11), 1345–1360.
- Ford, J.K., Schmitt, N., Schechtman, S.L., Hults, B.M., Doherty, M.L., 1989. Process tracing methods: contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes* 43 (1), 75–117.
- Gary, K., Uzsoy, R., Smith, S.P., Kempf, K.G., 1995. Measuring the quality of manufacturing schedules. In: Brown, D.E., Scherer, W.T. (Eds.), *Intelligent Scheduling Systems*. Kluwer Academic Publishers, Boston, pp. 129–154.
- Hayes-Roth, B., Hayes-Roth, F., 1979. A cognitive model of planning. *Cognitive Science* 3, 285–310.
- Lawler, E.L., Lenstra, J.K., Rinnooy Kan, A.H.G., Shmoys, D.B., 1993. Sequencing and scheduling: algorithms and complexity. In: Graves, S.C., Rinnooy Kan, A.H.G., Zipkin, P.H. (Eds.), *Logistics of Production and Inventory*. North Holland, Amsterdam, pp. 445–522.
- McKay, K.N., Buzacott, J.A., 2000. The application of computerized production control systems in job shop environments. *Computers in Industry* 42 (2/3), 79–97.
- McKay, K.N., 1992. Production planning and scheduling: a model for manufacturing decisions requiring judgement. Ph.D. Thesis. University of Waterloo.
- Payne, J.W., Bettman, J.R., 2001. Preferential choice and adaptive strategy use. In: Gigerenzer, G., Selten, R. (Eds.), *Bounded Rationality: The Adaptive Toolbox*. The MIT Press, Cambridge, pp. 123–145.
- Rasmussen, J., 1986. *Information Processing and Human–Machine Interaction: An Approach to Cognitive Engineering*. North Holland, Amsterdam.
- Sanderson, P.M., 1989. The human planning and scheduling role in advanced manufacturing systems: an emerging human factors domain. *Human Factors* 31 (6), 635–666.
- Sanderson, P.M., 1991. Towards the model human scheduler. *International Journal of Human Factors in Manufacturing* 1 (3), 195–219.
- Schneeweiss, C., 1999. *Hierarchies in Distributed Decision Making*. Springer, Berlin.
- Wiers, V.C.S., 1997. Human–computer interaction in production scheduling: analysis and design of decision support systems for production scheduling tasks. Ph.D. Thesis. Technische Universiteit Eindhoven.
- Wood, R.E., 1986. Task complexity: definition of the construct. *Organizational Behavior and Human Decision Processes* 37 (1), 60–82.