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Citation for published version (APA):
Wiers, V. C. S. (1996). A quantitative field study of the decision behaviour of four shop floor schedulers. *Production Planning & Control*, *7*(4), 383-392. https://doi.org/10.1080/09537289608930366

DOI:
10.1080/09537289608930366

Document status and date:
Published: 01/01/1996

Document Version:
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
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PRODUCTION PLANNING & CONTROL, 1996, VOL. 7, NO. 4, 383–392

A quantitative field study of the decision behaviour of four shopfloor schedulers

VINCENT C. S. WIERS

Keywords human decision behaviour, quantitative decision models, job shop scheduling

Abstract. In this article the decision behaviour of four production schedulers in a truck manufacturing company is investigated by means of a quantitative model. The model consists of there parts: performance variables, action variables and disturbance variables. The outcomes show that there is a large difference between schedulers that apparently have the same type of decision problem. Another interesting finding is that some scheduling actions work positively in the short term, but negatively over a longer term. Other results, along with methodological issues of quantitative research, are discussed.

1. Introduction

Production scheduling is both an essential and intangible factor of the operational performance of production organizations. Much research has been carried out in production scheduling (some review papers are: Graves 1981, Gupta and Kyparisis 1987, Rodammer and White 1988, Ramasesh 1990, Suresh and Chaudhuri 1993). However, there still seems to be a large gap between scheduling theory and practice (King 1976, Graves 1981, McKay *et al.* 1988, Rodammer and White 1988, Buxey 1989, McKay *et al.* 1989). The reason for this gap is that scientific research on scheduling often deals with relatively 'simple' scheduling problems that are: one-stage; one-processor; static; deterministic. In contrast, scheduling problems in practice mostly are: multi-stage; multiple-processor; dynamic; stochastic. Therefore, although many techniques exist for production (an overview of techniques is given in Wortmann *et al.* 1995), scheduling is still a typical human task in most companies.

In spite of the vast literature about scheduling, almost no insight into the decision behaviour of human schedulers in practice exists. In practice, formal techniques are rarely used straightforwardly, and schedulers mostly still use their own 'rules of thumb', especially in dynamic, uncertain and complex scheduling environments. The research described in this paper aims at gaining more insight into the decision behaviour of schedules.

This paper describes a field study in which a comprehensive quantitative model has been used to describe the decision behaviour of four schedulers in a truck manufacturing company. Previous quantitative research about the decision behaviour of production schedulers has essentially been oriented towards some particular aspect of scheduling (a review of human factors in scheduling can be found in Sanderson 1989), for example: the job runtime estimator of the scheduler (Dutton and Starbuck 1971). However, we are interested in all aspects of the decision behaviour of the scheduler, and therefore, the model consists of the

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following three elements: performance criteria, actions, and disturbances. These elements have been operationalized by 16 variables, which have been measured weekly during a period of 4 months. By means of statistical techniques, relationships between the variables have been studied.

In Section 2, a description of the company and the task of the schedulers will be given. In Section 3, the research model will be presented. In Section 4, the gathering and analysis of the data by statistical techniques will be described. In Section 5, the results of the analysis will be given. A methodological discussion of the research is given in Section 6, which will be followed in Section 7 by recommendations to improve the scheduling process in the company. Lastly, in Section 8 our conclusions will be given.

2. The production system

2.1. *The production units*

The field study has been carried out in a truck manufacturing company. Each day an amount of approximately 60 trucks is manufactured, a number that is still rising as a result of an increasing amount of market demand. The company uses an assemble-to-order production strategy, which means that there are a number of standard models of trucks that are customized according to specific customer demands. The company uses a customer lead-time of six weeks.

In the truck manufacturing company four schedulers have been selected for the field study. These schedulers control separate production units. Scheduler one controls a welding production unit that consists of a number of parallel workplaces. Scheduler two controls a pipe manufacturing production unit with a flow-oriented production organization. Scheduler three controls a metal cutting and punching workcell and a bending machine. Scheduler four controls a pressing production unit that consists of seven large presses. The operational characteristics of the production units of the schedulers are given in Table 1. As shown in Table 1, schedulers 1 and 2, and schedulers 3 and 4 schedule production units of comparable complexity. (Note: the characteristics in Table 1 show the complexity of the production units *relative to each other* and not in an absolute way.)

Because of the large setup times, schedules 3 and 4 use a cyclic production scheduling procedure. A cycle consists of a period of 4 weeks. Products are assigned to a specific week within a cycle according to their product families. For example: if product A is required in week 5, and the product family of product A is produced in week $\{2, 6, 10, \ldots\}$, then production has to take place in week 2. Therefore, the cyclic scheduling procedure results in higher utilization through less setups, and less product-mix flexibility for schedules 3 and 4.

2.2. *The scheduling process*

Within the truck manufacturing company, the four schedulers are responsible for the availability of a specific set of products that is manufactured in a specific production unit. The place of the scheduling function in the production planning and control structure of the company is depicted in Figure 1. The scheduling process is depicted in Figure 2, and will be described below.

At the start of each week, the MRP-system calculates the material requirements for 1 week using customer orders (within a time fence of 6 weeks) and prognoses (beyond a time fence of 6 weeks), both on truck level. The material requirements are translated to workorder suggestions, according to parameters that have been set per product for safety time/stock, throughput time, batch size, and stock level. The list of workorder suggestions is transferred to the scheduler. The scheduler checks each suggestion and places workorders in the schedule against infinite capacity. Then the scheduler performs an aggregate capacity check (i.e. for the whole week) per machine and adjusts the schedule if necessary. Finally, the schedule for the whole week is transferred to the production unit by downloading a file with the schedule to PCs on the shopfloor. The exact sequence of the workorders is set on the shopfloor, and in the production units of schedules 3 and 4 is mainly determined by changeover times between product families.

Table 1. Characteristics of the production units.

	Material complexity	Capacity complexity	Throughput-time	Setup times
Scheduler 1	medium	low	low	low
Scheduler 2	medium	low	low	low
Scheduler 3	high	high	medium	medium
Scheduler 4	high	high	high	high

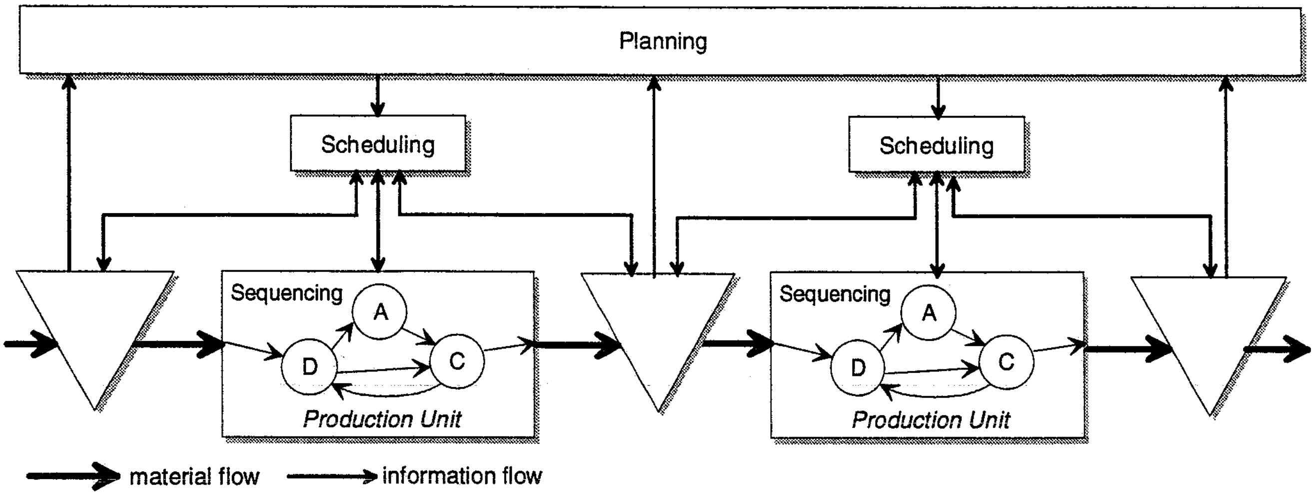

Figure 1. The production planning and control structure in the track manufacturing company.

3. The model

The model of the decision environment of the schedulers contains three blocks: performance, actions, and disturbances. We have attempted to measure these blocks with quantifiable variables. The variables to measure the blocks have been set in co-operation with the operations management of the company. Because of the availability of certain data, the set of variables had to be reduced somewhat for schedulers 1 and 2. It is important to note here that the model describes the *inputs* and *outputs* of the decision behaviour of the schedulers, and not the decision behaviour *process* of the schedulers (see Figure 3). Further methodological aspects of using such a model will be discussed in Section 6. The variables of the model will be described below.

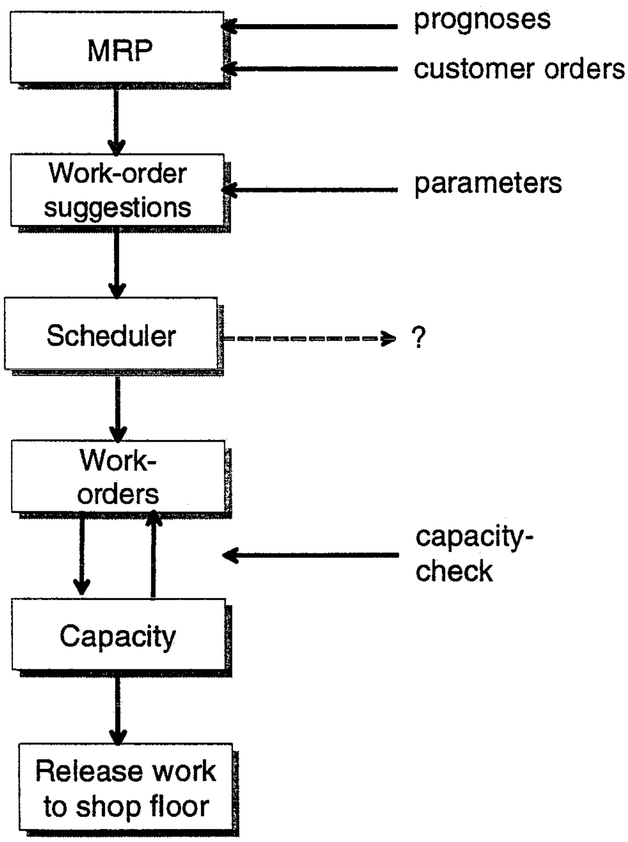

Figure 2. The scheduling process.

3.1. *Performance parameters*

The performance parameters in the model are not used in the first place to measure and evaluate the schedulers' performance. Instead, they represent parameters that the schedulers attempt to influence

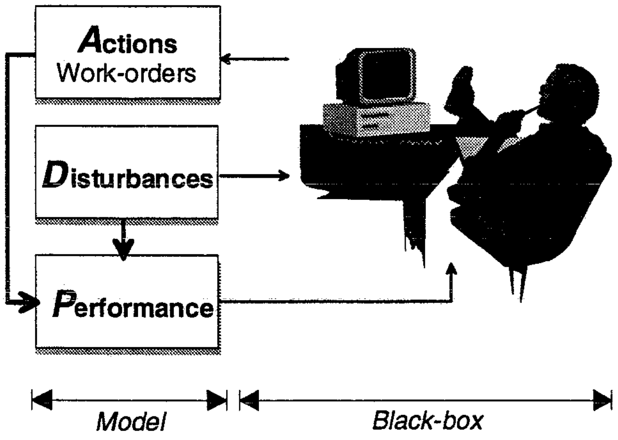

Figure 3. Elements of the model.

with their actions. Three performance parameters are distinguished for each scheduler:

P1: Internal service level
P2: Runouts
P3: Turnover rate of stock

P1: Schedule service level. The internal service level represents the fraction of workorders that will be finished on time, *according to the initial schedule.* Some workorders are scheduled too late on purpose, e.g. when start material is not available, or when not enough capacity is available. P1 therefore is a mixture of a performance variable and an action variable.

P2: Runouts. Each time a requirement for a certain product within the assortment of the scheduler cannot be fulfilled, a runout occurs. The amounts of runouts represents the service level as perceived by the (internal) customer. Therefore, within the company this parameter is also known as *external service level.*

P3: Turnover rate of stock. The turnover rate of stock is a relative measure of the stock costs. It is calculated by dividing the turnover of the total product assortment of the scheduler by the average stock value of the product assortment.

3.2. *Disturbance parameters*

In the model, five disturbance parameters are distinguished for schedulers 3 and 4, and four disturbance parameters are distinguished for schedulers 1 and 2:

D1: Unscheduled production
D2: Material availability
D3: Lost stock
D4: Reliability of prognoses
D5: Available capacity

D1: Unscheduled production. Unscheduled production occurs when work is carried out on the shop floor that is not scheduled beforehand. Unscheduled production influences the other orders in the shop by consuming capacity that has been reserved for the other work according to the schedule.

D2: Material availability. When the start material for a workorder is not available it cannot be produced. If this is the case, the scheduler will not schedule the workorder until the start material is again available. The availability of start material is only measured for schedules 3 and 4 and is determined by the service level of the production unit that produces the larger part of the material for schedulers 3 and 4, i.e. the metal cutting production unit.

D3: Lost stock. The inventory information about end-product of the scheduler does frequently not match the real inventory on the shopfloor. For example: products within product families look alike considerably and can get mixed up.

D4: Reliability of prognoses. In order to be able to meet customer due dates, the company has to use prognoses. Prognoses are used for production activities that have throughput times beyond the 6-week time fence. In particular, schedulers 3 and 4, who are dealing with long lead-times and low flexibility, have to rely on these prognoses.

D5: Available capacity. Every week, a certain amount of operator capacity will be available to the production unit. The amount of operator capacity determines how much workload a scheduler can put in the production unit.

3.3. *Action parameters*

The action parameters have been derived from the schedules that the human schedulers transfer to the shopfloor. In the model, four scheduling parameters and four scheduling parameters are distinguished for schedulers 3 and 4, and two scheduling parameters are distinguished for schedulers 3 and 4, and two scheduling parameters are distinguished for schedulers 1 and 2:

Scheduling parameters
A1: Workload
A2: Mean batch size
A3: Mean slack
A4: Mean order slack

Rescheduling parameters
A5: Mean rescheduled start-weeks
A6: Mean rescheduled batch size
A7: Mean rescheduled operation slack
A8: Mean rescheduled order slack

All parameters except A1 are calculated per workorder. The parameters A5–A8 are calculated by weekly comparing two subsequent schedules. For schedulers 1 and 2 only A1 and A2 have been measured.

A1: Workload. The workload indicates the amount of work (in man-hours) that is released to the shopfloor by the scheduler in a specific week.

A2: Mean batch size. The workload indicates the amount of work *per batch* (in man-hours) that is released to the shopfloor by the scheduler in a specific week.

A3: Mean operation slack. The slack indicates the throughput time (= processing time + waiting time) relative to the processing time of a batch released by the scheduler. For example: if the throughput time of a workorder is 100 hours, and the processing time of a workorder is 10 hours, then the slack is 10.

A4: Mean order slack. The order slack is the time between the scheduled due date of a workorder and the customer delivery date of this workorder. The order slack can be seen as a safety time for unforseen delays of the production of this workorder. Other slack is regularly the result of producing orders within the cyclic production scheduling (see Section 2.2).

A5: Mean rescheduled start week. The scheduler moves (the start week of) workorders forward or backward in time if changes have to be made in the schedule. These changes sometimes relate to this specific workorder, e.g. the material is not available, or can be caused by other orders, e.g. another order has to be finished before the original scheduled order.

A6: Mean rescheduled batch size. The scheduler will adjust the amount of work in a batch if the amount of required products has changed since the batch was scheduled, and if the scheduler does not want to schedule another batch of the same product.

A7: Mean rescheduled operation slack. The operation slack will be adjusted by the scheduler if the batch size is adjusted but the throughput time of the batch stays the same, if the throughput time of the batch is adjusted but the batch-size stays the same, or if the processing times of products are adjusted and the throughput time stays the same.

A8: Mean rescheduled order slack. The order slack will be adjusted by the scheduler if the throughput time of a batch is adjusted but the end date stays the same, or if the customer delivery date is adjusted but the end date stays the same.

3.4. *Relationships*

The relationships between the variables are shown in Figure 4. Some relationships are *expected* to be present according to operational theory, or relationships that are obvious in practice. For example: there could be a relationship between the reliability of prognoses and the service level of the shop. However, it is also possible that the shop is able to cope with the fluctuations in the prognoses and, therefore, in this case, no relationship will be found. It is also possible that we find *infeasible* relationships, i.e. relationships that can not easily be explained. There are two possible causes for this. The first possible cause is that the model does not perfectly describe the actual decision process. The second possible cause is that there is noise in the dataset. For example: a correlation between two factors could be caused by a third factor that is not measured in the model.

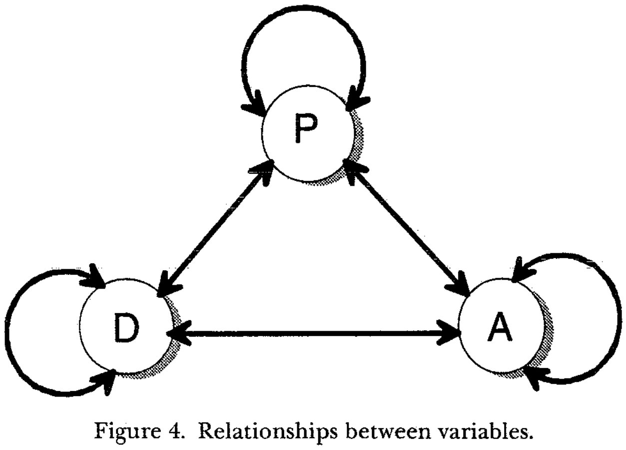

Figure 4. Relationships between variables.

In this paper we will not discuss every hypothetical relationship between the variables, because the total amount of hypothetical relationships is rather large. A complicating fact is that a pair of variables can have both an immediate relationship, and a relationship where one variable relates to another variable after a delay of one or more weeks. For example: the reliability of prognoses influences the service level with a time lag (i.e. delay) of 1 week. Therefore, we will only discuss what we think are the most interesting results, i.e. results that can be interpreted within the context of real-world relationships. Infeasible relationships will not be discussed here.

4. Data gathering and analysis

During a period of 4 months, the company data needed to measure the variables have been collected weekly. Some data were readily available, other data had to be collected by copying files from PCs on the shopfloor that had been downloaded from the MRP mainframe (also see Section 2.2). These files had to be converted and processed by a database program to be able to extract the action parameters of schedulers 3 and 4.

A number of statistical techniques have been used to analyse the data. First, a histogram of each variable has been generated. The distributions indicated that some variables did not match the correlation's and regression's assumption of homoscedasticity. Therefore, the data have been recoded in ranks. The ranked data have been the starting point for further analysis.

To simplify the analysis of the dataset, we assumed that the relationships between variables in the model are of a linear nature. Of course, in practice the variables will not always follow an exact linear relationship. However, previous research showed that real-world processes can often be well described with linear models (Slovic and Lichtenstein 1971).

To analyse relationships between pairs of variables, crosscorrelations have been calculated. The crosscorrelation shows relationships with different time lags between a pair of variables. We used a significance level of 0·05 in the correlation analyses.

To test the completeness of the model, regression analyses have been carried out with the three performance variables as dependent variables. Action-variables and disturbance-variables were placed in the regression equation for a specific time lag as independent variables if a significant correlation had been found at the crosscorrelation analyses. The regression had to be carried out with a limited amount of cases, relative to the amount of variables. The initial amount of measuring points was 18, but because of time lags between variables, the amount of usable measuring points decreased. Therefore, a maximum of two independent variables has been used per regression equation. Furthermore, each regression-coefficient has been 'shrunk', i.e. adjusted to the degrees of freedom, in order to get a reliable indication of the explained variance.

The data have initially been analysed per scheduler. Because the results of these analyses differed essentially from each other, the dataset has not been analysed as a whole.

5. Results

Figure 5 shows the amount of explained variance of the performance variables as calculated by multiple regression analysis. There are large differences in explained variances between the schedulers. The average percentage of explained variance is 51%. The amount of runouts (P2) is the most difficult factor to explain.

The results of the correlation analyses are given in Figure 6. A large number of results can be obtained from Figure 6 and the correlation matrices (which are mostly omitted here). We will present in this paper what we think are the most important and interesting results.

The first result that can be observed from Figure 6 is that schedulers who control equal production units—i.e. schedulers 1 and 2 and schedulers 3 and 4 (see Section 2.1)—show a quite different decision behaviour. Also, the amount of explained variance varies per scheduler. Apparently, the elements that are able to describe the decision behaviour of one scheduler are not well suited to describe the decision behaviour of other schedulers.

Second, it is surprising to see that the service level (P1) and the amount of runouts (P2) do not have a significant relation (except with scheduler 4). Apparently, a good schedule is no guarantee for a low amount of runouts. The question remains which factors determine the amount of runouts on the shopfloor.

Third, the action parameters of schedulers 3 and 4 show nervousness in scheduling. Consider for example Table 2. This table shows a part of the correlation matrix of the interrelationships between the action variables of scheduler 3. The amount of workload correlates positively with the amount of order-slack with a time lag of −5 weeks, i.e. the order-slack influences the workload of 5 weeks away positively. This can be explained by the fact that when orders have much order-slack, the pressure on the production unit decreases and the scheduler will put more workload

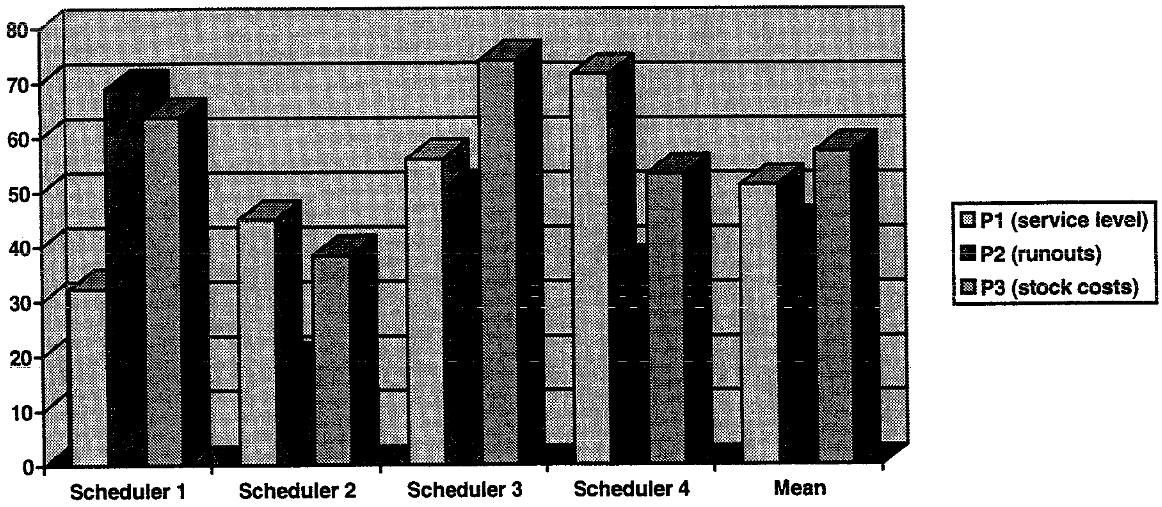

Figure 5. Explained variance R^2 (corrected for shrinkage) of the performance variables.

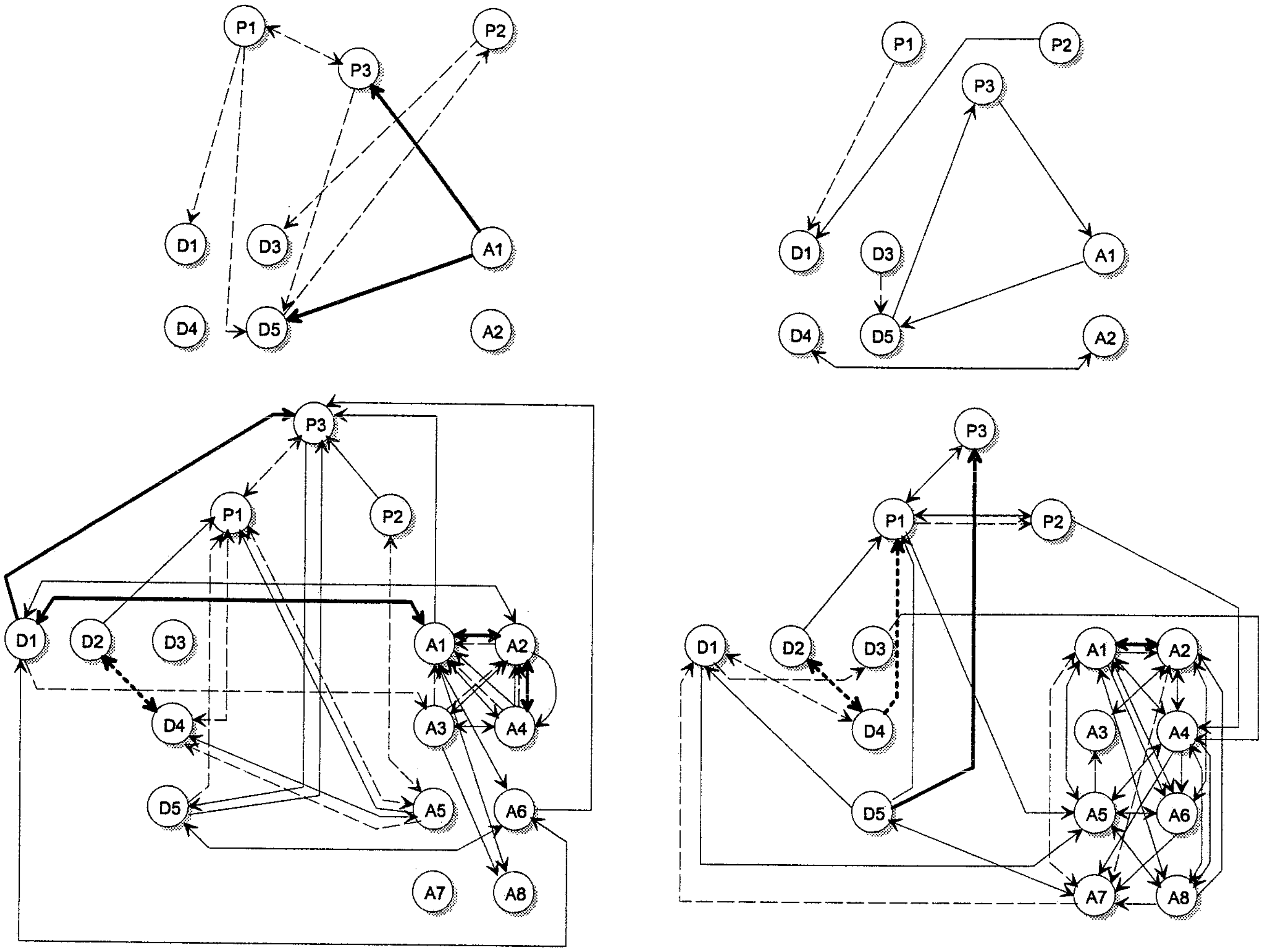

Figure 6. Results of the correlation analyses for schedulers 1, 2, 3 and 4. A double-arrowed line indicates a correlation with zero time lag. An arrow indicates a correlation with a time lag, where one variable causes the other, according to the sign of the time lag. A dashed line indicates a negative relationship. A thick line indicates a strong relationship ($r > 0\cdot750$).

P1	service level	D2	material availability	A1	workload	A5	Δ start weeks
P2	runouts	D3	lost stock	A2	batch size	A6	Δ batch size
P3	turnover rate of stock	D4	reliability prognoses	A3	slack	A7	Δ slack
D1	unscheduled production	D5	available capacity	A4	order slack	A8	Δ order slack

on the shopfloor in forthcoming weeks. However, 3 weeks later, the scheduler again *decreases* the workload on the shopfloor. And finally, the scheduler again *increases* the workload (note: this multiple relationship between variables is not caused by autocorrrelations within variables). Similar multiple relationships can be found between other action parameters and can be recognized in Figure 6 by multiple lines between variables.

Table 2. Part of the correlation matrix for scheduler 3.

	A1		
A4	lag = −5	+	0·654
	lag = −2	−	0·566
	lag = 0	+	0·605

Fourth, the action parameters of schedulers 3 and 4 show that at busy times (i.e. a high workload), almost all the other action parameters are adjusted in the same direction, i.e. putting more pressure on the shopfloor. This conclusion can be drawn from the fact that in Figure 6, many interrelations exist between the action variables at schedulers 3 and 4. For example: both schedulers have a very strong correlation between the

Table 3. Correlations between workload (A1) and batch size (A2).

Scheduler 3	Scheduler 4
0·770	0·963

workload and the batch size (see also Table 3). Apparently, if the production unit has to comply to a higher output, the scheduler increases the mean batch size of workorders. Similar relations exist between other action parameters.

Fifth, some actions of schedulers 3 and 4 work positively in the short term, but negatively over the longer term. Consider for example the relation between the amount of rescheduling of the start-date (A5) and the service level (P1) in Figure 6. There is a positive relationship with time lag + 1 (i.e. the rescheduling actions effect a higher service level) but a negative relation with time lag 0 (i.e. the rescheduling actions lead to a lower service level). The exact correlation coefficients are given in Table 4.

Sixth, the reliability of prognoses influences the performance of schedulers 3 and 4 in two ways (see Figure 7): first the reliability of prognoses influences the service level of the components (variable D2), because the production unit that manufactures components (also) has to depend on prognoses. If the prognoses are unreliable, the material availability will drop. Second, the reliability of prognoses influences the service level of schedulers 3 and 4 directly. The schedulers of these production units have to cope with low volume flexibility, long setup times, and long throughput times (see also Table 1), and the seventh result). Therefore, the schedulers cannot quickly react to rapid changes. Consequently, if the prognoses are unreliable, the service level will drop.

Seventh, when we look at Figure 6 it becomes clear that the production units of schedulers 1 and 2 are able to adjust their production capacity (D5) to the amount of workload (A1). However, the production units of schedulers 3 and 4 are *not* able to adjust their capacity (D5) to the amount of workload (A1).

6. Methodological discussion

Table 4. Part of the correlation matrix for scheduler 3.

	A5		
P1	lag = 0	−	0·596
	lag = 1	+	0·547

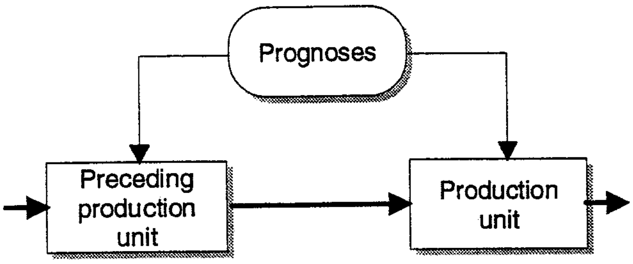

Figure 7. The impact of prognoses.

This paper has striven to shed more light on human scheduling in practice by presenting a research project in which a comprehensive quantitative model has been used to research the decision behaviour of four schedulers. We are aware that the quantitative research that has been described in the paper has its advantages as well as its disadvantages. The main drawback of using a quantitative model is the danger of oversimplification of a complex real-world process. The quantitative model only shows (a part of) the *inputs* and *outputs* of the decision behaviour of the schedulers. The actual scheduling *process* remains hidden in a black box. The decision processes of the scheduler could be studied by means of verbal protocols; i.e. think aloud protocols (Ericsson and Simon 1980). However, the relation between the decision process and the outcome of the process is very hard to understand in production scheduling. We think that quantitative research as presented in our paper, and qualitative research that, for example, uses verbal protocols, can be used complementarily to obtain the total picture.

The results of the statistical data analysis consist of a spaghetti of relationships that is not easy to interpret. However, we were not interested in detailed results—e.g. exact beta-coefficients of relationships between variables—of the analyses. When we keep this in mind, many interesting conclusions can be drawn from the complex results of the analysis, as shown in Section 5 of this paper. These results lead to recommendations for the company, which are described in Section 7.

Research as described in this paper is not applicable to any production unit. The reason for this is, that data about actions, performance and disturbances are not available in many production units. We also had to cope with limited data availability, especially with schedulers 1 and 2. Because these schedulers use a different information system from schedulers 3 and 4 to transfer workorders to the shopfloor, their schedule could not be copied.

An important methodological insight comes from the results of the analyses themselves. The results of the case study show that schedulers who control production units that are comparable have a different decision behaviour. Therefore, when we will study decision behaviour of schedulers in future research, we have to analyse the decision environment of the schedulers in greater detail to be able to understand these differences.

7. Recommendations

The results that have been presented in Section 5 of this paper can be used as a starting point for further measures to improve the scheduling process. These measures concern the following topics:

First, the amount of runouts is difficult to explain by the parameters in the model. We would expect that the amount of runouts (P2) would be influenced by the reliability of the schedule (P1). This is only the case with scheduler 4. It is advisable for the company to further investigate the causes for runouts. One possible way to decrease the amount of runouts is to let the schedulers discuss together how they try to prevent runouts. The scheduler that has the fewest runouts (scheduler 3) uses red marks to distinguish critical workorders on the shopfloor from other workorders. This sequencing technique could work for the other schedulers as well.

Second, the decision behaviour of the schedulers indicates that the throughput times—which have not been measured in this study—have the potential to become high and variable, especially in busy periods. When the workload (A1) rises, most other action parameters are adjusted in the same direction. In such cases, the shopfloor has to reach a higher output under more constrained conditions. A well-considered trade-off has to be made between utilization and throughput times. Also, the cyclic scheduling procedure (see also Section 2.2), which causes much inflexibility, can be reconsidered, along with the inflexibility of the production unit.

Third, the prognoses have a twofold impact on the performance of schedulers 3 and 4 as indicated in Figure 7. Also, the production units of schedulers 3 and 4 are not able to adjust their production capacity to the amount of work. Two measures can be taken to cope with these problems (1) increase the volume- and mix-flexibility of the production units; and (2) increase the reliability of the prognoses.

Fourth, it seems that the relationship between actions and effects is not always clear to the schedulers. The results of the study show that the decision behaviour of the schedulers sometimes shows nervousness, and that actions, taken to improve the schedule on the short term, impair the situation over a slightly longer term. The schedulers would be able to improve their decision behaviour if they would be able to relate their actions to the effects of their actions. This can be accomplished by providing *cognitive* or *learning oriented feedback* to the schedulers (Jacoby *et al.* 1984, Early *et al.* 1990, Johnson *et al.* 1994). While outcome feedback only shows the response of the production unit in terms of performance variables, learning oriented feedback shows how these performance variables relate to the actions of the scheduler. An example of learning oriented feedback can be found in den Boer (1994), where a decision support system for material planners is presented. In this decision support system—that by the way is implemented in another department of the same truck manufacturing company—the relationships between parameter values (e.g. safety stock) and performances (e.g. service level) are presented to the planner in scatterplots. We think that learning oriented feedback in the scheduling task can be provided by a simplified and adjusted version of the research model that is presented in this paper.

8. Conclusions

This paper described a case study that has been carried out in a truck manufacturing company. In the case study, a quantitative model has been used to study the *inputs* and *outputs* of the decision behaviour of four human schedulers. The model consists of three blocks: performances, actions and disturbances. These blocks have been operationalized by 16 variables, that have been measured weekly during a period of 4 months. The average percentage of explained variance of the performance variables is 51%. Results have been given regarding differences between schedulers, the relation between the schedule and production unit performance, nervousness in decision behaviour, putting pressure on the shopfloor in busy times, actions that work positively in the short term but negatively over the longer term, the impact of prognoses, and the flexibility of production units regarding capacity. A methodological discussion of the case study has been given, and recommendations for the truck manufacturing company have been presented.

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