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THE EFFECT OF TWO TRADING INSTITUTIONS ON PRICE EXPECTATIONS AND THE STABILITY OF SUPPLY-RESPONSE LAG MARKETS*

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ABSTRACT

A series of four experimental markets are described which examine the effect that different trading institutions have on sellers' price expectations and market behavior. The results suggest that when sellers trade in information rich auction markets, their price expectations are relatively complex and adaptive. When sellers trade in more information poor posted price markets, their expectations are relatively simple and extrapolative. This difference in the complexity of expectations is reflected in the stability of the markets, the auction markets being more stable than the posted price markets. Overall the study supports the notion that trading institutions contribute to the observed complexity of price expectations.

INTRODUCTION

Economic models of price expectation derive their predictions from general market conditions. Yet price expectations are formed under vastly different trading institutions, ranging from information rich auction markets to information poor posted price markets. Differences in trading institutions may help explain why price expectations are a "rich and varied phenomena" that may not be captured by any one model (Lovell 1986, p. 120).

The present study examines the effect that different trading institutions have on price expectations and market stability within a series of experimental markets. Previous studies have demonstrated the systematic effect that trading institutions have on other aspects of market performance, such as price or market efficiency (cf. Plott and Smith 1978). The effect that institutions have on price expectations has not been addressed. We focus in particular on supply-response lag markets. Such markets are unique in that supply or quantity decisions are made in a time period prior to that in which the supply actually becomes available. Price expectations are very central to the functioning of markets with a supply-response lag, affecting both individual as well as market level behavior.

Our research addresses three specific questions. First, which of the price expectation models currently available best describes the stability, or instability, of supply-response lag markets? Second, which models best describe the behavior of individual sellers facing a supply-response lag? Finally, does the appropriateness of these models vary with the trading institution involved? We begin by describing existing economic models of price expectation and their psychological complexity. We then describe the inherent differences in trading institutions and our predictions. Finally we examine expectations and market stability using naturally occurring market behavior under two very different exchange institutions, double-auctions and posted prices.

PRICE EXPECTATIONS IN SUPPLY-RESPONSE LAG MARKETS

A number of different models have been used to describe sellers' expectations and behavior in supply-response lag markets. Five prominent models, the traditional cobweb model, an extrapolative model, an adaptive model, a moving average rational expectations model, and Muth's (1961) original rational expectations model, exemplify increasing levels of judgmental complexity and market stability.

Traditional Cobweb Model

The traditional theory of price expectations in supply-response lag markets is the cobweb model. According to the model, suppliers base their price expectations and resulting supply decisions on the observed market price in the immediately preceding period. That is:

$$P^e_t = P_{t-1}$$

where P^e_t is the expected price in time t and P_{t-1} is the market clearing price in time t-1. This expectation function has important implications for market stability. The cobweb model predicts that when supply decisions are based on this expectation, both price and quantity fluctuations result. These fluctuations are by definition two periods long and will increase or decrease in magnitude depending on the relative slopes of supply and demand (cf. Carlson 1967). Whenever demand is steeper than supply the result is long run market instability. When supply is steeper than demand, price and quantity fluctuations decrease rather than increase over time and the market eventually reaches a stable equilibrium.

Extrapolative Model

The lack of long run cyclical instability in actual markets led to variations on the cobweb model to reconcile theory with data. Goodwin (1947) introduced a version of the cobweb model in which producers expect price to change by some constant factor times the most recent change in price. His expectation hypothesis can be stated as follows:

$$P^e_t - P_{t-1} = -p(P_{t-1} - P_{t-2})$$

where -p is termed the "extrapolative coefficient of expectation." In the extrapolative model, prices in periods t-1 and t-2 determine the suppliers' expected price and resulting supply decisions. Price expectations are essentially a weighted average of prices over the past two market periods. As in the case of the traditional cobweb model, this expectation function will result in either long run stable or unstable two-period cycling depending on the relative slopes of supply and demand. Muth (1961, p. 272) shows that stability will result whenever demand is more than three times as steep as supply.

Adaptive Model

As an alternative to both the traditional cobweb and the extrapolative variation, Nerlove (1958) postulated that suppliers more gradually change their expectations regarding price. Nerlove suggests that expected price is adjusted by how wrong the expected price was in the last period. The expected price in period t is a weighted average of the last expected price and the most recent actual price with the weights summing to one:

$$P^e_t = \mathbf{b}P_{t-1} + (1-\mathbf{b})P^e_{t-1}$$

with $0<\mathbf{b}<1$ where **b** is referred to as the "adaptive coefficient of expectation." Carlson (1967) presents a geometric interpretation of this model in which a decrease in **b** has the effect of rotating the demand curve counter clockwise, decreasing the absolute value of its slope and increasing the range of relative supply and demand slopes that should produce stable equilibriums. The traditional cobweb is a special case of the adaptive model when $b=1$.

A particular aspect of this model makes it qualitatively different from previous cobweb models. All past period observations are allowed some weight toward the current expectation. The model is more complex in its use of available market information or, put differently, less "biased" in its dependence on P_{t-1}. The weight of past period observations must simply decline exponentially into the past. No matter how steep demand is relative to supply, there exists a sufficiently small coefficient of expectation that will produce stability. The inverse, however, does not hold. Given an adaptive coefficient of expectation, there will always exist supply and demand curves which predict unstable cobwebbing (Carlson 1967).

Rational Expectations Models

Two potential problems persist in the cobweb models outlined above. First, in every model price expectations are biased toward immediate past period prices. Of course the heaviest bias exists in the traditional model. The economic argument against the existence of a bias is quite simple. Such a bias would result in systematic forecasting errors and profitable opportunities for sellers of more accurate forecasts and thus be eliminated over time. A second more serious concern is that the two period long price and quantity fluctuations predicted by the cobweb models are rarely found. Observed cycles tend to be much longer (Pashigian 1970).

The theory of rational expectations (Muth 1961) provides an alternative framework for analyzing supply-response lag markets without assuming biased price expectations. Under the rational expectations hypothesis, the mean price expectation of the firms in a market is simply the prediction made by the relevant economic theory (i.e., the law of supply and demand). Each actor or firm has an expectation and the economic equilibrium is the weighted arithmetic mean of these expectations.

$$P^*_t = (P^e_{t1} + P^e_{t2} + \ldots\ldots P^e_{tn})/n$$

where P^*_t is the equilibrium price in time t, P^e_{ti} is the expected price in period t by firm i (i=1 to n), and n is the number of firms in the market. Put simply, Muth's rational expectations hypothesis predicts that the price in time t is equal to the expected price in time t.

$$P_t = P^e_t$$

The rational expectations prediction of market stability in supply-response lag markets is quite clear. Expectations should lead directly to an equilibrium or stable value. Instability, if observed, can only result from shifts or shocks in supply and/or demand causing temporary disequilibrium.

However, Muth provides no description of the process by which rational expectation are realized. In response, Cyert and DeGroot (1974) introduced the concept of Bayesian revision of expectations into a rational expectations framework. According to their model, learning is continually taking place in the market. Priors are continually being modified as information is accumulated from period to period resulting in convergence toward the equilibrium price and quantity. Price expectations in this context are qualitatively equivalent to a moving average of previous market prices.

$$P_t = (P_1 + P_2 + \ldots P_{t-1})/(t-1)$$

Carlson (1968) hypothesized an expectation function along these same lines and proved that it leads to stable equilibrium conditions. When suppliers do not believe the market has changed and, as a result, they equally weight all previous observations, even supply-response lag markets must converge to equilibrium. Carlson argues that an "invariably stable" cobweb holds whenever Walrasian stability conditions are satisfied. Auster (1970) extended Carlson's proof, arguing that even when Walrasian stability conditions fail to hold, supply-response lag markets with a moving average expectation function are stable whenever demand is bounded from above. Rational expectations does not imply the absence of price cycles. Any cycling should, however, be qualitatively different, in both origin and form, from that predicted by cobweb models. The cumulative effects of random shocks on supply and demand may cause "apparent" cycles under rational expectations. These apparent cycles should be much longer than the two period cycles of a cobweb, and seldom less than four periods long (Pashigian 1970).

The Process Behind the Models

The five models described above, from the traditional cobweb to rational expectations, represent increasingly complex expectations and associated market stability. The traditional cobweb model posits an extremely simple expectation function and is the most likely to produce instability. At the other extreme, the rational expectations models posit complex expectation functions and always predicts stability. The extrapolative, adaptive, and moving average models, meanwhile, are particularly attractive from a judgment process standpoint. All three are essentially information integration models of judgment and represent some degree of information "averaging."

Averaging models are very common in judgment research (cf. Anderson 1981). Part of their appeal stems from their underlying consistency with the psychological process of anchoring and adjusting (Einhorn and Hogarth 1985; Lopes and Johnson 1982). According to anchoring and adjustment (cf. Tversky and Kahneman 1974), people anchor their judgment on some salient aspect or piece of information and make adjustments to incorporate additional information. In the adaptive model, sellers may anchor on their expected price from the previous period and adjust their judgment by considering the actual price for that period. Put differently, adaptive expectations imply that sellers hold existing beliefs that they adjust based on currently available information. In the moving average rational expectations model, the average of all past period prices serves as an anchor that is updated or adjusted each period. Although the adaptive and extrapolative models are "biased" relative to rational expectations, they appear more plausible from a judgment process standpoint.

The experiments described below test the ability of each of these models to both predict market behavior and explain individual supply decisions.

Empirical Studies

Existing research on price expectation has involved either survey-based data or controlled laboratory experiments. Although rational expectations is often invoked to explain the overall stability of markets, these studies often find that micro-level (individual) behavior does not conform to rational expectations. While in some cases forecasts may be described as rational, in many cases forecasts are more consistent with adaptive expectation functions (see Lovell 1986 for a review of the relevant studies).

Two studies deserve particular mention because of their focus on price expectations in experimental markets. In the only existing experimental test of supply-response lag markets, Carlson (1967) showed showed some support for rational expectations. However, shortcomings of Carlson's study negate the significance of his results. First, in three of the four experiments Carlson conducted, the markets started (by accident) at essentially an equilibrium position. Ideally, any test of expectations and market stability should demonstrate the tendency of a market to reach an equilibrium. To do so, a market should start at a sufficient disequilibrium position. Second, Carlson examined only one particular trading institution, a posted one-price market. All subjects were sellers who made quantity decisions and received price feedback from a prespecified or passive demand curve.

More recently, Williams (1987) used computer-based double auction markets (that did not contain a supply-response lag) to study price expectations. He found price forecasts to be more consistent with adaptive expectations than with either rational or extrapolative expectations. Again, however, only one trading institution was employed. As argued earlier, expectations appear to be a rich and varied phenomena that may not be explained or described independent of the trading institution involved.

TRADING INSTITUTIONS AND PRICE EXPECTATIONS

For our purposes, a trading institution is the procedure or rules under which transactions in a market are made and prices are determined. At one extreme, prices may result from a series of bids and offers by both buyers and sellers, as in the case of double-auction markets. At the other extreme, prices may simply be posted for buyers to accept or reject. Recall that expectation models derive predictions from "general" market conditions, such as a supply-response lag, without considering the effect of specific trading institutions on expectations or stability.

However, a central principle of economic theory is that available information is, in fact, used. This suggests that the greater the range and quantity of market relevant information available to sellers, the more complex their expectations should become and the more likely or quickly the market as a whole will reach a stable equilibrium. For example, a double-auction market provides sellers with a wealth of information regarding the quantity and prices of units traded. In contrast, posted price markets restrict the amount and type of information available to sellers; sellers may only have access to a single, posted or market clearing price and have no information regarding the total market supply. This suggests that relatively biased expectations and unstable supply-response lag markets are more likely under information restricted posted price trading than under information rich auction trading.

Yet one must consider whether sellers are, in fact, able to use the information that is available in a double-auction. Central to an information processing approach to judgment and choice is that individuals have a limited capacity to gather and process information (Lachman et al. 1979; Newell and Simon 1972). As the information available to form a judgment or make a choice increases, individuals may adopt simple rules and limit their information search in order to stay within their processing constraints. Studies by Lussier and Olshavsky (1979) and Payne (1976), for example, found subjects adopting simpler rules and using more incomplete information to make decisions among larger choice sets. An alternative prediction, therefore, is that sellers operating in simple posted price markets are more capable of using available information in their expectation than are sellers operating in more complex auction markets. Thus sellers' expectations may be more complex and markets more stable under posted price trading than under double-auction trading.

In the four experiments reported below, individual and market behavior was observed under both double-auction and posted price trading. This allows for a test between these competing predictions. We begin by describing the experiments and the overall performance of each market. We then model each sellers' expectations across the four experiments.

METHODOLOGY AND DESIGN

In the present study, laboratory markets retaining the essential economic features of supply-response lag markets are used to test the applicability of the different economic models to individual and market behavior (Smith 1976; Plott 1982). Subjects participate as either buyers or sellers trading units of a commodity in a sequence of market trading periods. A major advantage of the methodology is that these markets meet the preconditions upon which the theories and their predictions are based. To say that laboratory markets are simulations of real markets and, hence, artificial approximations of the real thing would be false. Laboratory markets are fundamentally real in the sense that people earn income by engaging in organized trading activity.

Laboratory markets differ from naturally occurring markets in two ways. In laboratory markets, individual values (supply and demand) are controlled to meet the preconditions of economic theories. This control is accomplished by way of reward structures that induce prescribed monetary values on actions. A second difference centers on the trading institutions. Institutions in naturally occurring markets are in a constant state of evolution, affecting and being affected by the market. The two trading institutions used here, double-auctions and posted one-price markets, are held constant. This allows a more objective test of the relevant theories.

Particular supply and demand parameters are required in order to use the market level results of our experiments to test between the cobweb type models and the rational expectations models. Rational expectations models always predict stability. It is theoretically impossible for the supply-response lag nature of markets to cause instability under rational expectations. Any cobweb model, however, should predict instability as long as demand is sufficiently steep relative to supply. Recall that when demand is more than three times steeper than supply, both the traditional cobweb model and the extrapolative model predict instability. The adaptive model poses a different problem. Stability conditions under this model depend on the size of the adaptive coefficient of expectation. Predictions can only be determined after the fact. In each of the four experiments conducted here, demand is eight times steeper than supply. The adaptive coefficient will be estimated for each seller on the basis of individual supply decisions. If the estimated coefficients predict instability in the markets and they fail to be unstable, this would suggest rejecting the whole class of cobweb models in favor of rational expectations at the market level.

Experiments one and two use a double-auction trading institution in which buyers and sellers make bids and offers to buy and sell units of a commodity. Buyers and sellers are directly involved in the trading process. Experiments three and four utilize a passive one-price market. In these markets, sellers made quantity decisions and received feedback regarding the market clearing price from a passive demand curve. Sellers were not directly involved in the trading process. These two market institutions represent extremes in the involvement of sellers in the trading and, as a result, represent varying amounts of information available to sellers making supply decision. It is reasonable to assume that most actual supply-response lag markets are either equivalent to or lie between these two extremes.

EXPERIMENT ONE

Procedure

In both experiments one and two, six participants were sellers and six were buyers. The participants in all four experiments were a mix of graduate and undergraduate students at The University of Chicago. Values for the units traded were established using Induced Value Theory (Smith 1976). Each seller received a marginal cost schedule containing the cost incurred for each unit sold. Each buyer received a similar schedule containing the value at which each unit purchased could be redeemed to the experimenter after the experiment. (See Plott (1982) for more details regarding the schedules and instructions used in these types of laboratory markets.) Each experiment consisted of a series of market trading periods. As mentioned, the institution used in experiment one was a double-auction. In each trading period, buyers were free to make oral bids to buy units and sellers were free to make oral offers to sell units. Each trading period lasted seven minutes. The currency used in the experiments was francs. All cost schedules, redemption values, bids and offers were stated in francs. At the end of the experiment, the subjects multiplied their total earnings in francs by an exchange rate to determine their earnings in dollars.

Experiment one involved ten trading periods. In period one no supply-response lag was imposed on the sellers in order to familiarize both buyers and sellers with the trading procedure. Sellers (buyers) could sell (buy) as many units as they wished, one at a time, while continuing to make a profit. Beginning with period two and continuing through period ten, a supply-response lag was introduced. Sellers were required to make supply decisions prior to the beginning of each period. Once this decision was made, the sellers incurred the costs of all units declared for that period. Any unsold units represented a loss to the sellers equal to the marginal cost of those units.

A particular goal of our procedure was to create a disequilibrium state and then observe the tendency or failure of supply-response lag markets to reach an equilibrium. To do so, two different demand schedules were used.

Insert fig. 1 about here

The supply and demand schedules used in all four experiments are shown in fig. 1. In trading periods one and two, the trial periods, sellers faced supply S and buyers faced Demand D_1 (equilibrium p=90, q=6).[1] In periods three through ten, the experimental periods, sellers faced supply S (slope = .5) and buyers faced demand D_2 (slope = -4). Shifting the demand parameters from the trial to the experimental periods was intended to start the experimental periods at a sufficient disequilibrium position. If rational expectations is correct, price and quantity should converge to their long run equilibrium values (p=120, q=18). If supply-response lag markets follow cobweb model predictions, price and quantity should fluctuate systematically around the equilibrium price and quantity in two period long cycles. These fluctuations should increase over time resulting in an unstable market.

Results

The average contract prices for experiment one are presented at the top of fig. 2. (The dotted line represents the equilibrium price of 120.) The results reveal a clear tendency for market stability over time. After a period of initial instability following the parameter shift, market prices converge toward and remain close to the rational expectations equilibrium in subsequent periods. This long run price stability is mirrored by reasonable stability in both individual and aggregate quantity decisions. The table reports the individual quantities and total market supply by period. Here too an initial period of instability is followed by general convergence. (In equilibrium, each seller should be supplying three units.)

Insert fig. 2 and table about here

Market supply in any given period implies a corresponding short run equilibrium price. These short run price predictions, along with the average prices, are presented in the table. What is interesting is that changes in the overall quantity supplied from period to period did not drastically affect prices. Under the supply and demand parameters of this market, small deviations in quantity supplied away from the equilibrium value imply rather large deviations in short run equilibrium prices. However, price remained close to the rational expectations or long run equilibrium despite short run economic predictions.

The market in experiment one was fairly efficient. In an experimental context, market efficiency refers to the amount of money earned by the market participants relative to the maximum amount that could be extracted from the experimenter. In a supply-response lag market, efficiency can be measured as a function of either short run or long run quantity supplied. The amount of money extracted as a percentage of possible earnings given the actual quantity supplied in each period reflects short run efficiency. The amount of money extracted as a percentage of possible earnings given the long run or optimal quantity supplied reflects long run efficiency. These measures (not shown) reveal that by the third experimental period (period 5), both efficiencies converged and remained close to 100%.

EXPERIMENT TWO

Procedure

At least at the market level, experiment one supports the stability of supply-response lag markets and the rational expectations hypothesis. However, a potential problem with experiment one was the failure of short run prices to adjust to short run changes in demand. This phenomena limited the disequilibriating effects of the trial period parameters. There seems to be two possible causes for this phenomena. Sellers may have been "soft" in accepting bids because of inadequate sales incentives under the trial period parameters. (As described in footnote 1, the supply schedule was flat for sellers over the first six units sold in experiment one.) The increased seller profits early in the experimental periods may have appeared quite satisfactory compared to trial period earnings. A second possible cause relates to the parameter shift itself. Price may eventually reach the short run equilibrium given sufficient time to adjust to the change. The lack of adjustment in experiment one may have contributed to the market's stability.

Experiment two replicates experiment one while correcting for these potential problems. Experiment two differs from experiment one in three respects. First, sellers' costs for the first five units supplied were reduced to correspond with the supply curve in fig. 1. This should provide sellers with more adequate incentives during the trial periods. Second, the quantity decisions for experimental period one (period 3) were held constant for the first two experimental periods (periods 3 and 4). Finally, the subjects were told that a parameter shift had occurred. Informing the buyers and sellers of a change and allowing short run price more time to adjust to the initial disequilibrium position should avoid the potential problems confronted in experiment one.

Results

The average contract prices by period, shown in fig. 2, again reveal a clear tendency for stability and support for the rational expectations hypothesis at the market level. Similar to experiment one, a period of initial instability following the parameter shift is followed by convergence to the long run equilibrium. Moreover, most of the initial instability can be attributed to the disequilibriating effects of the trial period parameters. The procedural changes instituted in this experiment accomplished their objective. Referring to the table, short run prices adjusted to the short run equilibriums early in the experimental periods. The quantity decisions, similar to those in experiment one, became increasingly stable over time. And once again the market was efficient. By period six, both short run and long run efficiency (not shown) were at the 95% level.

EXPERIMENTS THREE AND FOUR

Procedure

Sellers in the double auctions of experiments one and two witnessed the transaction price for each unit traded. This gave them access to both aggregate quantity and substantial price information. The information available to sellers in a posted one-price market, in contrast, is limited to their own quantity supplied and the market clearing one-price. Experiments three and four replicate experiments one and two using a passive one-price trading institution.

Sellers in the experiments faced the same parameters as in experiment two. These parameters should place the markets in an initial disequilibrium position. Short run price in a passive one-price market adjusts automatically to the level of demand that clears the market. This avoids the short run adjustment problems encountered in experiment one. The automatic adjustment also allows for more observations (trading periods) under the experimental parameters.

In each experiment six participants were sellers in a sequence of market trading periods. Unit values were again established using Induced Value Theory. Before the beginning of each period, sellers made their supply decisions and the costs for units supplied were incurred at that point. Once the sellers made their decisions, the experimenter aggregated the supplies (without revealing the aggregate supply to the sellers), and determined the market clearing one-price. Sellers recorded this price as the contract price for all units supplied and calculated their earnings. This process continued for twenty periods. In trading periods one through four, sellers faced demand D_1. In the experimental periods, trading periods five through twenty, sellers faced demand D_2 (equilibrium quantity=18, price=120). As in experiments one and two, the trial periods familiarized the subjects with the procedure and served to start trading at a disequilibrium position when the parameter shift occurred. Unlike experiment two, it was unnecessary to hold quantity decisions constant from the first to the second experimental period.

Again, rational expectations predicts price and quantity will converge to their equilibrium values while the cobweb models predict systematic fluctuations around price and quantity. These fluctuations should be two periods long and increase over time resulting in long run market instability. Our prediction is that limiting the available information by instituting posted price trading should result in a decrease in the complexity of price expectations and associated market instability.

Results

The short run market clearing prices for experiments three and four are presented in fig. 2. Although the markets in experiments three and four generally converged toward equilibrium, price and quantity fluctuated in two-period cycles more than they did in experiments one and two. There are brief periods of cobweb like cycling in both of the posted price markets, though no prolonged cycling occurs. Overall the results of all four experiments fail to support the long run instability predicted by the cobweb models. At the same time, and consistent with our prediction, posted price markets appear less stable than double-auction markets.

MODEL ESTIMATIONS

In this section we examine each model's ability to explain each sellers' quantity decisions. Assuming that each subject was acting to maximize profits, it is possible to derive expected prices from the subjects' quantity decisions. Expected price is simply that which maximized expected profits for the actual quantity supplied in any given period.[2] These expected prices, along with the actual prices in the market, allow us to estimate each model for each subject. Estimating the adaptive expectations model also provides this model's market level predictions.

Analysis

Each subject's quantity decisions were used to derive estimations of their expected price in each experimental period of each experiment. For experiments one and two, the actual price in each period was assumed to be the average of all the contract prices observed during that period.[3] For experiments three and four, the actual price in each period is simply the short run market clearing price.

The traditional cobweb model was tested by estimating a linear function of the form:

$$P^e_t = \mathbf{a} + \mathbf{b}(P_{t-1}) + \mathbf{n}_t$$

where $\mathbf{a}$ is a constant and $\mathbf{n}_t$ is an independent and identically distributed random variable with zero mean and finite variance. (These assumptions are implicit in all further analyses.) The extrapolative model was tested by estimating a linear function of the form:

$$P^e_t - P_{t-1} = \mathbf{a} - \mathbf{b}(P_{t-1} - P_{t-2}) + \mathbf{n}_t$$

The adaptive expectation model was tested by estimating a linear function of the form:

$$P^e_t - P^e_{t-1} = \mathbf{a} + \mathbf{b}(P_{t-1} - P^e_{t-1}) + \mathbf{n}_t$$

(Recall that under our supply and demand parameters, this model predicts instability when the adaptive coefficient, $\mathbf{b}$, is greater than .22.) Muth's original rational expectations model was tested by estimating a linear function of the form:

$$P_t = a + b(P^e{}_t) + n_t$$

In its strictest form, Muth's model predicts that **a** should equal zero while **b** should equal one (Lovell 1986). Finally, the moving average rational expectations model proposed by Cyert and DeGroot was tested by estimating a linear function of the form:

$$P^e{}_t = a + b[(p_1 + p_2 + \ldots p_{t-1})/(t-1)] + n_t$$

Each model was estimated for each individual in each experiment, or 120 estimations.

Only a subset of the experimental periods were included in the estimation of particular models. The overriding criterion here was to estimate each model using parameter estimates based only on information from the experimental periods. Muth's rational expectations model, which presumes no lag, was tested using all of the experimental periods. The traditional cobweb model, the adaptive model, and the moving average rational expectations model, all of which require parameter estimates from time period t-1, were estimated using n-1 observations (where n is the number of experimental periods). The extrapolative model, which requires parameter estimates from time periods t-1 and t-2, was estimated using n-2 observations. Because supply decisions were held constant for the first two experimental periods of experiment two, the first of these periods was ignored. Of the 120 possible estimations, 8 could not be estimated due to a lack of variance in one or more parameters over the experimental periods leaving 112 usable estimations.

The dependent measure of interest is the fit of each model as reflected by the squared correlation coefficient. Whereas R-squared reflects the variance explained by the model, a simple correlation coefficient has no such clear-cut, intuitive interpretation (Neter and Wasserman 1974, p. 90). Looking only at R-square, however, we lose the direction of the relationship. Therefore, the R-square fit measures were given positive values as long as the estimated relationship was in the direction predicted by the model. The R-square measures were assigned negative values if the estimated relationship was in the opposite direction from that predicted by the model. (For example, the extrapolative model predicts a negative relationship while the adaptive model and Muth's model predict positive relationships.)

An analysis of variance model, using a general linear models procedure, was estimated in order to test for significant differences in fit across the five models and the two trading institutions. The critical independent variables in the analysis were the economic model estimated (Cobweb, Extrapolative, Adaptive, Moving Average Rational Expectations, or Muth Rational Expectations), the type of institution involved (Double-Auction or Posted Price), a model by type of institution interaction, and a random effects variable for experiments one through four (nested within type of institution). Again, we predict that the more complex expectations models are more applicable in the more complex double-auction markets. Alternatively, if subjects faced information processing limitations, we may observe the opposite: the more complex models may be more applicable in the simpler, posted price markets. In either case the prediction is a significant interaction between the model estimated and the type of institution.

Results: Model Fits

The analysis of variance results reveal a significant difference in fit across models ($F=46.57$, $p<.001$). The average fits equaled .042 for the traditional cobweb model, .356 for the extrapolative model, .501 for the adaptive model, -.005 for the moving average model, and -.363 for Muth's model. Notice that these average fits, ordered from the simplest expectation function of the cobweb model to the most complex expectations of Muth's model, are nonmonotonically related to the complexity of the expectation functions. Sellers' expectations, though more complex than those assumed by the traditional cobweb model, do not appear as complex as those assumed by rational expectations. The adaptive and extrapolative models provide the best descriptions of the implicit price expectations. Muth's model is the lowest scoring model on our fit index. In fact, the negative average fit of Muth's model supports a negative rather than positive relationship between actual and expected prices, or "irrational" expectations. Of the 23 subjects for which this model could be estimated, 20 showed a negative relationship between actual and expected price. The overall superior fit of the adaptive model is consistent with William's earlier experimental results as well as the results of several survey-based studies described by Lovell (1986).

Insert fig. 3 about here

The important result is the model by type of institution interaction effect depicted in fig. 3 ($F=6.03$, $p<.001$). Driving the interaction is a reduction in fit for the three most complex models (adaptive, moving average, and Muth rational expectations) and a corresponding increase in fit for the two simpler models (traditional cobweb and extrapolative). This is consistent with our general prediction. Of the remaining independent variables in the analysis of variance, type of institution had no simple main effect on model fit, and experiment one differed from experiment two ($F=29.74$, $p<.001$), probably due to the procedural differences in the two experiments. There was no significant difference between experiments three and four. The overall model R-square was .84.

The model by type of institution interaction is very evident for the superior fitting adaptive and extrapolative models. The extrapolative model, the simpler or more biased of the two, improves in fit from the complex double-auction markets of experiments one and two to the simple posted price markets of experiments three and four. In contrast, the fit of the more complex adaptive expectations model decreases. A separate analysis of variance model including only these two models again reveals the predicted model by type of institution interaction ($F=16.82$, $p<.001$).

Results: Model Coefficients

Under the experimental parameters of the four experiments, the adaptive expectations model predicts instability only when the adaptive coefficient of expectation exceeds .22. Despite the large difference in slopes for supply and demand in the experiments, the estimates of the adaptive coefficient averaged .92, .13, .16, and .16 respectively for experiments one through four. Thus the adaptive model and the rational expectations models all predict stability in experiments two, three and four. Recall that in strict form, Muth's model predicts a constant (**a**) equal to zero and a coefficient (**b**) equal to one. The average estimated constant and coefficient were not as predicted. The average constant (379.14) was significantly greater than zero and the average coefficient (-2.097) was significantly less than one ($p<.001$). These results are consistent with the observed poor fit of Muth's model at the individual level.

SUMMARY AND CONCLUSIONS

Price expectation models vary from simple and biased cobweb models to complex rational expectations models. The present study examined the ability of different economic models of price expectation to explain both market and individual behavior within four experimental supply-response lag markets. Two markets were operated under an information rich double-auction trading institution while two operated under more information restricted posted price trading.

Contrary to the predictions of both the traditional cobweb model and an extrapolative expectations model, all four experimental markets were relatively stable as price and quantity converged toward the long run economic equilibrium. These market level results are very consistent with the rational expectations hypothesis. It appears that both the traditional cobweb and extrapolative expectations can be rejected in favor of rational expectations as a model of market behavior. The adaptive model predicted instability only in experiment one. While this provides some evidence to reject the model at the market level, this conclusion is obviously tentative.

Although rational expectations explains the general convergence of the markets toward equilibrium, it does not explain the relative instability of the posted price markets compared to the double-auction markets. It also fails to describe the behavior of individual sellers. Both Muth's (1961) "black box" model and Cyert and DeGroot's (1974) moving average model were very poor at explaining sellers' quantity decisions. At a micro-level, rational expectation does not appear to explain the behavior observed here.

The main contribution of the present study is the observed dependence of individual expectations and market stability on the trading institution. Across the four experiments described here, an adaptive expectations model provides the best description of sellers' behavior under double auction trading markets while an extrapolative expectation model best describes sellers' behavior under posted price trading. The difference in the complexity of the sellers expectations was evident from the overall behavior of the markets. As predicted, sellers' expectations were more complex and market behavior more stable under information rich auction trading than under information restricted posted price trading. From a psychological standpoint, the superiority of the adaptive and extrapolative models at explaining individual behavior is not surprising. Both of these models represent variations on the averaging models often found in studies of human judgment (Anderson 1981). Both extrapolative and adaptive expectations are consistent with an anchoring and adjustment process. Finally, both are more realistic than rational expectations in terms of their inherent psychological complexity.

Overall the study provides three general conclusions. First, rational expectations explains the observed stability of supply-response lag markets. Second, individual behavior is more consistent with averaging rules of intermediate complexity, particularly adaptive and extrapolative expectations. Finally, individual seller behavior and resulting short-run market stability appear critically linked to the trading institution involved. Naturally the experiments presented here are limited. The failure of these markets to exhibit prolonged instability may, for example, be attributed to the compressed time span involved. It would be interesting, for example, to test the competing models by experimentally inducing longer time periods between decisions.

FOOTNOTES

1. In experiment one, sellers actually faced a constant cost schedule of 90 francs over the first six units sold. Experiments two, three and four operated under the exact supply schedule in fig. 1.

2. Our use of implicit, behavior-based estimates of price expectation rather than explicit price forecasts is consistent with Carlson's (1968) study. Williams (1987), in contrast, used explicit forecasts to model price expectations. Our double-auction results and model estimations are very similar to Williams, suggesting that both approaches are reasonable.

3. Alternatively one could argue that the relevant price for each subject in each period is either the average selling price of that subject's own units or the short run market clearing price for that period. The models were estimated under all three price assumptions and the sensitivity of the results examined. Overall the pattern of results and their significance did not vary with the price assumption.

FIGURE 1

SUPPLY AND DEMAND PARAMETERS FOR EXPERIMENTS

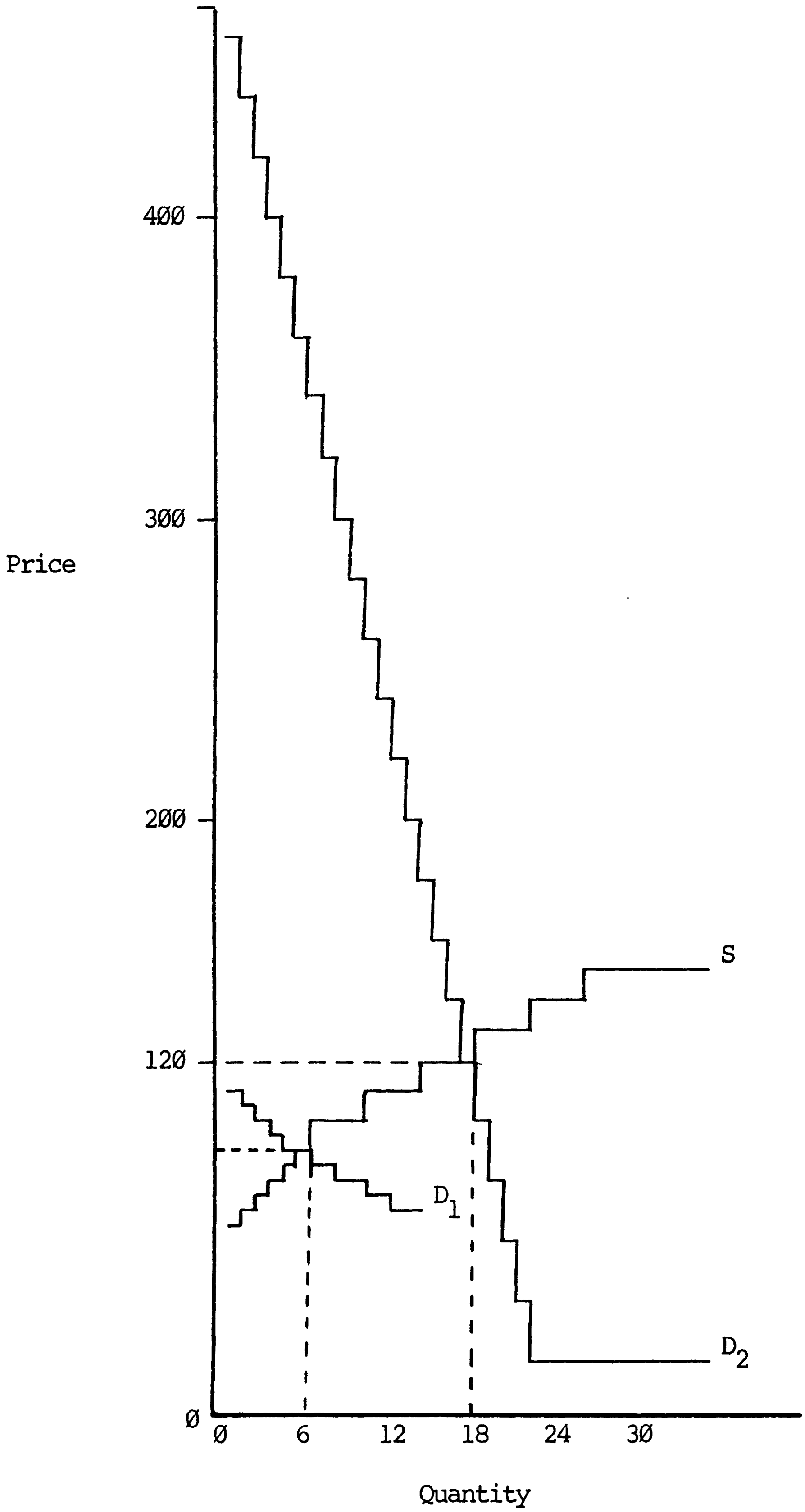
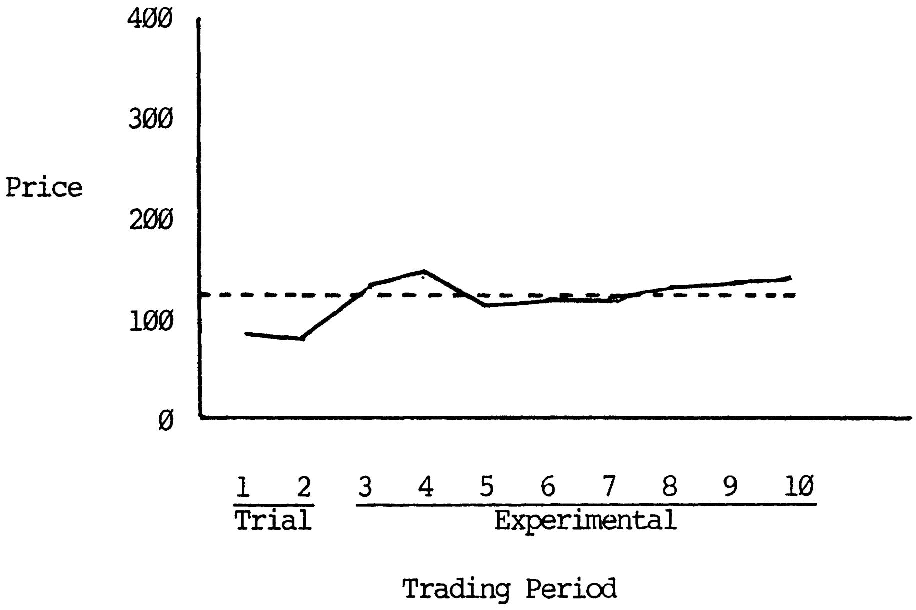


FIGURE 2

CONTRACT PRICES ACROSS EXPERIMENTS

Experiment One: Average Auction Prices



Experiment Two: Average Auction Prices

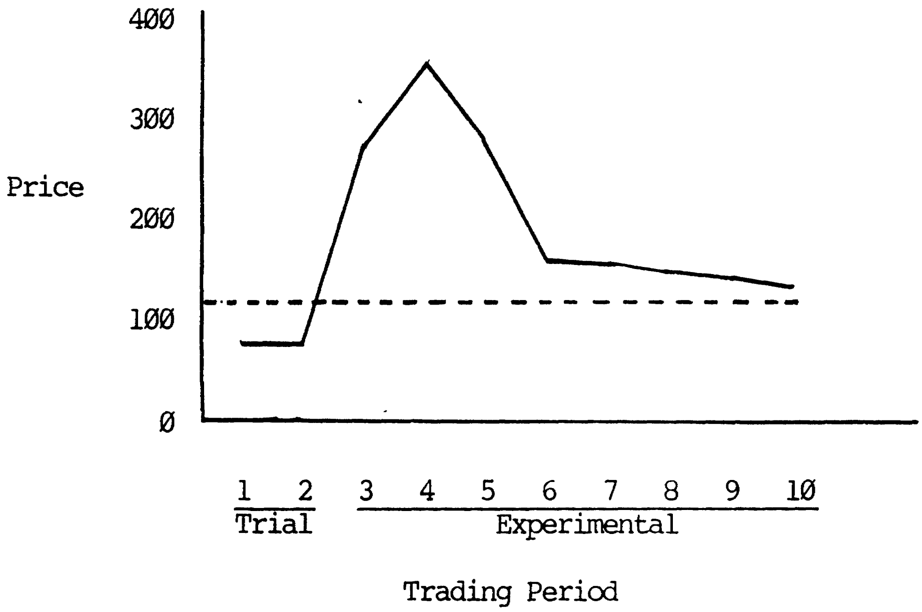
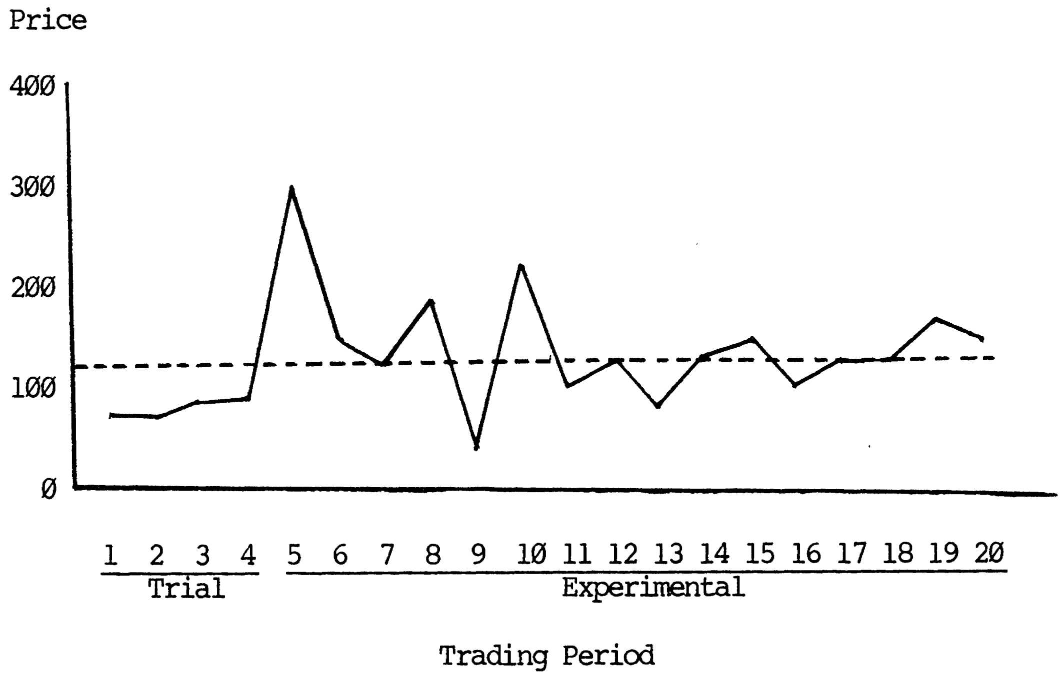


FIGURE 2

(Continued)

Experiment Three: Posted Prices



Experiment Four: Posted Prices

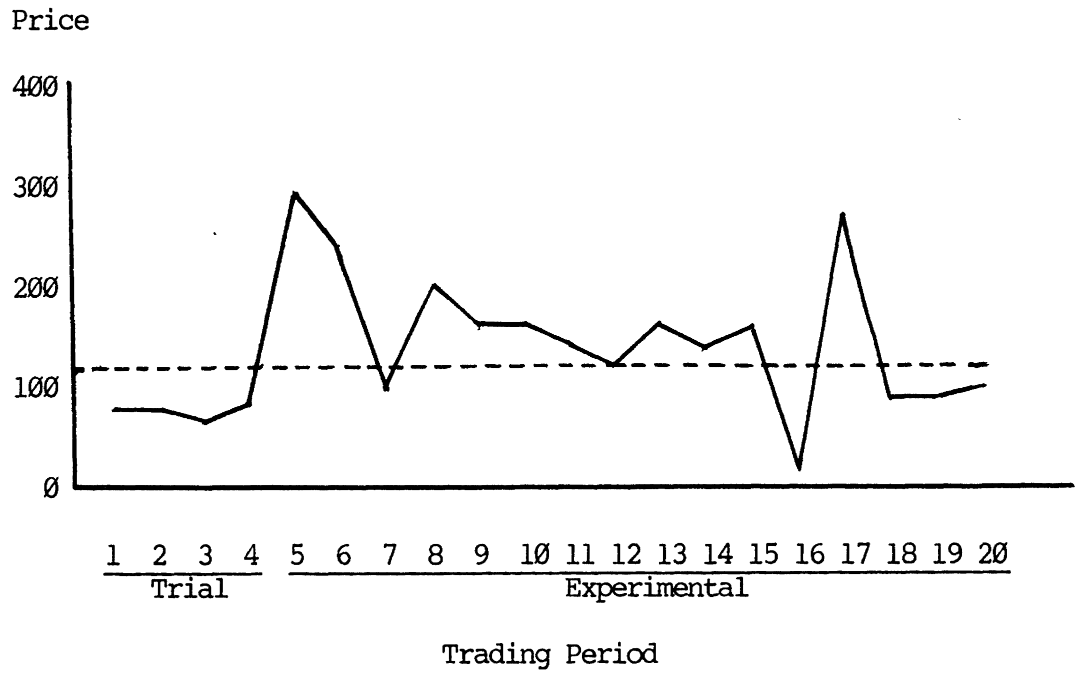
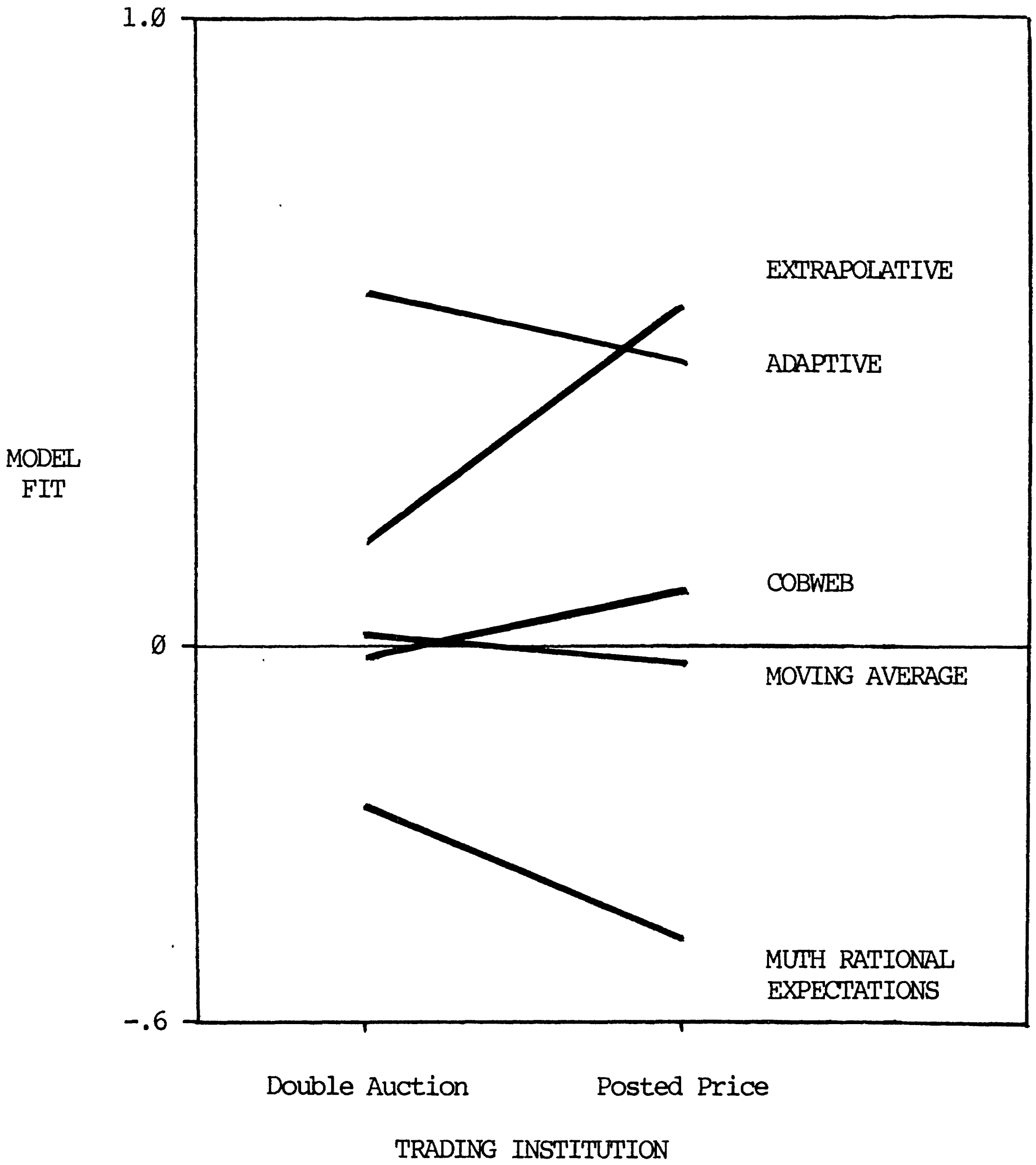


FIGURE 3

MODEL FIT BY INSTITUTION



TABLE

QUANTITY DECISIONS

EXPERIMENT ONE

	Trial Periods		Experimental Periods							
	1	2	3	4	5	6	7	8	9	10
Seller A	-	2	2	4	4	3	3	2	2	2
Seller B	-	1	1	2	3	3	3	3	3	3
Seller C	-	2	2	4	3	3	2	2	3	3
Seller D	-	2	2	2	2	3	2	3	3	3
Seller E	-	2	2	4	4	4	3	4	4	3
Seller F	-	1	1	5	3	3	3	1	3	2
Total	-	10	10	21	19	19	16	15	18	16
SR Price	-	80	280	60	100	100	160	180	120	160
Avg.Price	91	86	124	142	114	118	118	125	128	134

EXPERIMENT TWO

	Trial Periods		Experimental Periods							
	1	2	3	4	5	6	7	8	9	10
Seller A	-	5	1	1	5	2	2	2	4	4
Seller B	-	1	1	1	2	2	2	2	2	2
Seller C	-	1	1	1	3	3	1	2	2	2
Seller D	-	1	1	1	3	5	4	4	4	4
Seller E	-	2	1	1	3	3	3	3	3	3
Seller F	-	2	2	2	2	3	3	3	3	3
Total	-	12	7	7	18	18	15	16	18	18
SR Price	-	70	340	340	120	120	180	160	120	120
Avg.Price	87	87	273	347	278	160	155	142	138	130

TABLE

QUANTITY DECISIONS

(continued)

EXPERIMENT THREE

	Trial Periods				Experimental Periods															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Seller A	2	2	1	1	1	2	3	2	4	2	3	3	4	4	3	3	3	3	3	3
Seller B	3	2	1	1	1	5	3	2	4	1	3	2	3	2	2	3	3	3	3	2
Seller C	3	5	2	2	1	2	2	2	1	2	2	2	2	2	1	2	1	1	1	1
Seller D	3	3	3	1	3	3	4	3	5	3	5	5	5	5	5	5	5	5	5	5
Seller E	3	2	1	1	1	2	3	3	4	3	3	3	3	3	3	3	3	3	2	3
Seller F	3	2	2	2	2	3	3	3	4	2	3	3	3	2	3	3	3	3	2	3
Total	17	16	10	8	9	17	18	15	22	13	19	18	20	18	17	19	18	18	16	17

EXPERIMENT FOUR

	Trial Periods				Experimental Periods															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Seller A	3	3	2	2	2	3	5	2	4	5	3	3	3	3	2	5	2	3	3	4
Seller B	2	1	1	1	1	2	3	2	3	2	2	3	2	3	2	3	1	5	5	5
Seller C	1	1	1	2	3	3	4	3	3	3	4	4	4	3	3	5	3	3	3	3
Seller D	1	1	3	2	1	1	2	3	1	2	3	3	3	3	4	3	1	3	3	3
Seller E	3	4	4	1	1	2	2	2	2	2	2	2	1	1	2	4	2	3	3	2
Seller F	2	2	2	1	1	1	3	2	3	2	3	3	3	4	3	3	1	3	3	2
Total	12	12	13	9	9	12	19	14	16	16	17	18	16	17	16	23	10	20	20	19

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School of Business Administration

A KNOWLEDGE-BASED APPROACH TO PART TYPE SELECTION CONSIDERING DUE DATES IN FLEXIBLE MANUFACTURING SYSTEMS

Working Paper #563

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A KNOWLEDGE-BASED APPROACH TO PART TYPE SELECTION CONSIDERING DUE DATES IN FLEXIBLE MANUFACTURING SYSTEMS

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Abstract

This paper applies artificial intelligence to the short-term production planning function of flexible manufacturing systems(FMSs). A knowledge - based approach is used to solve the part type selection and production ratio determination problems. The part type selection problem is to select a subset of the part types that have been ordered to be produced on an FMS, often with due dates and/or production requirements, for simultaneous machining over some upcoming period of time.

A knowledge-based system is implemented in the language, Knowledge Engineering Environment (KEE). This system both selects part types and determines their mix ratios under constraints on due dates and tool magazine capacity. Further research needs are also discussed.

1. Introduction

A systemic analysis of a manufacturing company shows three interrelated subsystems: *management system, physical system,* and *information system*. The *management system* refers to the managers and their functions at the strategic, tactical, and operational levels. The business tasks of the managers consist of physical activities and information processing activities. The managers delegate their physical activities to the *physical system* which consists of physical manufacturing facilities and their operators. The managers' information processing activities are supported by the *information system*. The *information system* uses models to process data into information useful to the managers so that they can direct the *physical system* effectively.

The growing global market competition and shortened product life cycle have emphasized the need for *flexibility* as well as *productivity* in the physical system. A flexible manufacturing system (FMS) is a high-technology solution to that need, which combines the benefits of a *flexible* job shop and a highly *productive* flowshop. The physical system of an FMS comprises computer numerically controlled machine tools served by automated materials-handling equipment and supervised by a computer to ensure practically no set up time wasted between different operations. The *flexibility* of an FMS allows the concurrent production of several part types through different routes and the production of modified new part types with minimal lead time and cost.

To highly utilize the *flexibility* in the physical system, *intelligence* in the FMS information system could be useful. Without the help of an *intelligent* information system, it could be difficult for FMS managers to perform well in dynamically changing FMS operation environments. Their decision making can fail quality and timing goals because of the difficulty and complexity in FMS operations.

An *intelligent* information system is different from conventional information systems in that it has a *knowledge base* and an *inference* *engine* as system components in addition to data and models. The *knowledge base* stores knowledge necessary to solve problems in a certain domain. The *inference engine* generates inferences and decisions using the stored knowledge to aid or replace human decision making processes.

The purpose of this paper is to propose a knowledge-based system, a component of an intelligent information system, which supports FMS managers' decisions on the use of production planning models in dynamically changing system environments. Models are defined here to comprise qualitative human judgments as well as quantitative models such as optimization models, algorithms, and heuristics.

Although several OR models and heuristics have been suggested to perform better on FMSs, the effective use of such quantitative models in real FMSs is not a simple task. The quantitative models have different assumptions and input data to generate solutions and may not be understandable to FMS managers. FMS managers usually rely on their judgments and simple analytical methods. For FMS managers to effectively and easily incorporate the solutions of the OR models and heuristics in their judgments, an *intelligent* information system would be useful.

Several studies [BrEL86] [ShCh86] [ThLe86] present knowledge-based approaches to FMS scheduling. Bruno et al. [BrEL87] use production rules to FMS scheduling problems in order to improve the tardiness-based performance. They state that the rule-based system provides FMS schedulers with more transparency, modularity, and flexibility than the previous system written in Fortran. Shen and Chang [ShCh86] suggest frames as a knowledge representation tool for FMS schedule generation. They show a pseudo-code for a frame representation of scheduling algorithms. Thesen and Lei [ThLe86] use production rules to represent some heuristics for dispatching parts to a manufacturing cell.

To FMS production planning, however, there is no extensive study using a knowledge-based approach. Before exploiting a knowledge-based approach to FMS production planning including due date information, FMS production planning problems will be reviewed in Section 2.

2. FMS Production Planning

According to Stecke [Stec85], FMS production problems can be decomposed into four: 1) design, 2) production planning, 3) scheduling, and 4) control.

Design problems include the choice of machine tools and layout, the selection of material handling systems, and the computer control architecture. The *production planning* problems include five subproblems :part type selection, machine grouping, production ratio determination, resource allocation, and machine loading. The solutions to these planning problems for system set-up provide that all cutting tools required for each operation of the selected part types are loaded into the appropriate machines' limited capacity tool magazines. Once the FMS is set up, FMS *scheduling* is the next function. This problem include determining of part input sequences and releasing parts into the system. *Control* problems include monitoring the shop floor situations.

The first subproblem of the FMS *production planning* function - *part type selection* problem - is to select a subset of part types that have been ordered, often with production requirements and due dates, for concurrent and actual machining over some upcoming period of time. The objectives of the part type selection problem are to meet due dates (or minimize mean tardiness) while trying to maximize system utilization. Part type selection must satisfy the following constraints: 1) the production requirements of part types should be produced by their due dates; 2) the cutting tools required for all operations of the selected part types are loaded into the appropriate machines' limited capacity tool magazines; and 3) the number of fixtures of each type is limited.

The approaches to production planning can be classified into two categories: *flexible* and *batch approaches*. A *flexible approach* [StKi86] to select part types is implemented as follows: when the production requirements of some part type(s) are finished, spaces in tool magazines are freed up. Some new part type(s) can be introduced into the system for immediate and simultaneous machining, if this input can help system utilization. A *batch approach* [WhGa84] [Hwan86] [Raja86] partitions the part types into separate batches and distinct machining horizons. All production requirements of the selected part types are produced continuously in one batch. The tools are changed for the next batch.

For different types of FMSs, either a flexible or batch approach is appropriate. In general, using the *flexible approach* enables the system to be more highly utilized [StKi87]. Moreover, the *flexible approach* seems to cope better with due dates, which has not yet been incorporated in the previous studies. There are some situations where the *flexible approach* to solve the short-term production planning problems is useful: 1) production requirements of some part type(s) are finished; 2) some urgent order arrives; 3) some production orders change; 4) one or more new part types begin production; 5) a machine tool goes down; and 6) preventative maintenance is to be performed. The *flexible approach* is employed in the design of the knowledge-based system to FMS production planning.

3. A Knowledge-based Approach to FMS Production Planning

The proposed architecture for an intelligent information system for FMS production planning is shown in Figure 1. The architecture has a knowledge-based system and a data base management system. The knowledge-based system can store and retrieve data about FMS operations in the data base of the data base management system. The knowledge-based system has three components: 1) knowledge base including model base; 2) inference engine; and 3) user interface.

To design the knowledge-based system, we extract FMS planning knowledge from FMS managers and FMS modelers. According to Thesen and Lei [ThLe86], the present situation in FMSs differs from other application of knowledge-based systems in two important aspects. First, there are not many expert FMS managers available. Second, the problem is well structured in the sense that it is possible to build simulation models that predict the effects of applying acquired knowledge from FMS modelers.

A graphical method, diagram, is used to aid the knowledge acquisition process. The diagram in Figure 2 shows a set of FMS

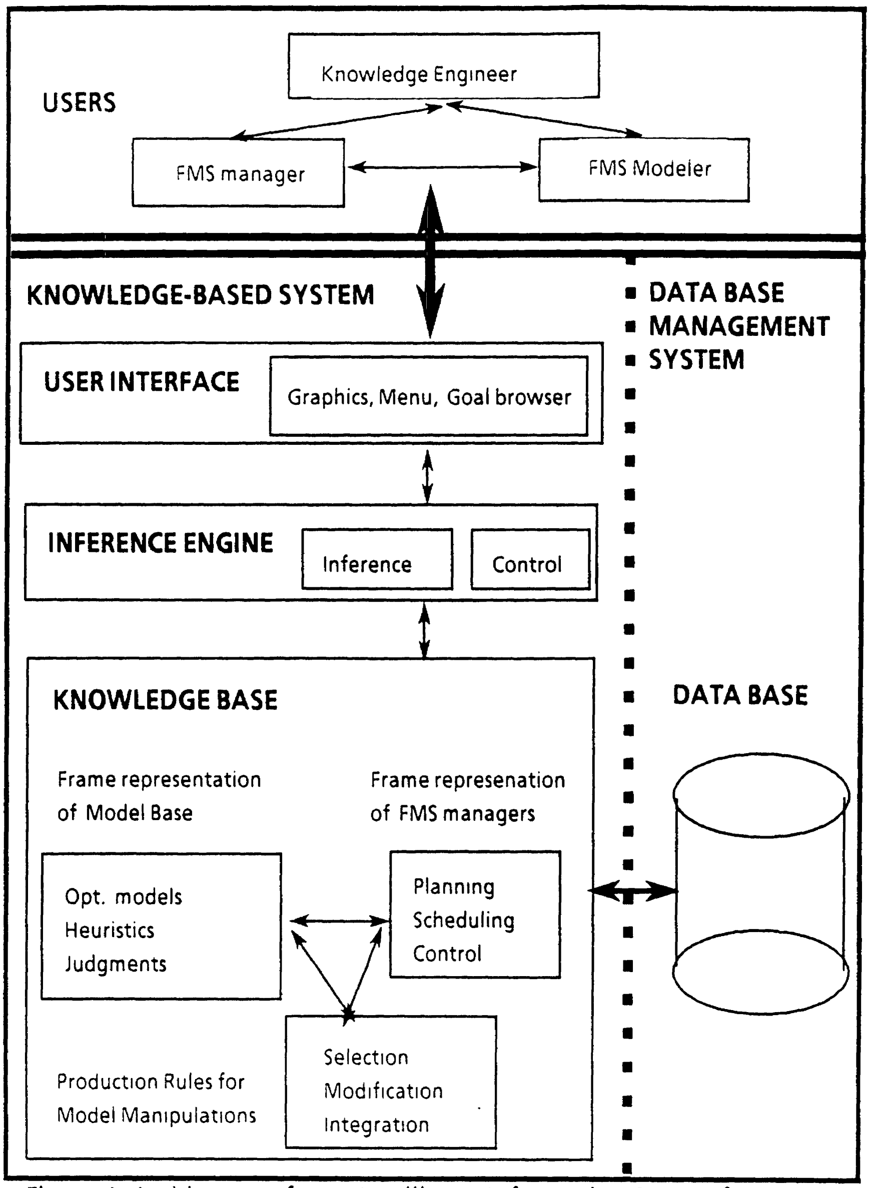

Figure 1. Architecture for an Intelligent Information System for FMSs.

production planning models connected by input edges and output edges. Input edges are used to represent sets of data necessary to produce information to be stored in output edges. The graphical representation is useful to represent knowledge using knowledge representation methods developed in artificial intelligence such as *frames* and *production rules*.

Applegate et al. [AKKN85] compare the advantages of each knowledge representation method with regard to the representation of models and model manipulations. A *frame* is a data structure describing an object or class of objects in a knowledge-based system. *Frames* are composed of slots which contain declarative and procedural information. *Frames* are useful for the representation of problems and model characteristics. *Production rules* are condition-action pairs of the form IF

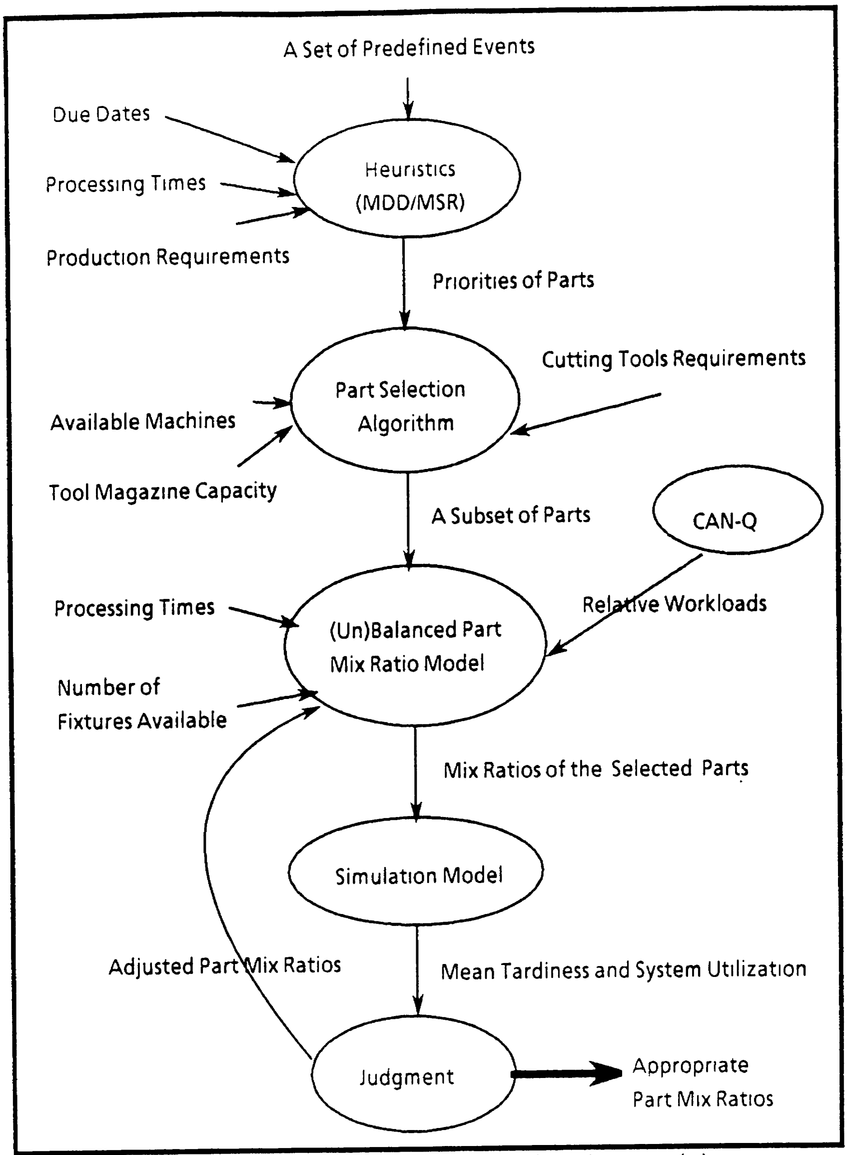

Figure 2. Diagram for Production Planning Models.

[condition] THEN [action]. The use of *production rules* in the model manipulations provides a powerful inferencing structure for model selection and query processing.

KEE (Knowledge Engineering Environment) is used to prototype the knowledge-based system. The knowledge base in Figure 3 shows frame-representation of models and FMS problems that FMS managers should deal with. The knowledge base also shows rule-representation of model manipulations.

A model is viewed as a frame which has slots for model input data, output data, and model processing procedures. An input data slot is a procedural slot which retrieves the input data from a centralized data base. If the data are not found in the data base, it calls for the execution of other model to get the required data. An output slot contains results of model execution.

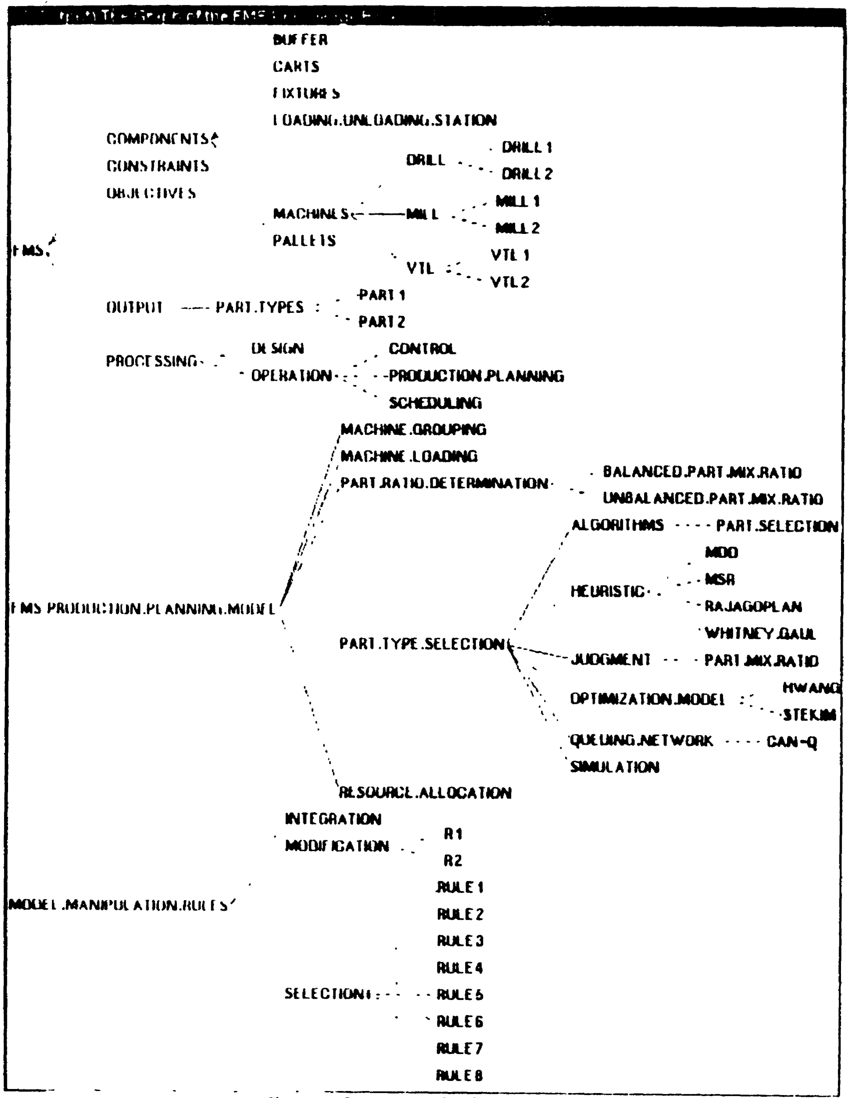

Figure 3. Knowledge Base.

As an illustration, the *unbalanced part mix ratio model* has an input slot which retrieves data about selected part types, number of fixtures available, processing time requirements, and relative workloads. The *unbalanced part mix ratio model* executes a *closed queueing network model*, CAN-Q [Solb77], to calculate the relative target workloads which provide the maximum expected production. The part mix ratios from the execution of the *unbalanced part mix ratio model* are stored in the output slot. The model processing slot contains procedures to call external solution packages such as LINDO [Shra81].

Model manipulations are represented in production rules. The production rules include selection rules, integration rules, and modification rules. The selection rules represent model selection procedures to provide the user with an appropriate model to solve problems. If there is not an appropriate basic model in the model base, the knowledge-based system is able to integrate a new model using existing basic models. Modification rules describe how models can be dynamically changed. Especially, models for adjusting part mix ratios can be modified by learning, based on data about their historical and statistical performances in the specific FMS environment.

Synthesis of knowledge representation methods - frames and production rules - is achieved by an object-oriented view, where both frames and rules are considered as objects. KEE allows production rules to be stored within and activated from frames to make inferences. The strength of an object-oriented view lies in its ability to represent models and their interactions in cogent form, i.e., objects. It provides "inheritance" of attributes of models. It also can represent interactions among models by "messages" sent between them, which provides a natural way of representing the interactions.

The following sample session shows a sequence of fired production rules of which the IF CONDITIONS are met when an urgent order arrives. It also demonstrates the "message sendings" between the objects (boldface) in the knowledge-based system.

IF	<	Some urgent orders arrive >
THEN	<	The stage of **OPERATION** is part priority determination >
	<	Send a message to **FMS.CONSTRAINTS** to update due dates, processing times, and production requirements >
IF	<	The stage of **OPERATION** is part priority determination >
THEN	<	Send a message to **MODIFIED.DUE.DATE.HEURISTIC** to determine priorities of part s >
	<	The stage of **OPERATION** is part selection >
IF	<	The stage of **OPERATION** is part selection >
THEN	<	Send a message to **FMS.CONSTRAINTS** to update available machines and tool magazine capacity >
	<	Send a message to **PART.SELECTION.ALGORITHM** to select a subset of part types for simultaneous processing >
	<	The stage of **OPERATION** is part mix ratio determination >
IF	<	The stage of **OPERATION** is part mix ratio determination >
AND	<	The size of groups of pooled running machines is unequal >
THEN	<	Send a message to **FMS.CONSTRAINTS** to update the number of fixtures available >
	<	Send a message to **UNBALANCED.PART.MIX.RATIO.MODEL** to determine mix ratios >
	<	Send a message to **CAN-Q** to determine relative workloads >
	<	The stage of **OPERATION** is part mix ratio evaluation >
IF	<	The stage of **OPERATION** is part mix ratio evaluation >
THEN	<	Send a message to **SIMULATION.MODEL** to estimate mean tardiness and system utilization >
	<	The stage of **OPERATION** is part mix ratio judgment >
IF	<	The stage of **OPERATION** is part mix ratio judgment >
THEN	<	Send a message to **JUDGMENT** to examine whether mean tardiness and system utilization are improved >
IF	<	Mean tardiness and system utilization are improved based on **JUDGMENT** >
THEN	<	Send a message to **UNBALANCED.PART.MIX.RATIO.MODEL** to determine new part mix ratios >
IF	<	Mean tardiness and system utilization are not improved based on **JUDGMENT** >
THEN	<	Return the selected part types and mix ratios to the system user >

4. Conclusions and Future Research

This paper proposes a knowledge-based system, a component of an intelligent information system, to the part type selection/production ratio problems at the FMS production planning stage. KEE is used to prototype the knowledge-based system.

The knowledge-based system incorporates due date information in the production planning stage. The information has usually been considered in the scheduling stage. A machine learning mechanism is considered to make the proposed knowledge-based system *truly* intelligent. Especially, the learning mechanism helps compare the alternative part mix ratios by observing historical data concerning previous judgments and by analyzing and learning from such experiences.

The proposed knowledge-based approach for FMS operation also has the following advantages: 1) integration, 2) transparency, and 3) modularity. The knowledge-based approach provides FMS users with an *integrative* view of solution over different problem domains such as production planning, scheduling, and control. The knowledge-based approach provides a transparency and coherence in the representation of different types of models. The knowledge-based approach provides modularity in the use of the knowledge for FMS operations. Modularized production rules and frames can be easily added, modified, and deleted from the knowledge-based system.

To evaluate the performance of the suggested knowledge-based system, a simulation model will be written in a knowledge-based simulation language such as SIMKIT. Simulation results will show how much the performance of the FMS is enhanced by applying artificial intelligence to the information system for FMS production planning.

There are further research needs along these lines. This study should be extended to the subsequent production planning problems such as grouping and loading problems. Also, the proposed knowledge-based system for production planning problems should be integrated with those for FMS scheduling and control to help operate an FMS on-line.

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