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DECISION SUPPORT SYSTEM FOR DEMAND FORECASTING IN BUSINESS GAMES

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ABSTRACT

Several studies in the last 20 years have focused on business simulator's demand functions. However, little attention has been given to the development of a decision support system to forecast the demand for business games players. This paper describes the development of a novel model for demand prediction from the perspective of the business game player. The model was tested in a business game course, where it considerably reduced the error in the demand prediction. This model can be applied to different business games to evaluate whether it can improve both results and the students understanding of the demand prediction problem, contributing to the field of education with business games.
Keywords: demand prediction, business games, decision support system

PREVIOUS RESEARCH

Considerable work has been done concerning the market demand functions in computerized business simulators. Nevertheless, the demand function has not been approached from the player's perspective, considering the development of a model for the player in forecasting demand, and the benefits of applying such a model. In this paper, a model to be adopted by players is developed, and a preliminary assessment is presented.

Gold and Pray (1982) explored the validity of certain demand functions and consequently, (Gold and Pray, 1983) developed a new function to model market share and market demand, while showing (Gold & Pray, 1984) how the function satisfies the microeconomic principles of the law of demand and diminishing returns. Goosen (1986) provided a graphical approach for incorporating Gold and Pray's (1983, 1984) market demand function in a computerized business simulator.

Decker, LaBarre and Adler (1987) developed two equations to achieve the same result as Gold and Pray, but with two additional features. The functions include an "optimum" value of the demand determinant. By using a set of reference values, the concept of ordinal utility was incorporated into the equations. The set of optimum values, one for each demand determinant, can be interpreted as the consumer's point of indifference. The other feature is an administrator-controlled parameter to provide a family of functions with one set of codes, rather than the usual single function.

Teach (1984) provided a geometric model for calculating market share to be used with Gold and Pray's (1983) market demand function. Thavikulwat (1988) pointed out that the demand function of business simulations, especially those of independent-across-firms design, should be composed of equations and algorithms simple enough for players to deduce the parameters by observing results. Later, Thavikulwat (1989) developed a market function that does not model competition for market share, but does incorporate a reference price concept, and adjusts period demand for the values of the non-price demand determinants. Furthermore, it incorporates the product life cycle concept to model the long-term trend in demand.

While the aforementioned work constitutes an important advance for business simulator designers, the player's prediction of demand in business games has not received enough attention despite being considered quite relevant by researchers. Peach (1996: 65) believes that "demand forecast is a pivotal aspect of operating a business. Few decisions can have as great an impact on profitability as serious errors in production levels. Overproduction due to rosy sales forecasts leads to high inventory costs (many of these costs are not immediately apparent to teams). Underproduction results not only in immediate lost sales but also in a reduced competitive strength and lost future sales. The larger the stock out, the greater the future impact. Because there are typically significant variations in market demand growth over the course of the simulation (instructor controlled), *coeteris paribus,* a team's projected sales should rise and fall with market demand". Weir (1978: 232) proposes that "in order to plan for the next period's production, the effective manager attempts to forecast demand for the firm's products and services".

Teach (1992) has investigated the link between the ability of simulation team participants to forecast either the expected market share and sales of the product for which they were making decisions or to forecast the cash flows and profits of the simulated firm. The managerial position a student held during the simulation determined the type of forecast (market share, cash flow, etc.) he or she would be assigned. The experiment showed a very strong link between the ability of the management team to forecast outcomes and their firms performance, as measured by profitability, demonstrating the importance of the demand prediction.

The purpose of this paper is to develop a set of models for both the industrial and the firm demand functions useful for business game players. This development encompasses: (a) Description of the experiment environment; (b) Definition of the model requirements and recommendations; (c) Selection of the techniques to be used by the method; and (d) Mathematical description of the model. Furthermore, a preliminary assessment of the model is performed in a business game course.

MODEL DEVELOPMENT

The model development embodies the definition of the model requirements, the selection of the techniques to be used by the method, and the mathematical description of the model. A useful model should cope with the experiment environment, and the methodology employed in the simulators to calculate the demand.

Business games are conducted in a computational environment, where market conditions are described, and a player or group of players, representing different firms make managerial and financial decisions about their firm. Following these decisions, the result of each firm is calculated by the simulator. These decisions allow students (players) to develop their rational decision-making skills while having to cope with subjectivity due to personal values, risk-taking propensity, and the uncertain behavior of competitors. The students receive direct and impartial feedback on the financial effectiveness of their decisions, and they can simulate the decision-results cycle many times to improve their skills. Computerized, competitive, business simulators are, therefore, powerful pedagogical devices, and it is critical that the simulations approximate as much as possible real-life situations.

There is great variation in the profile of the players of business games. Most players have scarce management experience, and a limited mathematical background. The decision time also varies widely, ranging from a few minutes to days. The number of decision cycles, or periods to be simulated also varies significantly. The model requirements imposed by the environment are: (a) Low dependence on the player expertise; (b) Simplicity, consistent with the low degree of expertise of most of the players, and with the possible small decision time; (c) Flexibility to deal with different data availability, and (d) Ease of usage.

Gold and Pray (1984) describe the market demand functions for several simulators. Accordingly, the major features of the demand functions are as follows: First, the calculation of the demand in business simulators is divided into two steps: (a) calculation of the industrial or market demand; and (b) calculation of the firm demand, or market share. Second, simulators' demand calculations employ algebraic equations, rather than statistical or discrete functions, which are represented by linear or exponential series equations. Third, the variables that affect the demand in these functions are the price, marketing expenditures and research and development (R&D) expenditures of all firms, and economical indexes related to economic activity and seasonal variations. Fourth, temporal smoothing effects are considered for the marketing and R&D expenditures. Hence, it is recommended that the developed model also divide the calculation in two steps, relying on linear or power series expressions, and consider the same variables used on the simulators.

Montgomery (1990) has defined factors that should be accounted for during the demand model selection. He emphasized the following aspects: (a) Behavior of the process to be predicted; (b) Data availability; (c) Time to decide and number of decisions; (d) Ease of usage. Note that the first aspect was reached through the recommendation of relying on linear or power series expressions to predict the demand. The second, third and fourth aspects are reached through the defined requirements. Defining the model requirements, it is necessary to survey the techniques to predict the demand, and likewise, using the model requirements and recommendations, select the appropriate techniques to be used in each model step.

The demand prediction is of great interest to the business community, given its importance for production planning and inventory reduction. A myriad of techniques are being used to establish a demand prediction methodology. Lin (2000) and Mudie (1997) have summarized these techniques, presented in Figure 1.

The first decision to be made in the model definition process is whether the prediction should be divided in two steps. The option for dividing the prediction in two calculations was selected, consistently with the process behavior, as proposed by Montgomery (1990). Furthermore, it is easier to set the variables separating the calculation into the industrial demand and market share.

The techniques in Figure 1 were considered in the model developed. Qualitative technique cannot be used directly given the inexperience of the players. . The only possible source to be used in the prediction is the data provided to the player each period. Therefore, the core of the model should be based on temporal series data, augmented by other techniques. Temporal series techniques do not consider the known dependencies of the demand function. For this reason, its usage was disregarded, since the model would be highly inaccurate. Therefore, by

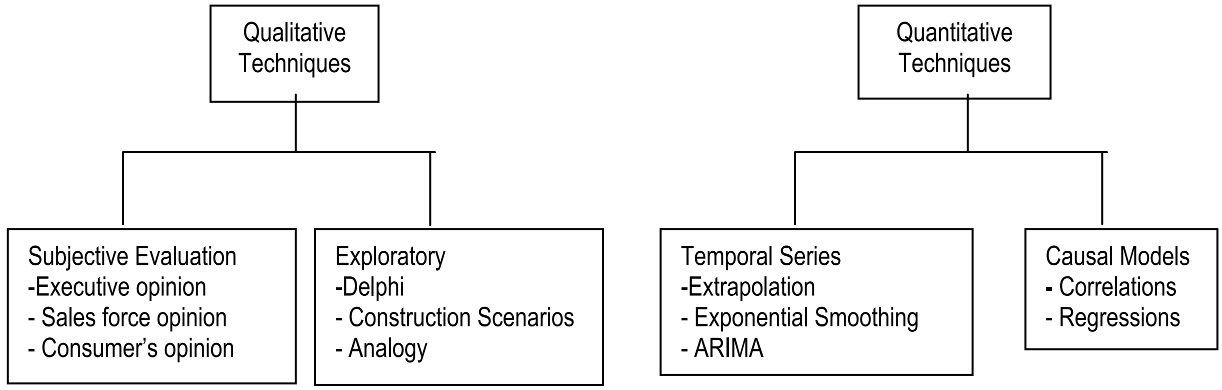

Figure 1: Demand prediction techniques (adapted from Lin, 2000 and Mudie, 1997)

elimination, a causal technique should be used in the core of the model. Since correlations are not known, the regression technique was chosen to establish the relationship between the predicted demand, and the temporal series data. Among the several functions that could be used in the regression,the power and linear series were considered, given its usage in the simulators. Between these functions, the linear was chosen because of its ease of understanding, which addresses the simplicity requirement. Although this technique was chosen, two issues still need to be addressed: the selection of variables and the multiple variables dependence.

The examination of the demand functions of several simulators shows that the variables affecting the industrial demand are the volume of expenditures of the industry in marketing, and R&D, the average price charged by the industry, and the economic indexes. The market share calculation variables consist of the price charged by the firm, and the marketing and R & D expenditures of the firm. These variables are structured differently in each simulator. Some of them use the absolute value, whereas other firm demand functions are based on ratios.

For the industry demand model, it was considered convenient to calculate a changing factor to correct the total industrial market for the next period. This procedure was considered adequate because the actual market, determined from the data available (the sum of the market of each firm over the previous period) is an excellent value to be corrected, and, given that the decision time is brief, it is more accurate to correct the previous value than to use an equation relating the variables with the potential total market. Hence, the linear regression is established to obtain the changing factor (a ratio between the market at that period and the previous period) as function of the variables affecting the industry demand. Consistent with this procedure, the variables considered were the ratio between the variables at the period of interest with the previous period. Consequently, as shown in the formulation that follows, the variables used were the ratio between the economic indices, price, and marketing and R&D expenditures of one period and the previous period. For the marketing and R&D expenditures the effects of temporal smoothing were considered.

For the firm demand, the market share was used as dependent variable, and the ratio of the firm prices, marketing and R&D expenditures with the average industry value were used as independent variables. It is intuitive that what is of interest is how the variable relates to the average value, and not the absolute value. The effects of temporal smoothing were also considered in the firm demand prediction.

Even though the simplest regression model was chosen, the multiple dependence of the demand is still an obstacle to complying with the short time to decide, and to the limited mathematical background of most of the players. An additional step was necessary to simplify the model further. This step combines all dependencies of the two demands in one factor, which has different weights for the several variables affecting them, and temporal smoothing coefficients. The factor used in the industrial demand estimation is named Modification Factor for the Industrial Demand (MFID), and the factor used in the market share estimation is named Modification Factor for Market Share (MFMS). The used demand decision process is sketched in Figures 2 and 3 for the industrial and firm demand respectively.

As shown in these Figures, the methodology used comprises two phases: (a) preparatory phase, and (b) estimate phase. During the preparatory phase, the variables affecting the demand are selected through subjective evaluation techniques. After the definition of such variables, weights and temporal smoothing coefficients need to be defined. Subjective evaluation techniques and elasticities from other simulators are used to obtain the weights and temporal smoothing coefficients (used to calculate cumulative effects of some variables). Then, the combined factors for previous periods are calculated, and plotted against the respective changing factors and market shares. Linear expressions are then obtained for the demands as function of the combined factors.

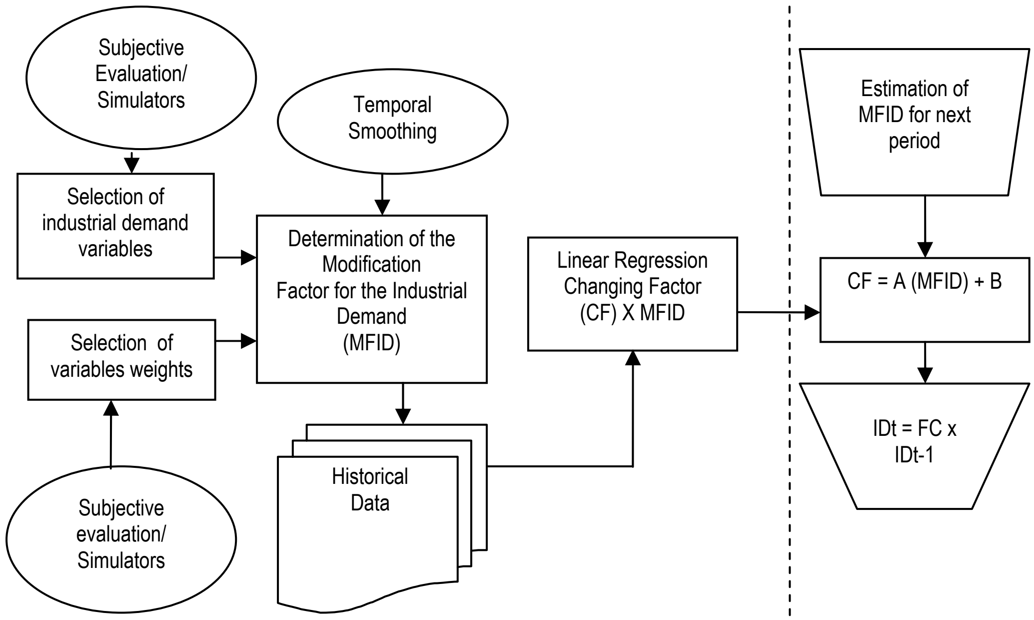

Figure 2: Techniques and procedure for the calculation of industrial demand

During the estimate phase, the average values of the variables for the next period are estimated, using subjective evaluation. From the variables chosen (price, marketing expenditure, and research & development expenditure), it is possible, using the linear correlation obtained in the preparatory phase, to estimate the industrial demand and market share, from which it is possible to estimate the firm demand.

A dashed line distinguishes between the preparatory and estimate phases. As mentioned earlier, the historical data of previous periods, once defined the variables, weights, and temporal smoothing coefficients, is used to obtain a linear regression between the MFID and the Changing Factor (CF). This last one corresponds to the ratio of variation of the industrial demand (ID) from one period to the previous. Once the linear correlation is obtained, it is possible to estimate the CF for the next period and obtain the future demand.

In Figure 3, the firm demand is calculated using the market share, obtained from the linear regression of the preparatory phase and the estimation of the MFMS of the next period. The obtained market share is then multiplied to the industrial demand. Note that both procedures are based on the assumption that the industrial demand and market share for every period is available, as well as all or some variables affecting both demands.

Therefore, the methodology proposed in this paper divides the calculation in industrial and firm demand. The core technique used is extrapolation of the demand behavior using temporal series data and a linear correlation. A combined factor aggregates all factors in a single variable. Subjective evaluation and observation of simulators dependencies are used as auxiliary techniques to estimate the weights and smoothing temporal coefficients, as well as the average values for the next period. Figure 2 shows the set of techniques used in the industrial demand model, and Figure 3 shows the same for the market share calculation.

The mathematical representation of the MFID and of the MFMS will depend on the variables affecting the industrial demand and market share, respectively. If these variables differ according to the simulator, a unique formulation is not possible. The set equations below contain a general formulation for these factors, considering the most common variables affecting each demand. However, adaptations can be required, depending on the data availability.

$$MFID = \alpha_1 F_{MKT} + \alpha_2 F_{P\&D} + \alpha_3 F_P + \alpha_4 F_{IAE} + \alpha_5 F_{IVE} \ldots.. \quad \text{(Equation 1)}$$

Where:

$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$, ... : weights of the several variables, in accordance with Equation 2:

$$\alpha 1 + \alpha 2 + \alpha 3 + \alpha 4 + \alpha 5 + \ldots\ldots = 1 \quad \text{(Equation 2)}$$

F_P: Price variable, given by:

$$F_P = Pm_{t-1} / Pm_t^{cor} \quad \text{(Equation 3)}$$

Pm: Market average price; the subscription corresponds to the period (t represents the next period) The superscription corresponds to the financial correction of the price

F_{EAI}: Variable considering the economic activity; given by:

$F_{EAI} = EAI_t / EAI_{t-1}$ (Equation 4)

EAI: Economic activity index. The subscription corresponds to the period.

F_{IVE}: Variable considering the seasonal variation, given by:

$F_{IVE} = SI_t / SI_{t-1}$; (Equation 5)

SI: Seasonal variation Index. The subscription corresponds to the period.

F_{MKT}: Variable considering the Marketing expenditure:

$$F_{MKT} = \beta_1 \frac{Gmkt_t^{Mcor}}{Gmkt_{t-1}^{M}} + \beta_2 \frac{Gmkt_{t-1}^{Mcor}}{Gmkt_{t-2}^{M}} + \beta_3 \frac{Gmkt_{t-2}^{Mcor}}{Gmkt_{t-3}^{M}} + \ldots \quad \text{(Equation 6)}$$

Where:

$Gmkt_t^{Mcor}$: Average marketing expenditure. The subscription corresponds to the period.

The superscription corresponds to the market average value (M), and the financial correction of the expenditures (cor).

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \ldots\ldots$: Temporal smoothing coefficient of the Marketing effect on the industrial demand.

$F_{P\&D}$: Variable for expenditure on research and development, given by:

$$F_{P\&D} = \lambda_1 \frac{Gp\&d_t^{Mcor}}{Gp\&d_{t-1}^{M}} + \lambda_2 \frac{Gp\&d_{t-1}^{Mcor}}{Gp\&d_{t-2}^{M}} + \lambda_3 \frac{Gp\&d_{t-2}^{Mcor}}{Gp\&d_{t-3}^{M}} + \ldots. \quad \text{(Equation 7)}$$

$Gp\&d_t^{Mcor}$: Average R & D expenditure of the market. The subscription corresponds to the period. The superscription corresponds to the market average value (M), and the financial correction of the expenditures (cor).

$\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \ldots\ldots$: Temporal smoothing coefficient of the R&D effect on the industrial demand.

$$MFMS = \alpha_1^F F_{MKT}^F + \alpha_2^F F_{P\&D}^F + \alpha_3^F F_P^F \ldots.. \quad \text{(Equation 8)}$$

Where:

$\alpha^F_1, \alpha^F_2, \alpha^F_3, \ldots\ldots$: weights of the several variables, in accordance with Equation 2:

$\alpha^F_1 + \alpha^F_2 + \alpha^F_3 + \ldots\ldots = 1$ (Equation 9)

F_P: Price factor of the firm, given by:

$F_P = Pm_t / P^F{}_t$ (Equation 10)

Pm: Market average price; the subscription corresponds to the period.

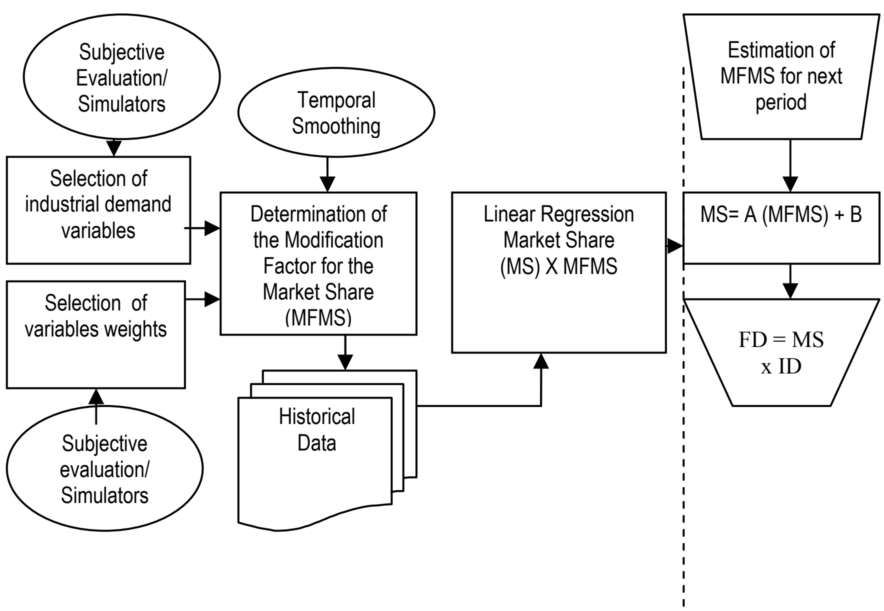

Figure 3: Techniques and procedure for the calculation of firm demand

P^F_t: Price charged by the firm over the period t

F^F_{MKT}: Variable considering the Marketing expenditure of the firm:

$$F^F{}_{MKT} = \beta_1^F \frac{Gmkt_t^F}{Gmkt_t^M} + \beta_2^F \frac{Gmkt_t^F}{Gmkt_t^M} + \beta_3^F \frac{Gmkt_t^F}{Gmkt_t^M} + ... \qquad \text{(Equation 11)}$$

$Gmkt_t^M$: Average Marketing expenditure of the market over period t

$Gmkt_t^F$: Marketing expenditure of the firm F over the period t

$\beta^F_1, \beta^F_2, \beta^F_3$, ... : Temporal smoothing coefficient of the Marketing effect on the industrial demand.

$F^F_{P\&D}$: Variable considering the expenditure on R&D of the firm, given by:

$$F^F{}_{P\&D} = \lambda^F{}_1 \frac{Gp\&d_t^F}{Gp\&d_t^M} + \lambda^F{}_2 \frac{Gp\&d_t^F}{Gp\&d_t^M} + \lambda^F{}_3 \frac{Gp\&d_t^F}{Gp\&d_t^M} + ... \qquad \text{(Equation 12)}$$

$Gp\&d_t^M$: Average expenditure of R & D of the market over period t

$Gp\&d_t^F$: R & D expenditure of the firm over the period t

$\lambda^F_1, \lambda^F_2, \lambda^F_3$, ... : Temporal smoothing coefficient of the R&D effect on the firm demand.

The factor calculation depends on subjective evaluation to define the weights and temporal smoothing coefficients. These parameters can vary greatly among the simulators due to the different products and markets they are intended to model. This subjectivity implies that the performance of the model will increase as long as the players gain experience, or the gains of this model are greater for longer simulations. However, initial values should be set for the model to be used on the initial decision cycles. In this case, the elasticities of several simulators, from Gold and Pray (1984) and Thavikulwat (1988) can be a useful reference. These elasticities are presented in Table 1.

There is also necessity to estimate the average price and expenditures for the predicting period. In this case, when there are no signs of great environmental changes, which is a normal situation in stabilized economies, it is recommended to use the average value of the previous period. For the smoothing coefficients, it is recommended to initially consider two periods for the smoothing interval for the Marketing effect, with emphasis on the current period. For the R & D effect, four periods for smoothing interval is recommended, with an even distribution of coefficients.

Uncertainties arise throughout the demand modeling process, related to the subjective nature of certain steps, adequacy of the variables selected and linear regression technique and data availability. It is not known to which extent the variables selected are capable of describing the demand. Also the weights and smoothing coefficients, which define the variable importance, were defined applying subjective techniques. The average value of the variables for the next periods needs to be estimated relying on subjective judgment. Business simulations data availability varies widely according to the simulators and the intentions of the business game instructor. Consequently, the model must be simplified according to the data availability, resulting in more uncertainty. Finally, the linear regression technique certainly cannot precisely represent the demand behavior. Thus, there are several sources of uncertainty accumulating throughout the process. This fact leads to the unavoidable question regarding the validity of using this model. A preliminary evaluation of this issue is provided in the following item, but more extensive use of the model is necessary to confirm the trend inferred from this initial assessment. Extensive use of the model is also needed to quantify its level of uncertainty.

Model limitations are related to the dependence of the model on historical data. This dependence has some important consequences. First, the model accuracy increases with the accumulation of data and the experience gain of the players, which can enhance the judgment capacity of the

Table1: Demand elasticities from selected simulators

Selected Simulators	Industrial Demand - coefficients			Firm Demand – coefficients		
	Price (100 %)	MKT	R&D	Price (100 %)	MKT	R&D
Executive	-2,20	0,26	0,13	-4,00	0,70	0,70
Decide	-0,90	0,10	0,05	-0,90	1,50	1,02
PROD- Product 1	-2,64	-	-	-2,64	-	-
PROD- Product 2	-0,85	-	-	-0,85	-	-
MMG: Product A	-0,88	0,21	0,25	-0,88	1,00	0,50
MMG: Product B	-1,59	-	0,50	-1,59	-	0,50
Microsim	-0,63	0,10	0,05	-6,00	1,45	0,96

Adapted from: Gold&Pray, 1984; Thavikulwat, 1988.

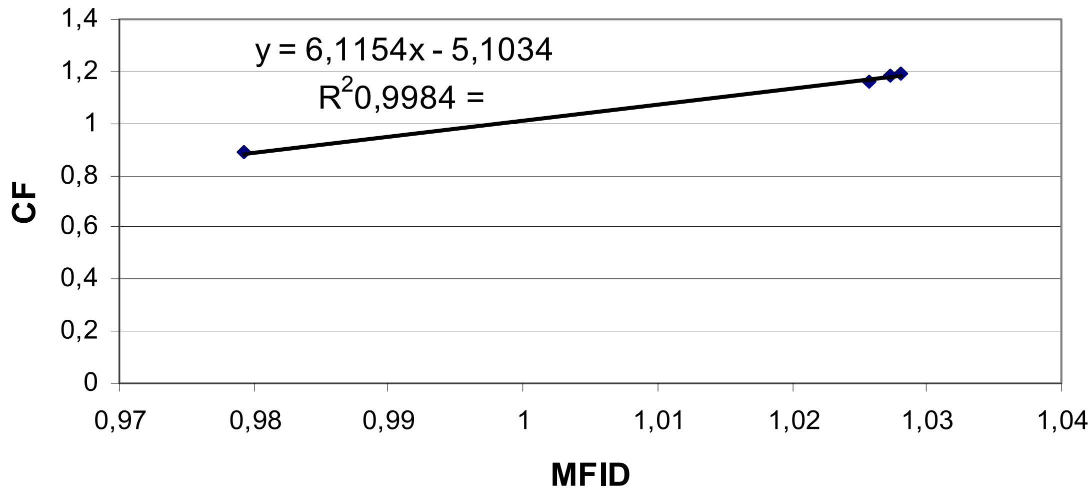

Figure 4 (a): Linear regression for a business simulation for the industrial demand

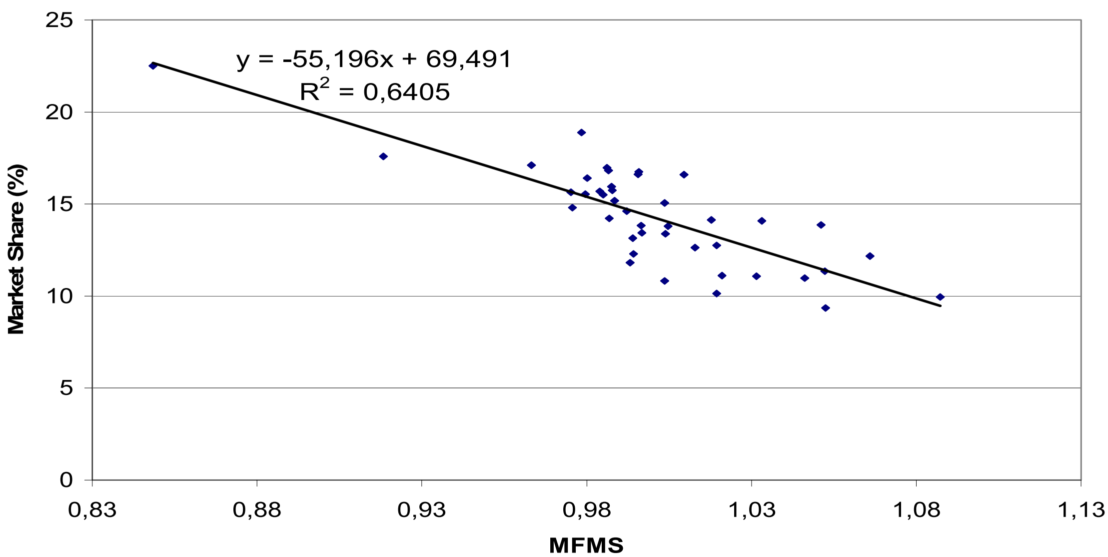

Figure 4 (b): Linear regression for a business simulation for the firm demand

players. Second, any event that disrupts critical routines and activities compromises all the predictions of the model. Events like raw materials shortage have this potential.

PRELIMINARY ASSESSMENT

The model was applied in simulations where the following data was available: (a) Economic activity index; (b) Seasonal variation Index; (c) Prices charged by all firms in the game. It was used by a firm to predict the price that should be charged to correspond to an expected demand. A decision support system to calculate this price was set on a worksheet that estimates the price to be charged.

The results of the first four decision cycles were used to perform the linear regressions for the industrial and the firm demand. The weights used were 0.5 for the price, and 0.25 for each of the indices (economic activity and seasonal variation). No data was available for the Marketing and R & D expenditures. The results for the changing factor and market share are presented in Figure 4.

In the industrial demand regression, four points were used, while 24 points were used in the market share regression. The data was processed in an electronic worksheet of the EXCEL software. The obtained linear equations used are presented in the Figure 4, as well as the R^2 coefficients.

Table 2 shows the error (comparison of the expected demand and the actual demand) in the demand prediction, identified market efficiency for six periods. In the four first periods, the model was not used, whereas it was used in the

Table 2: Market efficiency of demand forecasting in a business game with

Period	Without DSS model	With DSS model	Error
1	1.192	-	19.20%
2	0.94	-	6.00%
3	0.79	-	11.00%
4	0.83	-	17.00%
5	-	0.94	6.00%
6	-	0.981	1.19%

fifth and sixth periods. The average error without the DSS was 15.8%, whereas the error with the DSS was 4.1%.

DISCUSSION

The results of the preliminary assessment were as expected to a certain extent. Despite the uncertainties of the model, its use has reduced the prediction inaccuracy significantly, although the error remains high. The results in Figure 4 emphasize that it is a very difficult task for players to predict demand. For this reason, even tools with high levels of uncertainty are preferable to relying solely on the player's judgment.

A detailed examination of the model can reveal sources of improvement and possible uncertainty reduction. Other regression functions, for instance, can be tested. Nevertheless, the model was informed by requirements and recommendations. Simplicity and ease of use were difficult requirements to fulfill given the multiple dependence of the demand and little knowledge of the impact of each variable. In this way, the model was developed under these circumstances. It is the understanding of the authors that improvements should be made as long as the model is used, and knowledge is gained about the trade-off between accuracy and model options. The understanding of the model weaknesses and strengths is only possible as long as the model is used. A trade-off solution model was developed performing a careful selection process, but certainly, improvements can be done as long as the model is used. Therefore, a future approach would gather information of new applications of the model to estimate the model uncertainty, as well as improve its performance through measures that decrease the model uncertainty, as well as increase the model simplicity, flexibility and ease of use.

CONCLUSION

The focus of the demand research in business games has been on the improvement of the demand functions of these simulators. This paper has focused on the demand forecast from the players' perspective, developing a demand prediction model. Montgomery's (1990) factors were considered, together with the environmental requirements and recommendations resulting from the study of the business simulator's demand functions. Several techniques, shown in Figure 1 were considered. The model divides the calculation in two steps: the calculation of the industrial demand, represented by the changing factor, and the market share. Linear regressions are used to calculate the industrial demand and market share as functions of combined factors that aggregate all their dependencies. Qualitative techniques are used in the methodology, to obtain weights, coefficients, and estimate the factors for the following period.

The process of prediction comprises several steps, shown in Figures 2 and 3. Data on uncertainties are collected throughout the steps. They are related to the subjective nature of some steps, such as definition of weights and coefficients, data availability, and linear regression and adequacy of selected variables.

The model was tested in a business game course. The linear regressions are presented in Figure 4. The results have revealed that the performance of the firm adopting this tool was improved when the model was used, even though the significant error still remained. Further usage of the model is necessary to confirm the trend resulting from the preliminary assessment. Extensive use can also improve on the estimation of the model uncertainty and improve the knowledge about the model's performance and limitations, promoting forms for model enhancement.

From the pedagogical perspective, the model can be used to evaluate the improvement in the students' performance and demand understanding using a demand prediction decision support system. Performance of the player in terms of results and learning with or without the tool can be compared to assess the model's educational value.

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