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Integrated application of time series multiple-interventions analysis and knowledge-based reasoning

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ABSTRACT *This study examines the data that result from multiple promotional strategies when the data are autocorrelated. Time series intervention analysis is the traditional way to analyze such data, focusing on the effects of a single or a few interventions. Time series intervention analysis delivers good results, provided that there is a known and predetermined schedule of future interventions. This study opts for a different type of analysis. Instead of adopting the traditional time series intervention analysis with only one or a few interventions, this study explores the possibility of integrating time series intervention analysis and a knowledge-based system to analyze multiple-interventions data. This integrated approach does not require attempts to ascertain the effects of future interventions. Through the analysis of actual promotion data, this study shows the benefits of using the proposed method.*

1 Introduction

The market place today is a place of fierce competition. Marketing strategies have diversified in an attempt to adapt to the competitive nature of the market place. There are certain ways to analyze sales promotion data. For instance, some analysts choose to make forecasts based on a model proposed by Box and Jenkins (1970), called the autoregressive integrated moving average (ARIMA) model. In addition, to determine the fiscal impact of strikes or business promotional strategies, for

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example, people often choose another well-known technique called intervention analysis (Box & Tiao, 1975).

The various market strategies often result in substantial interventions. Typical intervention analysis emphasizes models generated from a single or very few interventions. As a result, the necessity of considering the effects of multiple marketing strategies complicates the process of modelling sales data. The present study departs from conventional approaches, by developing a method for handling multiple interventions. Considerable uncertainty surrounds the effects of future interventions. This study will raise and attempt to solve the challenges involved in dealing with this uncertainty. These future interventions are likely to be inconsistent with present and already known interventions.

In our study of multiple interventions, we attempt to integrate the time series intervention analysis (TSIA) technique with knowledge-based systems (KBSs). With the combined use of TSIA and KBSs, we believe that we can produce reliable results from the diverse marketing strategies. In our discussion, we critique data sets that track the sales promotion efforts for the product of a multi-national company. In the following section, this study describes the specific characteristics of the sales promotion data and, in Section 3, it discusses the inherent problems of employing typical TSIA techniques. In Section 4, we propose solutions to these problems. Section 5 presents the analysis and the results of the proposed approach. Here, we discuss and argue for the advantages of the integration of TSIA and KBSs.

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2 Characteristics of the promotional data

We contacted a company (which will remain anonymous) and obtained its permission to collect data on the marketing of a specific product over a five-year period between August 1991 and July 1996. The real data collected described the sales of the actual product over this period. During this period, 13 distinct promotional marketing strategies were employed to boost sales of the particular product. Some 18 observations were made over the course of each year; data were collected every 3 weeks—with the exception of two occasions when there were 2-week intervals between collections. Although these 18 observations were not gathered at precisely equal time intervals, they may still be considered to have been collected at roughly constant intervals. Figure 1 displays the time plot of these data. Table 1 describes the promotional strategies and lists the corresponding sales values.

Even a cursory examination of Fig. 1 reveals the difficulty in analyzing these data. The difficulty arises because there are a large number of unusual observations in terms of the total number recorded. In the past, future sales forecast through a simple forward projection of the sales trends observed during the past 2 years. Compensation for gaps in the availability of data and for market changes relied on 'human judgement'. Against a background of an increasingly fast-paced world and an intricate market structure, this kind of reliance on 'human judgement' rarely suffices.

In the firm being studied, the sales forecasts are estimated from two departments: marketing and inventory control. These sales forecasts frequently clash and firms often find themselves unable to analyze the situation effectively. Such uncertainty and contradictory forecasts consequently lead to confusion and the decline of inventory control. The company wanted to remedy these problems and looked for ways to correct the sources of forecast error. The management believed that the

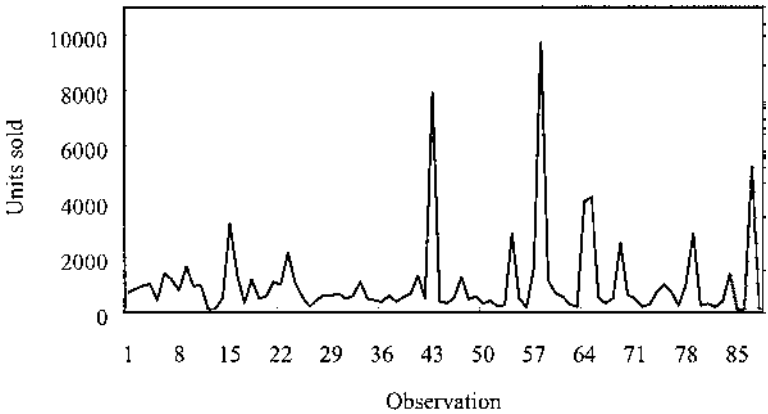

FIG. 1. Actual sales data.

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TABLE 1. The types of promotional strategy and corresponding values of sales promotion

Promotion strategy	Actual sales (units)
1. Purchase over $11, and receive a free set of combs	1661
2. 20% discount	3215
3. Buy one product, get one free lipstick (value of $2.50)	1188
4. Buy two products, get one free lip pencil or eye pencil (value of $3.5)	2162
5. Purchase over $18, and receive a free 'Flower' notebook (value of $10.0)	1107
6. Purchase over $181, and receive a free set of second-generation products	1326
7. Buy three products, get one free	7929
8. Buy two products, get one free lip pencil or eye pencil (value of $5.5)	1275
9. Buy first product with 5% discount, and receive 50% discount on second purchase	2858
10. 10% discount	1619
11. Buy three products, get one free lipstick and one free fingernail polish	9730
12. Buy three products, and receive a free 'Spring' bag	4008
13. 30% discount	4169

inaccuracies and inconsistencies of 'human judgement' were the principal causes of forecast error. The company decided to hold several brainstorming sessions to find the solution. In the end, the company selected the TSIA technique to model the sales promotion data.

3 The problems

Figure 1 illustrates three primary difficulties in applying the TSIA technique to the sales promotion data. First, there may be too many interventions and too few observations. Some 13 separate promotional strategies are employed during the period under consideration. Ideally, the data should be modelled to reflect 13 different interventions or promotional strategies. This process may result in an unreliable and misleading model, because it relies on data gleaned from too few observations with too many interventions.

Secondly, the dynamics and effects of future interventions are uncertain. Future marketing campaigns may be inconsistent with previously observed and recorded

sales promotions data. We can analyze recent sales promotion data to project a trajectory of future sales, but there is no guarantee that future promotional strategies will in any way resemble those that have already been employed.

Thirdly, even if the effects of future promotional strategies can be estimated by professional experience or by some other analytical methods, the outcome may not be as expected if experienced personnel are on vacation or ill, or if the other estimation techniques are not sufficiently precise. These difficulties raise a practical question: are there any methods that even inexperienced personnel can use to forecast effectively the future sales values for a specific promotional strategy?

4 The solutions

4.1 TSIA modelling

Autocorrelated data sets are often analyzed using time series techniques such as the ARIMA and Box–Jenkins approaches. Box and Tiao (1975) introduced intervention analysis based on the ARIMA methodology to evaluate the effects of unusual events. Such techniques have proven to be viable in a wide variety of applications, ranging from economics and finance to traffic control and engineering.

Wichen and Jones (1977) analyzed the impact of market disturbances using intervention time series. Bhattacharyya and Layton (1979) and Haque (1990) employed time series intervention techniques in the analysis of casualty accidents. Tiao and Box (1981) discussed the approaches of modelling and analysis of multiple time series. Using structural modelling intervention techniques, Harvey and Durbin (1986) examined the monthly data on road casualties in Britain, and studied the effects that seatbelt laws have had on casualty rates. Abraham (1987) analyzed Ontario's road-safety legislation, by applying TSIA. Sarkar and Kartikeyan (1987, 1993) investigated non-linear fitting in combination with intervention analysis. Martinez-Schnell and Zaidi (1989) utilized the TSIA model to investigate deaths caused by motor vehicles in the US from 1972 to 1983. Examining surveillance data through the TSIA model, Schnell *et al.* (1989) studied an increase in reported cases of gonorrhea in women participating in a control programme. Murry *et al.* (1993) studied an anti-drinking-and-driving advertising campaign with a sample survey, by modelling monthly traffic accident data using the TSIA technique. Deadman and Pyle (1993) used intervention analysis to study the influence of the abolition of capital punishment on the homicide rate in Britain. Somers and Gupta (1994) utilized similar means to study the effect of a manufacturer's change in advertising strategy on the units sold to its dealers. Applying the concept of time series multiple-interventions analysis, Shao (1997) used real sales promotion data to predict the values of future sales for different promotional strategies.

For the firm involved in the present study, consultations with personnel from the marketing and inventory control departments resulted in the selection of the TSIA model. This TSIA model was based on ARIMA modelling techniques, so was considered to be the most appropriate method for analyzing and forecasting the data. The sales data reflected in Fig. 1 may be described by the model

$$y_t = C_1 + V_t + N_t \tag{1}$$

where y_t is the units sold at time t; C_1 is a constant estimated from available data; V_t is the response function at time t; N_t is the noise function at time t.

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The response function V_t can be characterized as

$$V_t = \frac{w(B)B^b I_t^{(T)}}{\delta(B)}$$

where $w(B) = w_0 - w_1 B - w_2 B^2 - \ldots - w_s B^s$, and $\delta(B) = \delta_0 - \delta_1 B - \delta_2 B^2 - \ldots - \delta_r B^r$ are polynomials in B of orders s and r, respectively. Without loss of generality, we may normalize the coefficient δ_0 at unity. B is the backward shift operator, defined as $B^i y_t = y_{t-i}$. b is the number of periods that it takes before the intervention effect begins to influence sales. $I_t^{(T)}$ is the intervention variable, which can be modelled either by a step function, i.e.

$$I_t^{(T)} = S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geqslant T \end{cases}$$

or by a pulse function, i.e.

$$I_t^{(T)} = P_t^{(T)} = \begin{cases} 0, & t \neq T \\ 1, & t = T \end{cases}$$

with T being the time of the occurrence of intervention.

The noise function N_t can be characterized by standard ARIMA modelling (see Box *et al.*, 1994).

4.2 Grouping the interventions

SAS (1993) software was initially employed to identify the model and to estimate the model parameters based on equation (1). While estimating the many parameters that reflected the 13 unique interventions, we noticed a divergence of estimates of the model parameters. In order to avoid divergence of the estimates of the parameters in the process, it was essential to reduce the number of interventions.

By consolidating similar interventions into clusters and treating each cluster as a separate intervention, the total number of intervention models may be reduced. This system is advantageous in two respects. First, the simplification of the model allows the estimates of the parameters to converge, reducing divergence and ultimately producing more reliable results. Secondly, this clustering should help to resolve the differences between recorded and future interventions. Although future promotional strategies are unlikely to be identical to past efforts, they are likely to fall within one of the major clusters of strategies. By categorizing future interventions within established clusters, forecasts of future sales may be better obtained.

After further consultation with company personnel, the 13 types of intervention were condensed into three clusters. These clusters were categorized using three techniques based on the following aspects: first, an integrated assessment of the promotional strategies' primary traits; secondly, the relationship between the promotional strategies and the values of sales promotion; thirdly, correlations between the past promotional strategies and their results. Table 2 displays the results of clustering the 13 types of intervention into three groups.

4.3 Integrated use of a KBS

Following the preceding guidelines, a TSIA forecasting model can be established. However, even with a forecasting model, it is still difficult to estimate future sales

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TABLE 2. The results of clustering 13 types of intervention into three groups of intervention

Group	Description of promotion
1	Percentage discounted
2	Minimum amount spent to receive free gifts
3	Number of purchases required to receive free gifts

based on future promotions. How much weight to assign to each cluster of intervention variables has not yet been determined. If left to human judgement, then the accuracy of such estimates may be questionable, particularly when dealing with less experienced personnel. To alleviate such a problem, the TSIA forecasting model can be integrated with a KBS.

Armstrong (1988), Bunn and Wright (1991) and Reynolds *et al.* (1995) all addressed the need to integrate judgement (professional experience) and theory (statistical analysis). In addition, Lawrence *et al.* (1986) and Sanders and Ritzman (1990) supported the empirical approaches. In line with these concepts, Guerard (1989) combined an expert system with intervention analysis to solve outlier problems in Bethlehem Steel's quarterly earnings. Weitz (1986), Bintley (1987), Kwong and Cheng (1988), Lo (1994) and Vokurka *et al.* (1996) all utilized the expert system to choose the most appropriate forecasting model for their cases. Collopy and Armstrong (1992) developed a rule base, consisting of 99 rules, to make forecasts for economic and demographic time series. This study introduces the use of a KBS to determine the uncertain weights of intervention variables for a preselected TSIA model. Figure 2 shows a flow diagram of integrating the TSIA model with a KBS.

In Fig. 2, the TSIA model may be easily obtained using the traditional TSIA techniques (see, for example, Box *et al.*, 1994). However, in our case, it is very difficult to determine the values of intervention variables which are presented in the TSIA model. For example, observing Table 1, it is clear that the 20% discount on prices produced nearly twice as many extra sales as did the 10% discount. It seems that the linear relationship would exist in this intervention variable. This implies that, when such intervention occurs in the future, we may provide a value for such an intervention variable based on the linear relationship. However, examining Table 1, we notice that the 30% discount did not give three times the effect of the 10% discount. It is not a linear relationship. What value should we provide to an intervention variable, such as a '40% discount', in the future? We have used several analytical methods to perform this task but the results are not satisfactory. Consequently, we were motivated to use the KBS to accomplish this task.

A KBS is a system that performs tasks by applying 'rules of thumb' to arrive at a solution to a problem that exhibits the characteristics of ill-structured and incomplete input information. It is a suitable technique for determining the appropriate weights of intervention variables, because, apart from human expertise, there is no exact algorithmic method for computing these unknown weights.

The basic concept of the problem-solving method we used in our KBS is classification. Classifying something means to identify it as a member of a known class. For example, a biologist may use several features, such as shape, size and color, to identify a species of plants. In classification tasks, a set of classes (solution space) is given together with necessary conditions (data space) for identifying

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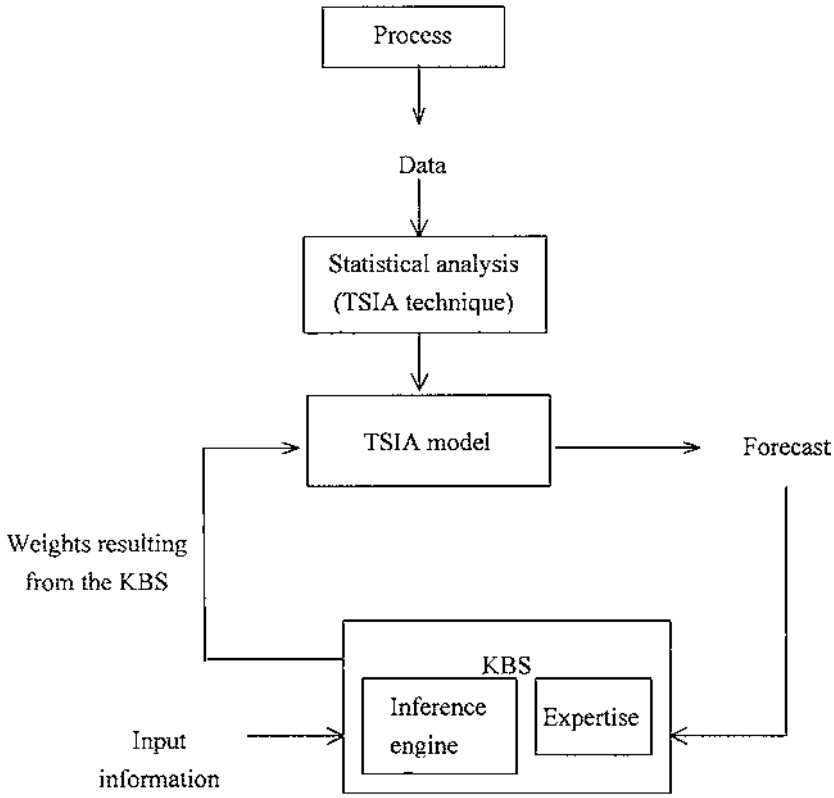

FIG. 2. Layout of process for integrating a TSIA model and a KBS.

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unknown phenomena, patterns, etc. As a result, the classification of problems begins with data and identifies classes as solutions. Heuristic knowledge is then used to match the elements of the data space and the corresponding elements of the solution space.

Figure 3 displays a graphical notation of a classification problem. The data space is a finite set with elements $\{d_i\}$ indicating all possible types of future promotion strategy. The solution space is a finite set with elements $\{s_j\}$ indicating all possible assignments of weights. The $\{d_i\}$ terms can be assigned data values, representing the data to be classified in a particular problem. In our study, a datum can take one value from the set $\{0, 1, ?\}$. While '0' or '1' indicates that the promotion strategy 'is not' or 'is' implemented, respectively, '?' implies that it is not known whether or not the promotion strategy is implemented. For every solution candidate in the solution space, there is a pattern that specifies necessary conditions for consistency of the solution with data. These patterns are heuristic knowledge and are represented by full links (indicating that the solution candidate is consistent with the datum of value 1) or broken links (indicating that the solution is consistent with the datum of value 0). Note that a solution is still judged to be consistent in the case where there are no known data that bear on it one way or the other. Finally, the process of determining a solution, given the available data, is based on the principle of 'covering more data', i.e. choosing a consistent solution candidate that explains the greatest number of available data.

For example, observing Fig. 3, s_1 is consistent with the solution of $d_1 = 1$ and

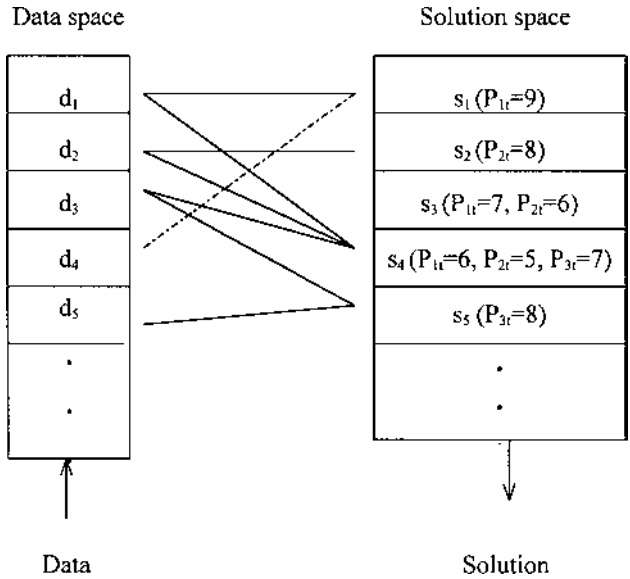

FIG. 3. The operation of a KBS: d_1, 10% discount; d_2, free gift with purchase over \$100; d_3, 40% discount in last or following campaign; d_4, free gift with purchase of product A; d_5, other promotion.

consistent with $d_4 = 0$. When the data of $d_1 = 1$ (with 10% discount) and $d_4 = 0$ (no free gift with purchase of product A) are available, the consistent solution candidate would be s_1. As a result, the weight which is assigned to the variable P_{1t} (i.e. percentage discount) is 9. The elements of information (or knowledge) represented in the data space, i.e. solution space, and their relations are obtained from intensive discussions with the company's experienced personnel. This information is updated by examining incoming observations. It took almost 5 months and considerable effort to realize the process of knowledge acquisition.

5 Analysis and results

5.1 Fitting sales promotion data with the TSIA model

Using the SAS software, the conditional least-squares (CLS) estimation approach was employed to estimate a class of TSIA models as described by equation (1). The sales data reported in Fig. 1 suggest that the intervention variables should be modelled as a pulse function. Based on the model selection procedure—the sample autocorrelation and sample partial autocorrelation functions, Akaike's information criterion (AIC) and standard error estimate—five models are selected as possible candidates for these sales data.

After conducting diagnostic checking procedures with residual sample autocorrelation functions, residual sample partial autocorrelation functions and the Q statistic of Ljung and Box (1978), a TSIA model was selected. This model is given by

$$y_t = \delta + w_1 P_{1t} + w_2 P_{2t} + w_3 P_{3t} + \frac{(1 - \theta_5 B^5)}{(1 - \phi_1 B)} a_t \tag{2}$$

Here, $P_{1t} = 0$ when the promotion does not offer any percentage discount, or P_{1t} equals a certain value (weight) when the promotion changes to offer a given

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percentage discount. $P_{2t} = 0$ when the promotion does not offer 'free gifts based on monetary purchase', or P_{2t} equals a certain value (weight) when the promotion changes to offer 'free gifts based on monetary purchase'. $P_{3t} = 0$ when the promotion does not offer 'free gifts based on product purchase', or P_{3t} equals a certain value (weight) when the promotion changes to offer 'free gifts based on product purchase'.

This model not only satisfies all requirements of model estimation and diagnostic checking, but is also easy to implement and use. However, as stated earlier, the determination of the values of P_{1t}, P_{2t} and P_{3t} is not straightforward. This task could be accomplished by the integrated use of the TSIA model and the KBS.

5.2 Integration of the TSIA model and the KBS

Following thorough consultation with personnel from marketing and inventory departments, we entered the data on sales promotional strategies and possible solutions into the appropriate spaces in the study sheet. The operation of this KBS may be described with the following example. With the TSIA model (i.e. equation (2)) as a forecasting model, a future promotional strategy that consists of a '10% discount' and a 'free gift with purchases over $100' is determined for campaign 14 of 1996. In doing so, campaign 13 of the same year, which offered a '40% discount', needs to be considered.

The data acquisition process of the integrated system can be observed in the following six essential questions. These questions can be answered in part or in full, depending on what information is available. The responses to these questions provide 'input information', which is shown in Fig. 2. The questions are as follows.

- Question 1: Are there any discounts?
- Question 2: Are there any free gifts with the purchase of certain items?
- Question 3: Are there any free gifts based on dollar purchases?
- Question 4: Are there any bonuses for sales personnel?
- Question 5: Are there any other combined sales promotions?
- Question 6: Are there any other promotions within one period before or one period after?

Campaign 14 of 1996 is concerned with questions 1, 3 and 6, and they should be answered individually. If a question is answered 'yes', then further inquiries will follow, such as the exact percentage of discount, or the minimum amount that needs to be purchased in order to receive a free gift. An affirmative to question 6 would lead to questions 1–5 again. After all relevant information has been entered, the KBS will determine the appropriate weights of intervention variables. In this example, the solution s_4 shown in Fig. 3 is chosen, since s_4 explains the greatest number of available data. Consequently, the weights of variables can be determined; i.e. $P_{1t} = 6$, $P_{2t} = 5$ and $P_{3t} = 7$. As a result, a forecast can be made for the campaign.

5.3 The results

Table 3 lists the actual sales that resulted from several different campaigns. Together with these sales figures are the forecasted values that were generated by the firm's previous system, those generated by a TSIA model system and those given by an integrated TSIA model with a KBS. To compare the effectiveness of each method, two performance measures, i.e. mean absolute percentage error (MAPE) and root

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TABLE 3. Actual observations compared with forecasts made by the company, by a TSIA model and by an integrated TSIA model and KBS

Campaign/ Year	Actual	Company	TSIA model	TSIA model and KBS
11/1996	3910	2900	3521	4079
12/1996	2372	2000	2196	2310
13/1996	12858	16600	13406	13136
14/1996	1848	2000	1851	1804
15/1996	1537	1055	1291	1472

TABLE 4. Performance measures for forecasts made by the company, by a TSIA model and by an integrated TSIA model and KBS

Performance measure	Company	TSIA model	TSIA model and KBS
MAPE	22.04	7.56	3.14
RMSPE	23.71	9.26	3.28

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mean square percentage error (RMSPE), were used. MAPE and RMSPE are defined as

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \frac{|e_t|}{y_t} \times 100$$

$$\text{RMSPE} = \left[\frac{1}{n} \sum_{t=1}^{n} \left(\frac{e_t}{y_t} \right)^2 \right]^{1/2} \times 100$$

where n is the number of periods of forecasting, and e_t is the difference between the actual observation and the prediction value at time t.

Table 4 displays these results. From Tables 3 and 4, it is apparent that the proposed integrated system is superior to the other forecasting methods used in this case.

6 Conclusions

Effective marketing strategies increase sales and company market share. An effective marketing strategy depends on a reliable forecasting model. This model helps a firm to avoid the risk of overstocking or understocking products, and the resulting inventory losses or inability to fill customer orders.

The present study examines a company that used 13 marketing strategies for the sales promotion of a certain product. The resulting data from these 13 (or multiple) marketing strategies present difficulties that cause us to adopt unconventional types of modelling. These difficulties arise because the effects of future interventions are unknown and the estimates of parameters may not converge to a reliable value—or may diverge. To resolve these difficulties, this study integrates two techniques: time series multiple-interventions analysis and a KBS. We have looked for cases that pertain to the uncertain effects of future interventions. In this study's approach, we have estimated model parameters. We have also strived to find the most appropriate modelling techniques and have run diagnostic checks to confirm the

validity of these models. Further, we have attempted to integrate TSIA forecasting models with KBSs and have presented the trajectory of future sales. The application of this study's approach to actual sales and promotional data from a real-like firm confirms the superiority of the results of our methodology.

In conclusion, one must not forget that marketing—despite its reliance on statistics, projections, or a KBS—is not a precise science. Subjective judgement will always remain an integral part of the process: the present study is no exception. The ultimate goal of systems such as that introduced in this study is to minimize the risk of inaccuracies arising from human error.

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