Transforming the Simple Moving Average Forecasting Technique into a Judgmental Bootstrapping Approach

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ABSTRACT

The simple moving average forecasting technique (SMAFT) uses a naïve arithmetic measurement for smoothing time-series data for various situations purposes, such as sales prediction. This paper attempts to rectify the contextual procedure of SMAFT by transforming the method into a judgmental bootstrapping approach, combining the statistical techniques of the $\overline{X}$ *- chart (x-bar) and the Hurwicz's Criterion. The proposed modeling approach generates a dual forecasting value, presented by the grand mean,* $\overline{\overline{x}}$*, of the x-bar chart and the expected weighted payoff of the Hurwicz's Criterion, which is used to improve the accuracy of the final forecast. This model will serve the need for a cost effective technique to address routine forecasting, especially for companies with large numbers of items.*

INTRODUCTION

The literature shows a vast spectrum of sales forecasting methods. The primary distinction among the forecasting methods is reliance on judgment versus estimation from quantitative data. Methods based on judgment include unaided judgment, prediction markets, experts' surveys, structured analogies, game theory, judgmental decomposition, judgmental bootstrapping, expert systems, simulated interaction, and intentions and expectations surveys. Judgmental methods also encompass experimentation and other methods that depend on quantitative data, such as extrapolation, quantitative analogies, rule-based forecasting, neural nets, casual models, and segmentation (Armstrong and Kester, 2011).

However, the boundary of this paper is limited to the extrapolation methods of sales forecasting - namely, the simple moving average forecasting technique (SMAFT). Extrapolation methods are widely used because of their cost effectiveness, as they require only historical data for sales forecasting. In addition, statistical extrapolations are cost effective when many forecasts are necessary. For example, some firms require frequent forecasts of demand for hundreds of inventory items. They are appropriate when little is known about the factors that affect the forecasted item (Armstrong, 2001b).

The basis of SMAFT is the use of a naïve arithmetic measurement, an average to smooth data and to predict sales units or values for a future period. However, Triola (2004, p.78) argued that the term "average" is open to different definitions of computations that measure the center of a data set, such as the mean, median, mode, and midrange, with the mean always being preferred over the average for references to the central tendency of a data set. In addition, McDaniel and Gates (2006, p. 373) maintained that the mean should be processed only from the interval or ratio of metric data. Render, Stair Jr., and Hanna (2003, p. 150) pointed out three obvious limitations of SMAFT, despite its wide use: the lack of causal knowledge of the real changes in the data that fluctuate narrowly up and down from the mean, the inability to highlight trends, and the necessity for large numbers of recorded observations. Alternatively, Lucey (1992) viewed the technique's limitations in terms of assigning an equal weight to the overall observations while ignoring the values outside the period of averaging. In this paper's view, SMAFT exhibits an improper use of statistics.

This paper is an attempt to transform the SMAFT contextual procedure by combining statistical and judgmental techniques. The modeling approach of this paper organizes time-series data into subgroups (samples) of interval types, and integrates the statistical technique of the $\overline{X}$ - chart to analyze paired samples (or more) of those subgroups arranged sequentially; the $\overline{X}$ - chart generates the grand mean, $\overline{\overline{x}}$ and the upper and lower control limits of the processed data. To determine the final weighted sales estimate, the proposed method adopts the decision criterion of Hurwicz, where the upper and lower expected values of the $\overline{X}$ - chart along a managerial-assigned optimistic/pessimistic index, α, ranges from 0 to 1, for adjusting sales estimates, which are then fitted into Hurwicz's formula (see equation 4). Therefore, this paper combines time series data, selected statistical techniques, and human subjective judgment—a judgmental bootstrapping approach. The methodology section of this paper explains further.

The structure of this paper consists of four broad headings: 1) the literature review, which underpins the venue of time series forecasting methods in particular; 2) the design of the modeling approach, which illustrates the contextual framework of the proposed judgmental bootstrapping approach; 3) the discussion and managerial implications, which argues the refurbishment of the practicality of SMAFT with the introduction of the judgmental bootstrapping model ; and 4) the conclusions, which provides fresh insights, reflects on the value of the proposed modeling approach, points to the limitations of the paper, and addresses the need for further research.

LITERATURE REVIEW

Sales forecasting represents an inevitable asset for organizations; it plays a pivotal role in supporting organizational activities, such as production activities, cost planning, and inventory management. The literature shows a great deal of concern regarding theoretical and practical sales forecasting techniques. Outstanding scholars, including Armstrong, Brodie, and McIntyre (1987) and Winklhofer, Diamantopoulos, and Witt (1996) have comprehensively demonstrated empirical research into forecasting technique practices. They attempted to review the literature and endeavored to understand firms' processes of forecasting. As a result, they advanced an organizational framework of forecasting processes to analyze the gaps in the past literature, and to establish guidelines for future research. Their critical remarks about previously published empirical research and their observations that forecasting practices seem to change over time reduced the authors' interests in investigating the literature regarding the relative adoption of SMAFT compared to other forecasting methods.

Among the forecasting techniques is time series analysis. Time series smoothing forecasting methods include moving average, exponential smoothing, regression, and double exponential smoothing. Hamilton (1994), Wei (2005), and Box, Jenkins and Reinsel (2008) have provided broad coverage of the use of moving average as a technique for analyzing time series, including the first order moving average, the *q*th moving average process, and infinite moving average methods. However, it is argued that longitudinal data may dictate selecting one technique over another. For instance, the moving average situational selection would apprehend the dispersions of discrete data values with a short time horizon, recorded by calculating the arithmetic mean of a few or more past values to predict values at a new point of time.

Pioneered by Bradley Efron's work in 1982, and Efron and Tibshirani (1993), the bootstrapping approach statistically processes small samples that violate the theoretical sampling distribution of normality, to match sampling from normal population(s). Although generally confined to the re-sampling of data, Huber (1975) perceived the significance of bootstrapping in terms of improving the reliability of data that are part of structured decompositional models; he had more concern over bootstrapping playing a part in decisions meant to improve the quality of subjective judgment and approximation. Regardless, the bootstrapping technique is computationally extensive (Everitt and Hesketh, 2001).

The term judgmental bootstrapping addresses the modeling approach of judges' or experts' regression rules to reduce forecasting errors and to improve estimation when forecasting the future (Armstrong, 2001a; Armstrong 2006; Goodwin, 2002). Judgment management in forecasting has received a great deal of attention in the literature (Moriarty, 1985). Armstrong (2001a) addressed the contributions of judgmental bootstrapping in reliability improvement, bias reduction, cost and time savings, and ease of use for average practitioners. Nevertheless, Henderson (2005) set up the prevailing conditions for the use of bootstrapping: a) where data are insufficient, b) where there are limited yet expensive data, c) when data are difficult to access, and d) when data distributional assumptions are unclear. For short term forecasting, both Armstrong (2001a) and Goodwin (2002) were in favor of the bootstrapping technique to anticipate time-series data, when possible. However, they stated— along with Fildes (1991), and Lawrence and O'Connor (1991) — that researchers had not adequately addressed product forecasting based on time-series data. Armstrong (2006) claimed that judgmental bootstrapping was seldom used in reality and that further research was necessary in order to understand the conditions under which the technique would be viable.

Herbig, Milewicz and Golden (1993), Winklhofer, Diamantopoulos and Witt (1996), Armstrong (2005), Chintagunta and Nair (2010, p.10) and other scholars have presented guidelines for developing bootstrapping models and setting up the conditions of their uses to improve forecasting methods, recognizing their limitations. These scholarly researchers have had different perspectives regarding model development, however. From previous research, then, this paper gained motivation to develop a simple transformational model that could process time-series data for a short-term time horizon, compared to the cross-sectional data.

Unlike the exponentially weighted moving average chart (EWMA chart), which is based on normal distributions, the $\overline{X}$ - chart would fit nonparametric data to smooth prior sample means exponentially. The $\overline{X}$ - chart can capture value fluctuations over a time-series span. The $\overline{X}$ - chart is an extension of the central limit theorem, and examines the center in a process (Triola, 2004). The $\overline{X}$ -chart becomes a convenient statistical technique when data are scarce, because it can process a sample size as small as two, with four being preferred

(Oakland, 2003, p. 123); the samples' average still conforms to a normal distribution (Render, Stair Jr. and Hanna, 2003, p. 679).

On the other hand, the adoption of the Hurwicz's Criterion in the proposed model aims to probabilistically lessen the two extremes of the $\overline{X}$ - chart, and to allow an agent to adjust these control limits heuristically, integrating α and inversed α that ranges from 0 to 1; the sum determines the weighted payoff. Lucey (1992, p. 22) considered the constant α as a representation of the decision maker's attitude toward the degree of risk, tending toward being an acceptor or an averter. This has an impact on prediction. A wide array of articles addresses the behavioral dimension in sales forecasting, all attempts to contain bias and errors and to improve forecasting performance. Gilboa, Postlewaite, and Schmeidler (2008), for instance, maintained that the notion of subjective probability used by people in uncertain modeling situations agreed with Bayes's rule for making decisions. Meanwhile, Einhorn and Hogarth (1981) argued the broad psychological context of the behavioral decision theory in terms of judgment processes and choice. Finally, Goodwin (2002) called for the integration of management judgment and statistical methods to improve short-term forecasts using bootstrapping. Integrating an averaging model and expert forecasts into judgmental bootstrapping contributes to accuracy (Franses, 2011). With that perspective, Saleh (2012a ; 2012b) introduced judgmental bootstrapping approaches that combined the statistical techniques of the X-bar chart and Hurwicz's Criterion into forecasting.

Next, the methodology section portrays the overall steps of the current modeling approach to transform the moving average forecasting technique into a judgmental bootstrapping format.

THE DESIGN OF THE PROPOSED MODEL APPROACH

The following illustrates the steps in the development of the proposed modeling approach.

1) Exploratory Data Analysis

To carry out the illustration of our proposed transformational approach, Table (1) lists the recorded time-series data of actual unit sales during 13 months (adopted from Lucey, 1992).

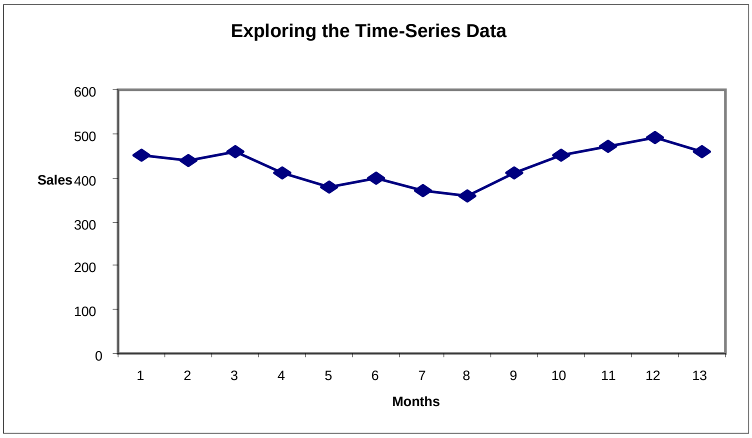
Table 1

Past Sales Data

Month	Actual Sales
Jan	450
Feb.	440
March	460
April	410
May	380
June	400
July	370
Aug.	360
Sept.	410
Oct.	450
Nov.	470
Dec.	490
Jan.	460

Exploratory data analysis is essential at this stage to investigate erratic value patterns (see Figure 1). However, data stability should exist; the control limits of the $\overline{X}$ - chart (used later) can be distorted if values are not normally distributed (Mitra, 1998, p. 289).

Figure 1



2) Developing the Sampling Plan

The sampling plan starts with organizing past time-series data into sets of *n* samples, each with a width of two or three values (more may be used), where x_1, for example, represents observations 1, 2, and 3, consecutively, and the second sample, x_2, represents dropping the oldest observation in the x_1 set and adding the newest observation, and so on with the rest of samples (see Table 2).

Table 2

Sampling Plan Development (3-months moving values)

x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
450	440	460	410	380	400	370	360	410	450	470
440	460	410	380	400	370	360	410	450	470	490
460	410	380	400	370	360	410	450	470	490	460

Luck and Rubin (1987) defined statistical analysis as "the refinement and manipulation of data that prepares them for the application of logical inference," while they endorsed the researcher to choose the formulas and data inputs objectively. Purposive - non-random - or judgmental sampling is a rational option for processing limited time-series data. Saunders, Lewis and Thornhill (2009, p. 233) argued for the use of non-probability sampling techniques to support a research objective when there was an inability to specify a sampling frame; they maintained that the sample size would have no rules and would be subject to the research goal and outcome pursued. On the other hand, Al Shanawany (2011, p.176) argued that non–normal data manipulation can be achieved through averaging subgroups, segmenting or stratifying, or using different transformations; this is to move toward normalization.

3) $\overline{X}$ - Chart Construction for Determining a Future Period Forecast

The $\overline{X}$ - chart is convenient to analyze the continuous data of limited size samples. Meanwhile, Triola (2004, p. 352) proposed the use of the nonparametric or computerized bootstrap method.

To perform the $\overline{X}$ - chart analysis and to predict a new point of forecast, the proposed model combines a minimum of two samples (i.e. x1 and x2; x2 and x3… x9 and x10) uninterruptedly. For each pair of samples, it calculates the grand mean, $\overline{\overline{x}}$ and the upper and lower control lines of the $\overline{X}$ - chart. For instance, it combines x1 and x2 for predicting the sales of May, and x2 and x3 to predict June's sales, and so on. This aggregation approach aims to reduce bias toward a particular data set and to smooth the means sets' measurements to extrapolate the grand mean $\overline{\overline{x}}$, and the upper and lower control limits of the $\overline{X}$ - chart; however, for the April forecast, it simply replicates the first sample, x_1, where the grand mean and the upper and lower limit values will be identical.

Worksheets (1) and (2) illustrate the calculation of the center line, $\overline{\overline{x}}$, and the control lines of the paired samples for estimating a future period forecast for May and June as an example (the numbers should be rounded up, however). It is worth noting that the grand mean, $\overline{\overline{x}}$ smoothes the time-series data and presents the estimate of the future period. Nevertheless, one can combine more subgroups to anticipate the future forecast of a point. This might improve the forecast as more samples reduce the bias of limited data values; worksheet (3) presents a combination of four samples to project the forecast for July in the previous example. $\overline{\overline{x}}$ for July equals 425 units.

Worksheet (1)

May Forecast

	Samples					
Observations	**x1**	**x2**	Mean	Range	$\overline{\overline{x}}$	$\overline{R}$
Value 1	450	440	445	10		
Value 2	440	460	450	20		
Value 3	460	410	435	50		
					443.3	**26.7**

A2 for 3 observation	1.023
Upper Control Limit	470.6
Lower Control Limit	416.1
Alpha	0.2
Alpha -1	0.8
Weighted forecast	**459.7**

Worksheet (2)

June Forecast

	Samples					
Observations	**x2**	**x3**	Mean	Range	$\overline{\overline{x}}$	$\overline{R}$
Value 1	440	460	450	20		
Value 2	460	410	435	50		
Value 3	410	380	395	30		
					426.7	**33.3**

A2 for 3 observation	1.023
Upper Control Limit	460.8
Lower Control Limit	392.6
Alpha	0.2
Alpha -1	0.8
Weighted forecast	**447.1**

Worksheet (3)

July Forecast

	Samples							
Observations	**x1**	**x2**	**x3**	**x4**	Mean	Range	$\bar{\bar{x}}$	$\bar{R}$
Value 1	450	440	460	410	440	50		
Value 2	440	460	410	380	422.5	80		
Value 3	460	410	380	400	412.5	80		
							425.0	**70.0**

A2 for 3observations	1.023
Upper Control Limit	496.6
Lower Control Limit	353.4
Alpha	0.2
Alpha -1	0.8
Weighted forecast	**468.0**

Figures 2, 3, and 4 present graphical representations of the $\bar{X}$ - charts for the above three worksheets.

Figure (2)

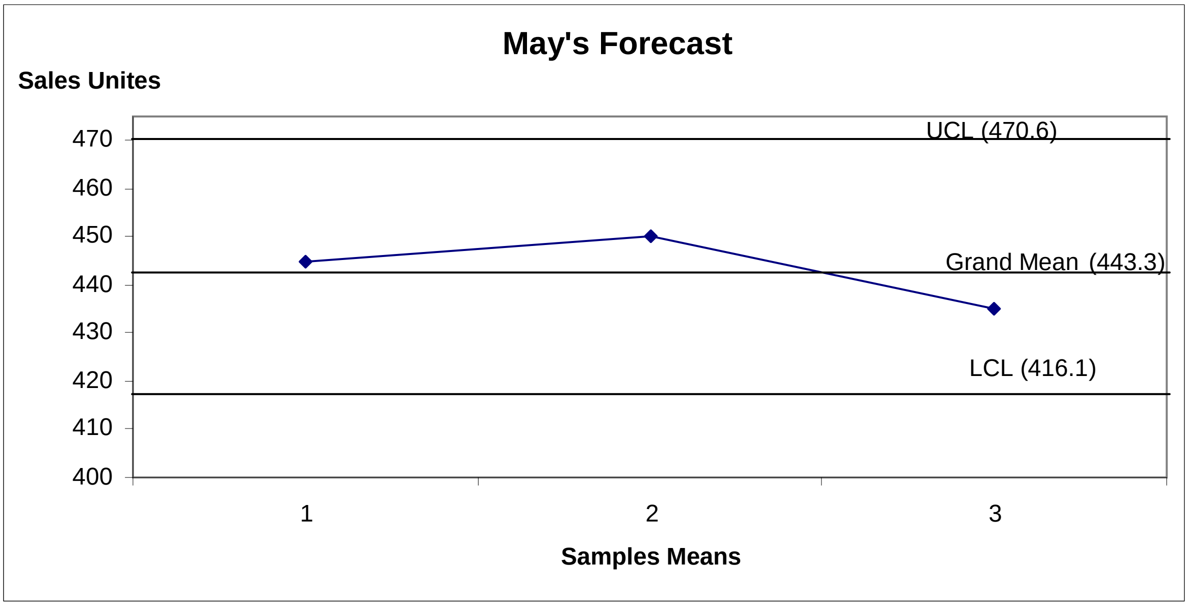


Figure (3)

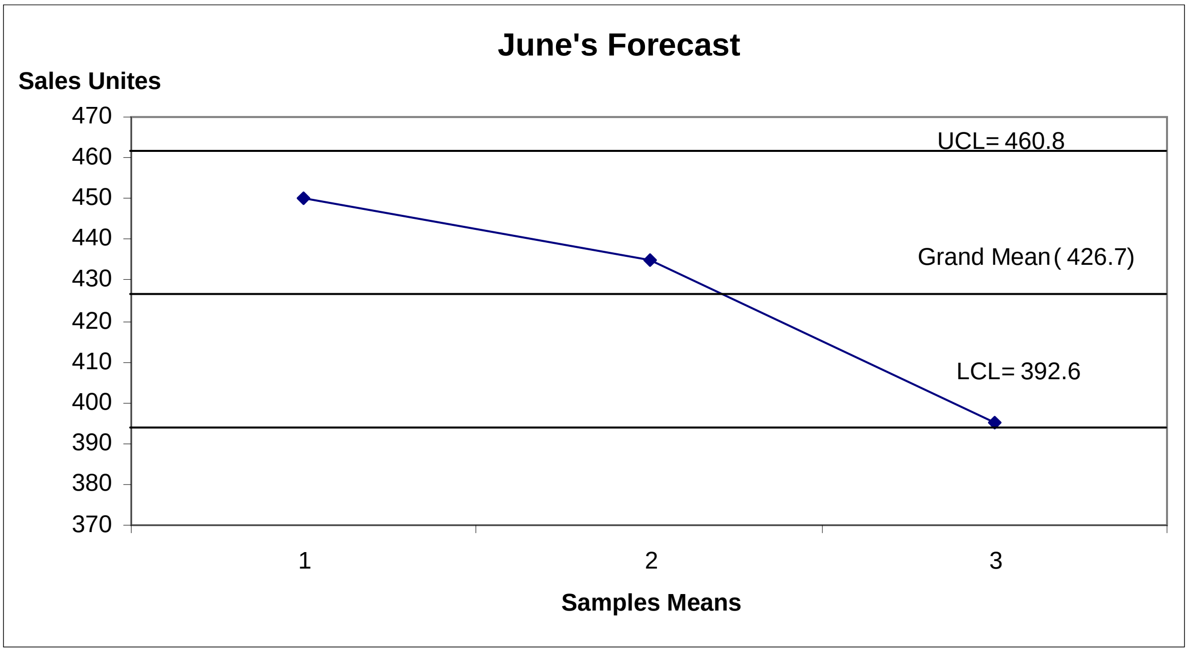
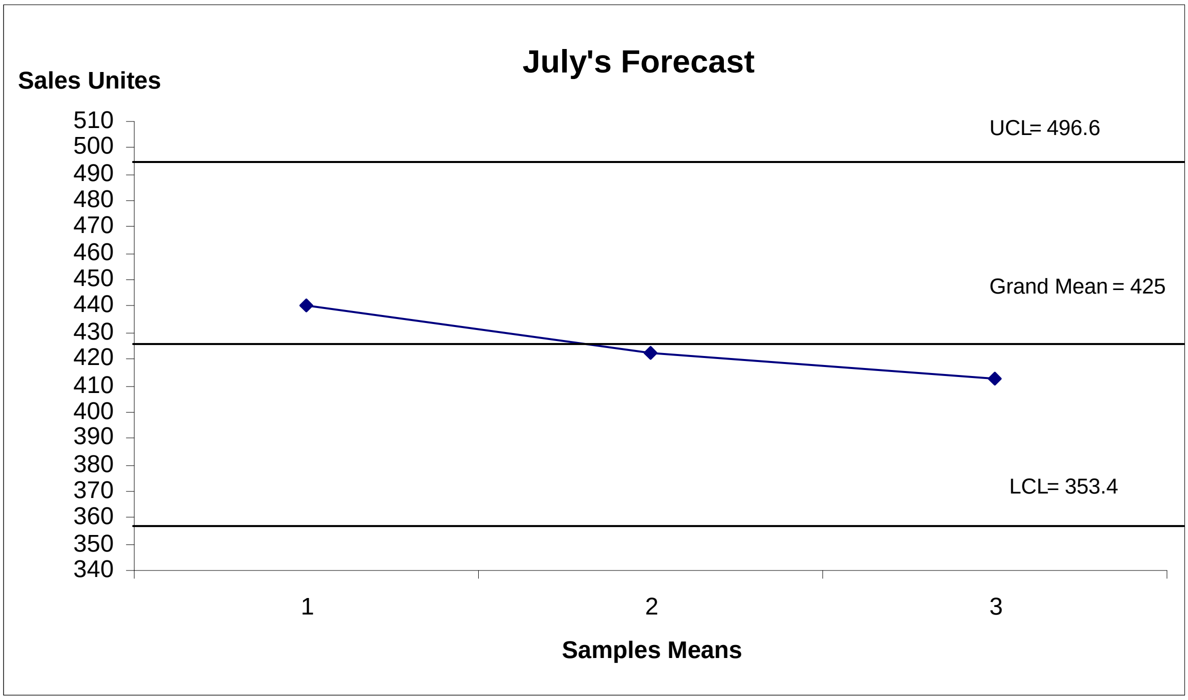


Figure (4)



The standard equations used to establish the upper and lower limits are

(1) UCL = $\bar{\bar{x}} + A_2 \bar{R}$ and

(2) LCL = $\bar{\bar{x}} - A_2 \bar{R}$,

where

UCL = Upper Control Limit (upper sales estimate),

LCL = Lower Control Limit (lower sales estimate),
$\bar{\bar{x}}$ = the average of sample means (grand mean),
A_2 = a factor for computing control chart limits for a sample size *n (for n=3, A_2=1.023)* as tabulated in the statistics and operation management text books, and
$\bar{R}$ = mean of the sample ranges.

4) Developing the Final Bootstrap Weighted Estimate
For further smoothing, the Hurwicz's Criterion incorporates the upper and lower values of the $\bar{X}$ - chart, and anticipates an agent's subjective beliefs, portrayed by α and 1- α assigned to the $\bar{X}$ - chart's extremes objectively to achieve reconciliation.

The following equation presents the standard Hurwicz's criterion:
(3) Weighted payoff = α × worst payoff + (1 – α) × best payoff

The modified Hurwicz's criterion proposed by this paper reads:
(4) Bootstrap weighted sales estimate =

$$= \alpha \times \bar{X} \text{-chart lower control limit} + (1 - \alpha) \times \bar{X} \text{-chart upper control limit}$$

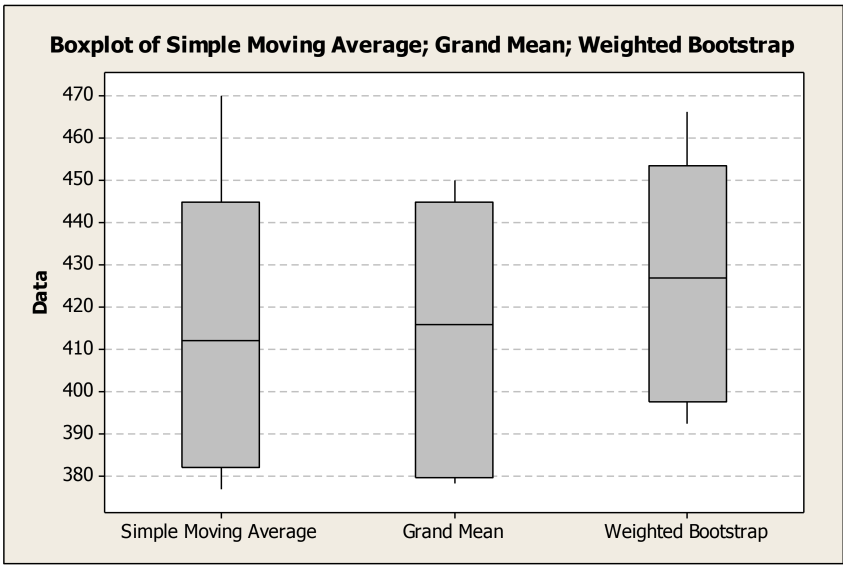
Equation (4) takes-in the upper and lower control limits of the $\bar{X}$ - chart; an agent would assign his or her subjective beliefs, expressed by the probabilities α and 1- α, to extrapolate a future period forecast.
For example, the bootstrap weighed sales estimate of May at α = 0.2 and 1- α = 0.8, as illustrated by worksheet 1, would be .2 × 416.1 + .8 × 470.6 = 459.7 = 460 units, approximately.
Worksheets 2 and 3 calculate June and July weighted forecasts, for further illustration.
Table (3) lists the post sales data of 13 months and presents the means of 3 months' moving averages, the grand means of the samples extrapolated by the X-bar chart, and the weighted bootstrapped prediction for forecasting a new point of time.

Table (3)
Forecasts Comparison

Month	Past Sales Data	Simple Moving Average	Grand Mean $\bar{\bar{x}}$	Weighted Bootstrap
Jan	450			
Feb.	440			
March	460			
April	410	450	450	
May	380	437	443.3	459.7
June	400	417	426.7	447.1
July	370	397	406.7	427.1
Aug.	360	383	390.0	406.4
Sept.	410	377	380.0	392.3
Oct.	450	380	378.3	396.7
Nov.	470	407	378.3	398.8
Dec.	490	443	425.0	447.5
Jan.	460	470	450.0	466.4

The boxplot graph (or box-and-whisker diagram) is a helpful exploratory data-analysis tool for comparing data sets. Graph (1) indicates the insignificance of the "median" value differences in the data, related to the traditional simple moving average and the grand mean approaches in particular. Presented below is a summary of the descriptive statistics of Table (3) above.

Graph (1)



Descriptive Statistics: Simple Moving Average; Grand Mean; Weighted Bootstrap

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median
Simple Moving Average	10	0	416.1	10.3	32.6	377.0	382.3	412.0
Grand Mean	10	0	412.83	9.46	29.91	378.30	379.57	415.85
Weighted Bootstrap	9	1	426.89	9.71	29.13	392.30	397.75	427.10

Variable	Q3	Maximum
Simple Moving Average	444.8	470.0
Grand Mean	444.98	450.00
Weighted Bootstrap	453.60	466.40

To assess the means' differences, one can conduct ANOVA tests, but first one must test the normality of the data by using the Minitab, for instance. Because normality cannot be reliably checked with small samples (less than 15), the authors recommend caution when interpreting the test results as the results do not provide sufficient evidence to conclude that there are differences among the means.

DISCUSSION AND MANAGERIAL IMPLICATIONS

In SMAFT time is the only independent variable used to forecast demand (the dependent variable) and that the pattern of past relationship between time and demand extends to future. The condition of the technique use assumes stability over the short term and the absence of a trend. The technique also disregards the effect of some other variables such as economic conditions, business cycle, sales efforts and advertising expenditure, competitors' actions…etc. In addition, the technique purely relies on mathematics and minimizes the integration of data, analysis, and information with judgment for improving forecast accuracy. On the other hand, SMAFT focuses only on measuring the center. It is always important to pay attention to the measurement of the key characteristics of data: the centre, variation, distribution, outliers, and time changes, collectively abbreviated CVDOT (Triola, 2004). Nevertheless, the proposed bootstrap modeling approach combines time series and explanatory (casual) approaches. The $\overline{X}$ - chart is competent to measure CVDOT; it summarizes important characteristics of time-series data. The $\overline{X}$ - chart sets the central line, the mean of all sample means denoted by $\overline{\overline{x}}$. The graphical chart representation of $\pm$ 3σ (three sigma) illustrates the differences between data values in terms of the range. This would guide managers to observe the time-series value changes, such as the dispersion of data values from the central line and the detection of outliers, if they exist. On the other hand, Hurwicz's Criterion incorporates the upper and lower control limits of the $\overline{X}$ - chart, and agent subjective judgment, where α and inversed α approximate the coefficient of realism and represent the decision maker's attitude towards the degree of risk or the anticipation level of market dynamics; in that perspective, alpha is a legitimate subjective value.

Quantitative techniques may require statistical software beyond the capabilities of small and medium size enterprises. Nevertheless, the proposed model can access a great deal of support as it can be conducted manually or through widely available software applications, such as Microsoft Excel® for instance, and it provides a cost effective way to conduct unassailable forecasts without high expense and expertise.

CONCLUSIONS

This paper endeavored to transform SMAFT into a judgmental bootstrapping approach. Misusing statistics and ignoring other data-characteristic measurements are the major limitations of SMAFT. Unlike basing the sales forecast of a future period on smoothing a number of observational values mathematically, probabilistically, or exponentially our hybrid forecasting approach combines both statistic and judgment. In our proposed approach, statistically forecasted past sales data are updated by the judgmental parameters of the Hurwicz's criterion for anticipating uncertainty in demand or adjusting the inventory level. The proposed approach supports routine forecasting in particular.

However, this paper cannot claim that the proposed approach is reliable, but tracking the proposed model's performance and comparing the stipulated weighted predictions with actual sales numbers for instance can justify its use. The paper cannot assert the new approach's validity, but researcher objectivity, and recognition of the perceived reliability of the statistical procedures can contribute to confidence in the proposed approach. In addition, empirical or experimental research that compares our approach and results with other methods is necessary.

It is difficult to lose faith in any of the techniques in the array of forecasting techniques applied to time-series data because different situational applications could justify the adoption of any one of them. However, incorporating non-traditional statistical techniques may become necessary— a driving motive for this paper was to advance a practical judgmental bootstrapping approach to transform SMAFT.

Finally, great potential remains in judgmental bootstrapping modeling. That potential should build passion for propagating new forecasting methods; it should inspire proactive research. Nevertheless, researchers should consider the objective of harvesting simple quantitative approaches. They must leverage their research and strike the right balance to meet end users' needs for realistic and practical techniques in forecasting.

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