JOURNAL OF FARM MANAGEMENT VOL.13. No. 11. PAGES 747-764

REFEREED ARTICLE

AGRIBUSINESS FORECASTING WITH UNIVARIATE TIME SERIES MODELLING TECHNIQUES: THE CASE OF A DAIRY COOPERATIVE IN THE UK

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This study forecasts milk supply of a dairy cooperative in the UK using univariate time series models. Two seasonally adjusted exponential models, specifically, Holt-Winter's seasonal model and seasonal autoregressive integrated moving average model (SARIMA) generated forecasts with error of less than 3 per cent, implying that such techniques could easily be applied to businesses having limited historical data characterised by trend and seasonality components. Results also show that longer series produces better forecasts than a shorter series. Forecasts for periods of more than a year could be used but with caution, and should be updated with actual data whenever opportunity arises, because data pattern may change substantially in response to policy changes and other related factors.

Keywords: Univariate time series models; milk supply forecasting; trends and seasonality in historical data.

Introduction and background

Entrepreneurs operate not only with limited funds but also with restricted information. In particular, small and medium businesses often make decisions under acute shortages of information. Given these constraints, managers estimate future sales volume to make budgets, predict operating expenses, cash flows, pricing, advertising outlays, etc. Actual turnover and profitability depend on the accuracy of these decisions.

In the UK, milk is channelled from farmers to consumers through cooperatives, processors (private limited companies or plcs) and supermarkets. The cooperatives are owned by the member farmers and constitute an important stage in the milk supply chain serving the farmers, acting as intermediaries between the farmers and processors and/or retailers. On behalf of the farmers, the cooperatives bargain with the processors, but in general cooperatives hold weaker market power than the processors (Smith and Thanassoulis 2008). In this situation cooperatives require accurate estimates of liquid milk supply from their members in order to bargain for competitive farm gate prices. The present study aims at improving the prediction of milk supply using a case study of a dairy cooperative, which characterises a limited information base. The cooperative has accurate records only of historical data of monthly milk supply from individual members over the years. The cooperative managers expressed the view that a one percent improvement in forecasting error could potentially save around £1M in preparatory expenses, such as planning for transportation and haulage as well as production plan for further processing into value added products (e.g., cheese, chocolate milk, etc.), which emphasises the importance of having an accurate forecasting of milk supply, even at a single-business level.

The paper proceeds as follows. The next section briefly discusses the milk industry in the UK, the dairy cooperative under study, and its existing forecasting methods. Section 3 provides the methodological framework. Section 4 discusses the results. The final section concludes and draws practical implications.

2. Dynamics of the milk industry in UK and the Milk Link Ltd.

The farmers' cooperative Milk Marque was formed from the Milk Marketing Board (MMB) after deregulation of the milk market in 1994. Before the deregulation MMB was responsible for the purchasing of almost all milk produced in England and Wales and supplying it to the processors. After deregulation some farmers discontinued their contracts with Milk Marque in order to sell milk directly to processors, although in 1999, this cooperative still handled around half of all liquid milk sales. In 2000, Milk Marque was divided into three regionally based cooperatives: Milk Link, Zenith Milk and Axis Milk. Zenith and Axis have subsequently merged with the Milk Group and Scottish Milk to form Dairy Farmers of Britain and First Milk respectively. These three cooperatives have over time moved from being solely concerned with the marketing of liquid milk into milk processing as a consequence of the structural changes in the industry. Traditional milk processors have meanwhile undergone a process of consolidation with, for example Unigate merging with Dairy Crest, and Arla Foods merging with Express Dairies (Tiffin 2006). There are three large public limited companies (plcs) which hold a stronger bargaining position than cooperatives, partly because they are able to source milk directly from farmers in the event of impasse with the cooperative or bidding an extra contract from a supermarket and by paying slightly higher prices (Smith and Thanassoulis 2008). Thus dairy farmers in the UK supply milk either to the cooperatives (as members of those cooperatives) or to plcs. Member farmers have contracts with cooperatives and other farmers have contracts with either the plcs or cooperatives (we call them non-members in this study).[1] Type of contracts differs widely depending on quantity and quality of supply, seasonality, duration of contract, proximity of the farm from a processing point, etc.

Externally, a number of changes in the EU policies have been influencing the industry directly and indirectly (FAPRI 2007). Between April 2001 and September 2004 the retail price increased by 8 per cent and the farm gate price increased by 4 per cent due to dynamic structural changes (Tiffin 2006). Prices are still rising but supply is falling due to the fact that the UK is losing 5-6 per cent of farmers every year.[2] Specialist dairy farming is also declining at nearly at nearly the same rate (Colman and Zhuang 2008). Cooperatives are gradually losing members in the UK. In addition, due to the strong competition with plcs that exists today, the cooperatives are striving to improve turnover. Accurate

1. These non-member farmers are often called direct farmers because they supply milk directly to the processors, thereby, bypassing the cooperatives. Cooperatives also purchase milk from these non-member farmers who are not completely free agents. They are to be contracted well ahead for supplying milk in the following year or afterwards but they are not shareholders like member farmers. Contract type varies widely but the duration of a non-member contract is at least a year. In the case of Milk Link members have to deposit 0.5 pence per litre of their supply to the cooperative to build capital but non-member farmers do not deposit a share.
2. The source of the information is http://www.fwi.co.uk/Articles/2008/06/20/110920/uk-milk-supply-can-recover-from-current-low.html by Paul Spackman, Arable editor for FWI. Also available in https://statistics.defra.gov.uk/

sales forecasting is certainly an inexpensive way to improve business performance (implying farmers could get competitive farm gate prices), since this leads to improved customer services, reduced lost sales and product returns, and more efficient production planning and human resources management. In particular, knowledge of farmers' supply well in advance would help a cooperative to contract non-farmers for balancing the required supply shortfall to meet processors/retailer demand.

Milk Link Ltd is a progressive integrated dairy business and the largest cheese producer in England, handling over 2 billion litres of milk every year from members and non-member farmers in the South West region. It started functioning initially as a milk broker but has moved to a vertically integrated dairy business, functioning also as a milk processor. At present it owns eight processing plants that process milk from members as well as balancing supply shortfalls directly from non-member farmers. Around 25 per cent of the milk supplied by the member farmers is sold to plcs. Milk Link also purchases milk from non-members on behalf of plcs. In 2005, it ranked 12th in the Top 20 of the European dairy cooperatives. However, according to its management, Milk Link faces a real challenge of not being able to forecast its monthly milk supply with less than 5 per cent error, with the associated financial risk. Its current forecasting practice is based on a complex mix of: (a) actual milk supply per member which, in turn, is based on historic or preceding year's supply, (b) an ad-hoc adjustment of presumed productivity increase per member for the coming year, (c) an adjustment to account for retirement of farmers and new recruits, and (d) a seasonal adjustment measure to account for fluctuation owing to calving practices and other unforeseen factors. In addition, a pro-forma is regularly distributed to members to encourage them to provide their own forecasts of milk supply, known as "farmer forecasts". But many members do not return the forms, and even when sent the forecasts are often inaccurate (Haye 2006). Milk Link also recruited a consultancy group to provide milk supply forecasts which are known as "C-forecasts". We have looked into the results of "C-forecasts" as well as "farmer's forecasts" for a 4-month period, i.e., for the months of May, June, July and August in 2006/7. The results show that farmer forecasts were more accurate than C-forecasts, which is somewhat surprising. Monthly variation in farmers' forecasts was wide with an extremely good forecast in May and extremely inaccurate forecast in August. The C-forecast for August 2006 was about 12 per cent lower than the actual realised production, and the farmers' forecast for the same month was 9 per cent lower (Haye 2006).

Given this backdrop, it is imperative that a scientific but simple approach is needed to provide a long-term forecast of milk supply with minimum error despite serious data constraints. In this paper we present how time series models could be used to produce reasonably accurate forecasts from limited data.

3. Analytical framework

Forecasting is prediction of the likely future value of a variable (or set of variables). There are various methods of forecasting, which can be classified into several different categories and none is free from error. Two broad categories are discussed below:

1.Univariate time series models

2. Multivariate time series models

In the univariate approach which is often referred to 'pure time series analysis', the relationship of past and current values of a variable from historical data series is used to forecast its future values (Verbeek 2000).[3] On the other hand, multivariate approach builds structural models based on interrelationships between variables to use them as the basis for forecasting and inference; relationships are often derived from well-specified theory, though this is not always the case. The multivariate approach tries to accommodate realistic situations but requires a large set of information for the related variables as well as their future values. Due to data constraints, and to avoid the complexity of deriving future values for related variables, our analysis is centred on univariate time series models.

It is often argued that from the predictive point of view, a pure time series approach often outperforms a structural approach because of the estimation problems of the latter (Gottman 1981). The history of the concerned variable in a univariate model provides enough information to predict future values. Structural models require forecasts for all 'exogenous' variables. This could introduce other sources of forecast error. As in the case of milk supply, a farmer or producer cooperative is a price taker. EU policies would affect milk market price as well as farm level management decisions. Appropriate futures forecasts for milk price, number of cows, etc., require an aggregate model (at sector, country level, or EU level). For a particular company it would be unrealistic to forecast all such variables. Also, building a structural model would be expensive and futures forecasts for exogenous variables are more likely to be inefficient if attempts are made to forecast all of them with limited data.

3.1 Milk supply pattern of the Milk Link Ltd.: What the data tells us?

Accuracy of forecasts using historical data depends on the recognition of data patterns, such as, average, trend and seasonality. We have collected milk supply data from the Milk Link internal records. Data on monthly milk supply from members is available from April 2000 and from non-members is available from April 2002. This gives us 96 monthly records of member supply and 72 monthly records of non-member supply. The cooperative started functioning with more than 3,000 member farmers and then gradually declined below 2,000. Monthly milk supply from member farms during this eight year period varied from around 80 million litres to more than 156 million litres with an average of about 118 million litres. The number of members who actively supplied milk varied from 1,522 to 3,057 farms. Average monthly collection from non-members is about 46.6 million litres with a maximum of 85.7 and a

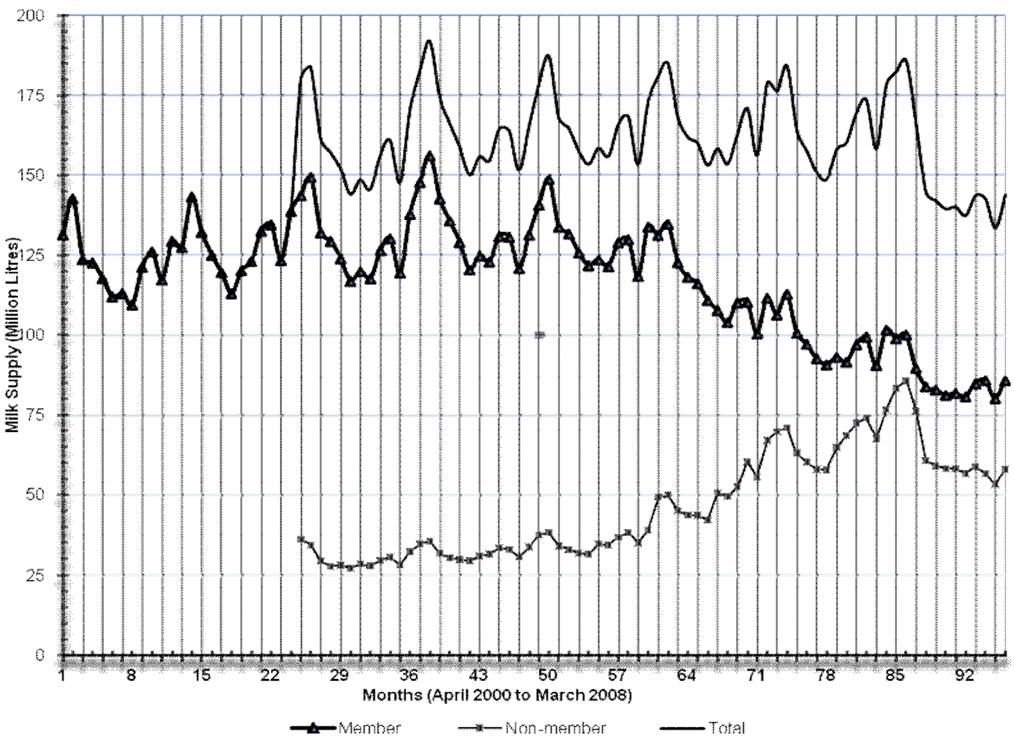
3. Time series is a set of observations measured at successive times or over successive periods.

minimum of 27.2 million litres.

Data on other related variables, e.g., milk price, number of cows per farm, etc, was available only in shorter series. Figure 1 shows fluctuations of monthly supply of milk volume since 2000 from members and non-members, showing a slight downward trend with seasonal fluctuations, and a yearly peak during the summer months. Milk supply was almost trendless until the 50th month (May 2004) for the series beginning in April 2000. Since then a decreasing trend is clear, possibly due to changes in the Common Agricultural Policies (particularly the 2003 CAP reform), which were gradually translating into decreasing farm production. Also milk processors were strengthening their power through consolidation as mentioned earlier, resulting in a loss of market power for farmers.

Although retail price was rising, farm gate price was rising at a much lower rate. Other processors were offering higher farm gate prices and, consequently, Milk Link was losing members. A seasonality pattern has been visible since the beginning of the series. Peak supply clearly occurred in the month of May every year until 2005. Additional peaks have been noted in March since 2006. However, the amplitude of seasonal fluctuation has been reducing gradually since 2004, possibly due to seasonality incentives introduced in 2004.

Figure 1: Actual milk supply from member and non-member, April 2000 to March 2008



X-axis: 1=April 2000, 2=May 2000 and so on

On the other hand balancing-supply from non-members is rising gradually with smaller seasonal fluctuations than in members' supply. Production incentives are used as an instrument to reduce drop-out of members, but with limited apparent effect. During the most recent year in the data (April 2007 to March 2008), total milk supply declined from both members and non-members: this is consistent with the national trend. In five months from 01 April to 31st August 2008, the UK farmers produced 120 million litres less milk (2 per cent of total supply) compared to the same period in 2007 (though a period of extremely unfavourable weather in 2008 will also have had a strong influence).

The changing pattern in seasonal fluctuation corresponds to the policy of seasonality payment in the form of differential pricing being introduced in April 2004 to encourage producers to supply milk more evenly over the year. The national policy is to change this payment over time depending on performance. Therefore, for the most accurate forecasting, such seasonality incentive needs to be explicitly accounted for, possible only if structural multivariate modelling can be used. As mentioned earlier, time series data of the related variables and policy changes are not available, and we make the assumption that the historical monthly supply data would have captured these seasonality effects.

Although Milk Link collects two distinct types of milk (organic and conventional (non-organic) milk) from specific locations, disaggregated data is not available in sufficiently long series to enable separate analysis. Therefore, we have aggregated milk supply from 6,030 farmer records (which include 4,469 members and 1,561 non-members) under two broad categories only: members and non-members, and then focussed on member supply for this analysis. We assume that the cooperative has a target demand for liquid milk for its processing plants and contracts with plcs and retailers. Once future supply from members is forecast, then the cooperative would take necessary steps to contract non-members for balancing supply, so forecasting member supply is the main priority.

Some suppliers have joined Milk Link at different points of time and some have left (either retired or joined other milk processors). However the current situation is that suppliers can only leave Milk Link on the 31st of March and have to give at least one year's notice, meaning that for at least a year (between the 1st of April and the 31st of March) the number of suppliers should remain relatively stable. Historical data of total milk supply would capture the pattern of net suppliers in the single variable framework. Removing data from suppliers who left Milk Link would produce inaccurate forecasts because entry -exit contributes to the trend as well as seasonality. Some members may be able to predict the changing policy circumstances and would expand their production scale to reap market opportunities; other may fail to do so and instead decide to leave. This behaviour is expected to translate in the supply pattern over several months or may be over several years.

3.3 Single variable time-series models used

Among single variable time series models, some popularly-used methods are:

- simple moving average
- seasonal additive and multiplicative moving averages
- single exponential smoothing
- double exponential
- Holt Winter's Additive
- Holt Winter's Multiplicative and Logarithmic models.

Moving averages are arithmetic means of a given number of past data points over the time series; variants consider the differences in the number of periods and weights for each period. Simple moving average, seasonal additive and multiplicative moving averages are commonly used for smoothing data and often produce poor out-of-sample forecasts, because the most recent observations are used to forecast future data points. Single exponential is a single parameter (average) method that smoothes data giving greater weight to values of the variable in more recent period, and less weight to values in earlier periods. Unlike moving average, it takes all previous periods into account. It can be adjusted for seasonality using a seasonality index resulting in a two-parameter model; the parameters are average and seasonality. Double exponential applies the single exponential smoother twice and could also be adjusted for seasonality as in single exponential model. Holt –Winters Multiplicative Seasonal is a three parameter (average, trend and seasonality) exponential smoothing method of forecasting (Chatfield and Yar 1988, Chatfield 2004).

Advanced time series methods of forecasting are based on Auto Regressive Integrated Moving Average (ARIMA) models (Maddala 2001, Box and Jenkins 1976, Hamilton 1994). Seasonal ARIMA (SARIMA) includes a seasonality component. Box *et al*. (1994) suggest starting with a multiplicative SARIMA model with any data that exhibit seasonal patterns, and then exploring other models if the multiplicative models do not fit the data well (Stata 2008). Box-Jenkins methods consider different autocorrelation patterns in the underlying time series to fit the "best" model.

As mentioned earlier, the prime objective of this exercise is to generate a forecast of members milk supply with minimal error while working with only a single time-series variable, i.e., milk supply per month. To this end, alternative models were applied to the time-series data in order to arrive at a choice that provides a best fit and a reliable forecast of members milk supply. According to Figure 1, milk supply exhibits considerable seasonality and so this influence should be included in the models. We have examined this hypothesis by comparing the results of models with and without seasonality component.

Details of the models and formulations are provided in the appendix. Holt Winter's methods are generally applied when a time series contains a global trend as well as a seasonal component. Holt Winter's multiplicative model (where smoothed, seasonal and trend components are multiplied together to give a more dynamic time series) is better adapted for the data pattern that shows trend as well as rising or falling seasonal component.[4] Figure 1 shows a

4.Visit http://www.ipredict.it/ for details.

pattern like this. In the SARIMA model, there is flexibility to include different autoregressive and moving average terms and type of seasonal effects (Stata 2008). We have examined alternatives and the best model is chosen based on statistical fit and forecast performance.
Performance of forecasts is evaluated by Mean Absolute Percent Error (MAPE), which is defined as follows:

$$MAPE = \frac{\sum_{t=1}^{T} |Z_t|}{T} \qquad Z_t = \frac{Y_t - \hat{Y}_t}{Y_t} \times 100$$

where , Y is the actual value, is $\hat{Y}$ the forecast value, t represents time and the lower the MAPE the better would be the forecast. Out-of-sample forecast performance was evaluated by leaving up to three years of data out of the sample. Last five values of the series were finally chosen to report the performance of out-of-sample forecast. The data series was not very long and forecast errors were higher when analysis was carried out with a shorter series.

The models implicitly assume that the estimated parameters (average, trend and seasonality) with usual statistical properties would capture all systematic changes in the underlying data series and that they will remain the same in the future.

4. Results and discussions

Table 1 shows a comparison of the models, ranked by MAPE.[5] The moving average seasonal multiplicative model fits the data best, followed by double exponential adjusted for seasonality, followed by Holt-Winters seasonal, then by SARIMA model.[6] The double exponential method does not

Table 1. Ranking of Forecasting Techniques (applied to monthly aggregate milk supply data of 4469 member farms for the period April 2000 to March 2008) by Mean Absolute Percent Error (per cent)

Rank	Technique	MAPE	Confidence Interval
1	Moving average multiplicative	0.94	0.75-1.12
2	Double exponential seasonality adjusted	1.09	0.93-1.44
3	Holt–Winters seasonal	1.82	1.51-2.13
4	SARIMA model	2.16	1.76-2.52
5	Single exponential seasonality adjusted	2.67	2.30-3.05
6	Single exponential	5.45	4.79-6.10

5. Parameters of all models but multiplicative moving average were chosen based on minimum mean square error (this is done by using STATA software automatic mode, ref. Stata 2008) and then MAPE was manually computed for each selected model for the purpose of ranking using the same software.
6. Autoregressive and seasonal terms in the SARIMA model were chosen based on correlogram and AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) criteria, where AIC= ln (sum of squared errors)+ 2 ((1+p+q)/T), and BIC = ln (sum of squared errors) + ln T, ((1+p+q)/T). The best model has the lowest AIC or BIC. The BIC can be preferred because it has superior large sample properties. Although unbiased, forecasts from an ARMA model are necessarily inaccurate; the variance of forecast error is an increasing function of forecast step. So the accuracy of short term forecast is higher than the long term forecast (Enders 2004).

take seasonality into account: since the data indicates a seasonality pattern, we adjusted the double exponential forecast with seasonality calculated from the moving average model, and its resulting performance appears satisfactory in terms of MAPE.

The models which produced less than 3 per cent prediction error with historical data were chosen to examine the performance of the out-of-sample forecast. The estimated forecast and actual data for 5 months beginning April 2008 presented in Table 2 shows that moving average when adjusted for seasonality though fits the historical data well but out-of-sample forecast error is higher than the other methods. Generally, the method is used for the purpose of smoothing the data, not for the purpose of out-of-sample forecast.

SARIMA is an advanced method and it is possible to include different autoregressive and moving average patterns in this model to make a dynamic forecast. Although its rank is fourth in terms of MAPE, its out-of-sample forecasts during the initial months were very good, but after that the forecast errors increased with time. Models that require initial values to be specified for recursion like the SARIMA models (as well as models 2-5 as described in the appendix) may be sensitive to initial conditions. The default starting values in the STATA software that is used for the analysis are generally good in large samples for stationary series (Stata 2008). Dynamic forecasts from SARIMA model are also sensitive to their starting values. We compared alternative starting points and a value that produced the lowest MAPE and best out-of-sample forecasts for the first 5 months chosen. We examined the impact of alternative starting point in Holt Winters' seasonal model and found that its forecast is less sensitive to starting point than SARIMA forecasts.

In general, Holt Winters' Seasonal model produced the most accurate forecast; its forecast error in initial 3 months was higher than SARIMA forecasts, but the error was much lower in the following 2 months. Although the method is usually used for short term forecasts, it may be possible to use it for a relatively longer term forecast by updating data with fewer out-of-sample forecasts and then re-run the model to make more forecasts and so on. In Table 2 we note that longer data series produces more accurate forecast than a shorter series.

The second best result in terms of MAPE of the historical supply data is 'double exponential adjusted for 3-months moving average seasonality'. Without the adjustment MAPE was higher, because single or double exponential addresses trend but not seasonality present in the data. Double exponential fitted the data better than single exponential. Double exponential when adjusted for seasonality fitted the historical data better than the Holt-Winters multiplicative seasonal model but the latter produced better out-of-sample forecast. This suggests that the cooperative may use Holt-Winters multiplicative seasonal model for milk supply forecast until it is possible to build up a database suitable for structural modeling for reliable forecasting.[7]

While evaluating forecast performance, we noted that Holt-Winters multiplicative seasonal model was performing better than SARIMA in

7. We also examined single exponential smoothing which is not applicable because it cannot do better than projecting an unrealistic straight horizontal line.

Table 2. Out-of-sample forecast error for member supply

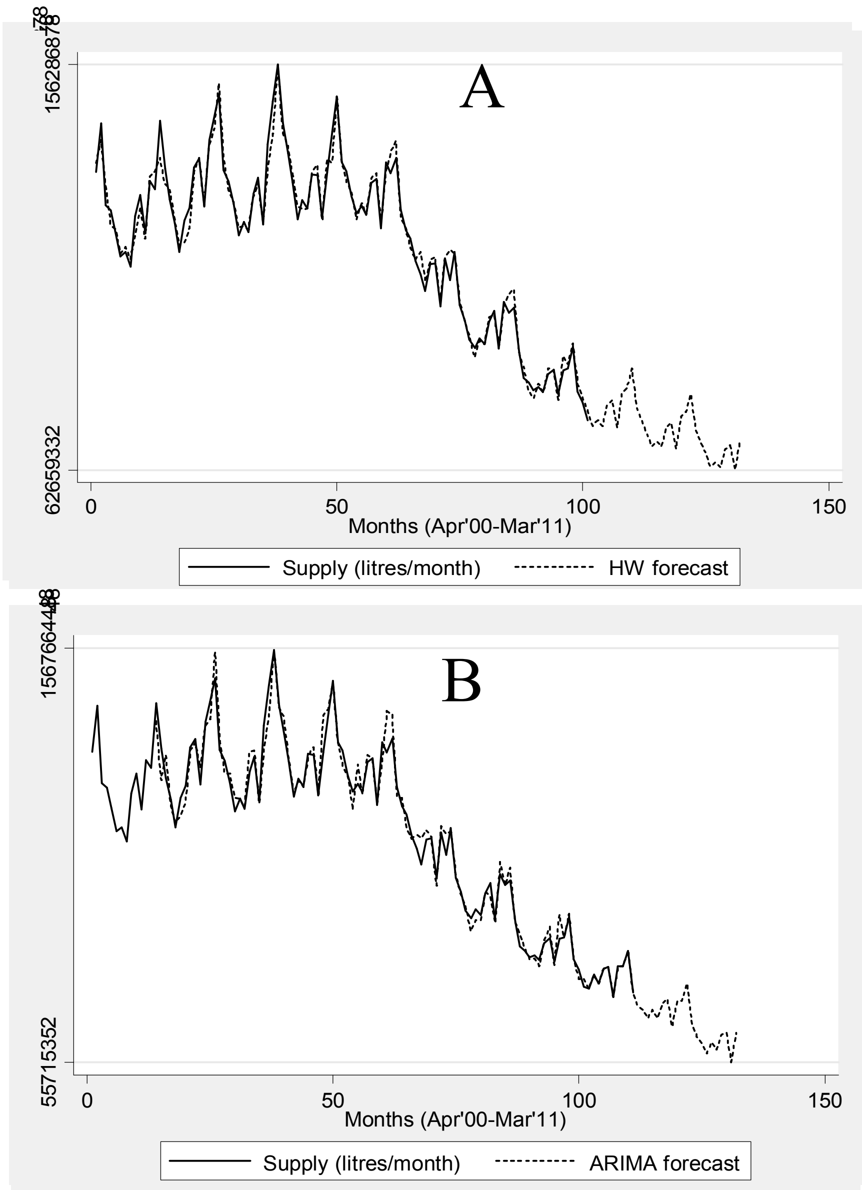
	Apr-08	May-08	Jun-08	Jul-08	Aug-08
Actual output	86,124,154	91,080,254	80,773,180	78,254,393	74,048,833
Holt-Winters' Seasonal (Multiplicative)					
Forecast 1	86,946,928	92,436,248	81,975,536	78,327,224	74,020,048
MAPE	0.96	1.49	1.49	0.09	0.04
SARIMA Model					
Forecast 2	86,156,392	91,779,136	80,416,520	76,028,800	76,099,304
MAPE	0.04	0.77	0.44	2.84	2.77
Seasonality adjusted double exponential (seasonality is calculated from 3-months moving average smoothed)					
Forecast 3	82,5684,72	85,806,120	79,252,592	79,69,4056	79,73,2240
MAPE	4.13	5.79	1.88	1.84	7.68
3-months moving average seasonal (Multiplicative)					
Forecast 4	82,081,739	86,029,626	80,144,262	81,291,736	82,044372
MAPE	4.69	5.55	0.78	3.88	10.80
Holt-Winters' Seasonal (Multiplicative)					
Forecast 5	91,060,696	92,947,376	83,316,760	78,793,480	77,881,288
MAPE	5.73	2.05	3.15	0.69	5.18
Seasonality adjusted double exponential (seasonality is calculated from 3-months moving average smoothed)					
Forecast 6	83,465,816	85,763,936	79,428,464	80,589,896	80,439,832
MAPE	3.09	5.84	1.66	2.98	8.63
3-months moving average seasonal (Multiplicative)					
Forecast 7	83,352,975	86,063,841	80,095,106	81,664,737	81,914,303
MAPE	3.22	5.51	0.84	4.36	10.62

Note: Forecasts 1-4 are based on monthly data series for 8 years from April 2000 to March 2008 (96 monthly data points aggregated from all 4469 members); forecasts 5-7 are based on monthly data series for 4 years from April 2004 to March 2008 (48 monthly data points).

forecasting up to two years (24 months). We have only eight years of data. Overall, MAPE was higher in all models if data series were shortened in the analysis to allow examination of longer-period out-of-sample performance (as in forecasts 5-7 in Table 2). Forecasts 1 and 2 are preferable due to lower errors. With Holt-Winters multiplicative seasonal model we obtained higher errors in the third year and with SARIMA we had higher errors in the second year. The last five values of the series were finally chosen to report the performance of out-of-sample forecast. This is because longer series in the analysis produced lower overall prediction error (mean square error as well as MAPE).

Finally, a three-year forecast beginning April 2008 using two models: Holt -Winters multiplicative seasonal model and ARIMA model are presented in graphs (Figures 2a and 2b), which show that forecast pattern is close to the historical pattern of supply. Actual monthly milk supply declined from a maximum of around 156 million litres in May 2003 to around 74 million litres in August 2008. Unless the current supply pattern is changed by policy factors, milk supply from members would continue to decline reaching 69 million litres in March 2011 according to Holt Winters model and about 63 million litres according to SARIMA model. We recommend the first year forecast as more reliable with the given data. However, second year forecast generated by Holt Winters seasonal model could also be used in decision making. Forecasts beyond the second year should be dealt with caution. In case forecasts for the third year are necessary, then the data series should be updated with the best first year forecast to re-run Holt Winters seasonal model and obtain another

Figure 2. Member Supply Forecasts from April 2008 to March 2011 based on historical data from April 2000 to March 2008.



two year forecast so that the new second year forecast is used for the required third year.

In this analysis, Holt-Winters multiplicative seasonal model appeared to be the best performing for generating longer term forecasts, but it is difficult to generalise with the given short data series. Forecast errors became higher as we further reduce the sampling period to investigate the time horizon of out-of -sample forecast performance. The question of how long we can forecast beyond the sampling period could be more precisely investigated when a longer data series is available.

5. Conclusions and practical implications

The main objective of this paper is to generate a low forecast error in predicting milk supply of a dairy cooperative with only a single time series variable, i.e., monthly milk supply of individual farms. Results show that Holt-Winter's seasonal, seasonal autoregressive integrated moving average models (ARIMA/SARIMA) and seasonally adjusted exponential models were able to generate forecasts with error of less than 3 per cent. The implication is that individual businesses constrained with limited information can still generate reliable forecasts if they posses a long time series data of a key variable of the business. We recommend either Holt-Winters' Multiplicative Seasonal model or SARIMA model to forecast supply for the first twelve months. Holt Winters multiplicative seasonal model can be used for relatively longer forecasts but up to two years could be more reliable. It may produce better forecasts for the third year if the estimation of the model is being repeated with updated data by adding the first year forecasts in the analysis and then forecast for two future years. The process may be repeated until the desired number of forecasts is reached. As SARIMA model is more sensitive to initial condition of the data and STATA is capable to find a good starting value in large samples, the size of longer horizon of forecast with this model is still undecided. Its short-term forecast performance is highly satisfactory. Moving average method fits the data well but its out-of-sample forecasts are not satisfactory. Double exponential method could be used if the seasonality component is taken care of.

According to Milk Link, significant savings in expenses could be made through better forecasting. It is beyond the scope of this study to assess the level of these savings, and to examine their impact on farm gate prices and efficiency. However this issue may provide fertile ground for future investigation.

Acknowledgements

This article arises from a Knowledge Transfer Project (KTP) conducted jointly by Milk Link Ltd and the University of Plymouth, UK. The authors gratefully acknowledge the funding provided by the UK Department of Trade and Industry and Milk Link. In particular they wish to thank Arnaud Haye, the KTP Associate employed by the project, the staff of the KTP office in the University of Plymouth, and the staff at the Plymouth offices of Milk Link Ltd for their assistance and support and their willingness to allow the results to be published.

The authors are also extremely thankful to two anonymous reviewers for valuable comments and suggestions, and the editorial help of the editor. All remaining errors are the sole responsibility of the authors.

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APPENDIX:SPECIFICATION OF MODELS

Model 1: Seasonal multiplicative moving average:
Step 1: The method first computed 3-month moving average trend such that[1]

$$(1),\qquad \hat{Y}_t = \tfrac{1}{3}*(Y_{t-1}+Y_1+Y_{t+1}),$$

where Y is the historical series.
Seasonality index (I_s) is computed as follows:
First, ratio to moving average (R_t), which is the original data divided by the moving average in each period $(R_t = Y_t / \hat{Y}_t$ is computed.

Step 2: Second, the estimated *seasonal index* (I_s) for each season 's' is computed by first averaging all the ratios for that particular season, and then normalizing the ratios so that they average to exactly 100 per cent for a season.

Taking example of member farmers in this case, we have data for 8 years and 12 months in each year (96 observations in total). Thus Y_t implies, Y_1, Y_2, Y_{96}, 1 indicates April'2000, 2 is May'2000 and so on; R_t implies R_1, R_2, …. R_{96}; the series has 8 different R's for each month, for example, for the month April we have R_1, R_{13}, R_{25}, R_{37}, R_{49}, R_{61}, R_{73}, and R_{85}; I_s stands for I_1, I_2, …. I_{12}; the unadjusted seasonality index for April is $I_1 = (R_1 + R_{13} + R_{25} + R_{37} + R_{49} + R_{61} + R_{73} + R_{85})/8$, similarly, I_2, …I_{12} were calculated and then all I's are normalised such that they add up 1200.

Step 3: The predicted value s obtained as follows:

$$(2)\qquad F_t = \hat{Y}_t \text{ x } i_s$$

where s refers to the corresponding season at t.

Step 4: Forecast error is calculated using mean absolute percentage error (MAPE) as follows.

$$(3)\qquad MAPE = \frac{\sum_{t=1}^{T}|Z_t|}{T} \quad \text{where} \quad Z_t = \frac{Y_t - F_t}{Y_t} \times 100 ,$$

T is the series size (sample size), the lower the MAPE the better would be the forecast.
Out-of-sample forecast (one step ahead) using this model is obtained such that

$$(4)\qquad F_{t+1} = \hat{Y}_t \text{ x } I_{s+1}$$

here s+1 refer to the corresponding season at period t+1.

Model 2: Single exponential

Single exponential is a method that smoothes data giving greater weight to values of the variable in more recent period, and less weight to values in earlier periods. Unlike moving average, it takes all previous periods into account. The equation may be expressed as follows.

$$(5) \qquad \hat{Y}_t = \alpha Y_t + (1- \alpha)\, \hat{Y}_{t-1}$$

where α is a smoothing parameter between 0 and 1, the larger its value the greater the weight given to the most recent value of the data series, Y's and t's are as defined above. Hence the exponentially smoothed moving average for period t is a linear combination of the current value and the previous exponentially smoothed moving average. In this study α was chosen based on minimum mean square error (i.e., when $\Sigma(Y_t-\hat{Y}_t)^2/T$ is minimum). This model assumes that the data fluctuates around a reasonably stable mean (consistent pattern of growth and no seasonality) and this may not apply to data in Figure 1.

$$(6) \qquad MAPE = \frac{\sum_{t=1}^{T} |Z_t|}{T}, \qquad \text{where} \qquad Z_t = \frac{Y_t - \hat{Y}_t}{Y_t} \times 100,$$

the lower the MAPE the better would be the forecast.

Out-of-sample forecast (one step ahead) using this model is obtained such that

$$(7) \qquad F_{t+1} = \hat{Y}_t$$

Model 3: Single exponential adjusted for seasonality

In this case, the average obtained in equation (5) is adjusted for seasonality using seasonality index as calculated in step (2) of the moving average method and equation (2), MAPE is obtained using equation (3) and the forecast is obtained as in equation (4). The model that takes seasonality into account should be more appropriate given the data pattern in Figure 1.

Model 4: Double exponential adjusted for seasonality

Double exponential applies the single exponential smoother in equation (5) twice to consider the trend as well as the series average. Exponential smoother considers only series average ignoring the trend and may cause the forecast to be always below (with an increasing trend) or above (with a decreasing trend) the actual data. Double exponential has the advantage of allowing for trend. Here also α was chosen based on minimum sum of square error as in Model 2. Next, seasonality adjusted forecast is obtained and MAPE is calculated as in Model 3.

Model 5: Holt–Winters Multiplicative Seasonal

Holt–Winters Multiplicative Seasonal is a three parameter exponential smoothing method of forecasting like the seasonality adjusted double exponential. The parameters are: (i) α considers series average, (ii) β considers trend, and (iii) γ considers seasonality. The general forecast function for the multiplicative Holt-Winters method is as follows (Chatfield and Yar 1988).

$$(8) \qquad F_{t+p|t} = (\hat{Y}_t + pb_t)c_{t-s+p} \qquad p=1,2\ldots$$

where $\hat{Y}_t$ is the component of level, b_t is the component of the trend/slope, and c_{n-s+p} is the seasonal component, with s signifying the seasonal period (e.g. 12 for monthly data as in our case) and is given by:

$$\hat{Y}_t = \alpha \frac{Y_t}{c_{t-s}} + (1-\alpha)(\hat{Y}_{t-1} + b_{t-1})$$

$$b_t = \beta(\hat{Y}_t - \hat{Y}_{t-1}) + (1-\beta)b_{t-1}$$

$$c_t = \gamma \frac{Y_t}{\hat{Y}_t} + (1-\gamma)c_{t-s}$$

The function tries to find the optimal values of α, β and γ by minimizing the squared one-step prediction error (mean square error) and these parameters lie between 0 and 1. Therefore if a monthly time series is considered as in our case, the one step ahead forecast is given by:

$$(9) \qquad F_{t+1|t} = (\hat{Y}_t + b_t)c_{t-11}$$

The seasonality component in models 3 and 4 is not optimally determined from minimising mean squire error (unlike this model 5) but calculated from simple moving average.

Model 6: ARIMA/SARIMA model with a constant and time trend

More advanced time series methods of forecasting are based on Auto Regressive Integrated Moving Average (ARIMA) models (Maddala 2001, Box and Jenkins 1976). SARIMA includes a seasonality component. These models assume that the time series has been generated by a probability process with future values related to past values, as well as to past forecast errors. These models require time series data to be stationary, which means that the statistical properties such as mean, variance and autocorrelation of the series are constant over time. Box-Jenkins methods consider different autocorrelation patterns in the underlying time series to fit the "best" model. A general autoregressive moving average model with p autoregressive terms and q moving average terms ARMA(p, q) without a structural component is given by (10) $Y_t = (1-\rho)\beta_0 + \sum_{p=1}^{p} \rho_p (Y_{t-p} - \beta_0) + \sum_{q=1}^{q} \theta_q \varepsilon_{t-q} + \varepsilon_t$

We have monthly data with seasonal pattern and so seasonal autoregressive integrated moving average (SARIMA) would be more appropriate. These types of models include seasonal component in addition to above autoregressive and moving average components. The number of autoregressive, moving average terms and type of seasonal effects to be included usually depends on the fits and forecasts of the model (Stata 2008). Box et al. (1994) suggest starting with a multiplicative SARIMA model with any data that exhibit seasonal patterns and then exploring other models if the multiplicative models do not fit the data well. Chatfield (2004) suggests that logarithm of the series makes the seasonal effect additive.

More generally, a (*p, d, q*) × (*P,D,Q*)*s* multiplicative SARIMA model is given by

$$Y_t = (1-\rho)\beta_0 + \sum_{p=1}^{p} \rho_p (Y_{t-p} - \beta_0) + \sum_{q=1}^{q} \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{11}$$

Where, p, d, q are non-seasonal components of autoregressive, differenced and moving average respectively; P, D, Q are seasonal components of autoregressive, differenced and moving average respectively; Δ , Δ_s are non-seasonal and seasonal difference operator respectively; Δ^d means apply the operator d times and similarly Δ_s^Dmeans apply the seasonal operator D times;

$\boldsymbol{\rho_p}(L^p) = 1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_p L^p;$
$\boldsymbol{\theta_q}(L^q) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q;$
$\boldsymbol{\rho_s}(L^P) = 1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_s L^P;$
$\boldsymbol{\theta_s}(L^Q) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_s L^Q;$

We applied restricted versions of equation (11) on the basis of the series autocorrelations, partial autocorrelations (Enders 2004), model fit and forecast performance. The selected model for our member supply is

$$\Delta\Delta_{12} Y_t = \rho_5(\Delta\Delta_{12} Y_{t-5}) + \rho_7(\Delta\Delta_{12} Y_{t-7}) + \theta_1 \varepsilon_{t-1} + \theta_5 \varepsilon_{t-5} + \theta_1\theta_5 \varepsilon_{t-6} + \varepsilon_t \tag{12}$$

Our SARIMA forecast of member supply is derived from this model (12).

1. We have also experimented with other smoothers like 4 months, 6 months, 12 months etc. and fnally this smother was chosen based on its forecast perfrmancce.