Forecasting Support Systems: ways forward

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Abstract

Forecasting Support Systems (FSSs) are designed to facilitate the performance of the organization's forecasters and planners. An FSS always includes a set of statistical methods but also can provide (a) support for management judgment and adjustments (b) procedures for storing, retrieving and presenting information and (c) an intuitive user interface.

In this article, Fotios Petropoulos, Foresight's FSS Editor, offers new ideas on how current FSSs can be improved. He sees three dimensions to the improvement strategy: (i) technological, through open-source software and web-based features, (ii) methodological, in the adoption of state-of-the-art methods and (iii) judgmental, supporting interaction between statistical output and managerial judgment.

Key points

- A Web-based FSS allows maximum flexibility for users, with availability from anywhere and at anytime. In addition, cloud-based solutions offer abundant processing and storage capabilities.
- Open-source software enables use of state-of-the-art methods for forecasting fast- and slow-moving data, as well as in hierarchical processes involving product and temporal aggregation.
- Judgmental integration is neglected in current FSSs and potential improvements arise from improved information for judgmental adjustments as well as from better support for judgmental model selection and interpersonal reconciliation.
- Go one-step further from producing the forecasts: expand the means of communication, collaboration and networking for translating the forecasts into decisions through a unified forecasting-foresight support system.

"I have a dream..."

Forecasting Support Systems (FSSs) are not simply forecasting software. An FSS is also linked with procedures to facilitate forecasting in practice, such as data pre-processing, statistical modelling, and monitoring processes. On top of that, an FSS should enable for *interactive* forecasting (Ord and Fildes, 2012) by offering the ability to integrate management judgment in all stages of the forecasting process.

The Spring 2015 issue of *Foresight* featured my interview, in which I was asked how I saw the future of the FSS. My reply was this:

> *Future FSSs should be described with three terms: web-based, open-source, and customizable. Consider the success of the R statistical software and the very powerful packages developed for this platform, an open-source, modern, and customizable*

web interface that employs freely available libraries to provide access to state-of-the art forecasting methods

This statement summarizes my view on the technological dimension of a future FSS. In this article I will expand on the technical dimension, while also discussing ways forward in the methodological dimension and the judgmental component. Finally, I will reintroduce the notion of a *unified forecasting-foresight support system* (Spithourakis et al., 2015).

Technological dimension

The typical software architecture comprises three tiers. The top-most layer, usually called the presentation tier, consists of the front-end user interface. The middle tier (logic/application tier) includes all processes concerning calculations, evaluations, and logical flow of the commands. In a FSS setting, the logic tier includes statistics and forecasting functions and procedures. Finally, the data tier contains the database, where all data, produced forecasts, and judgmental interventions are stored and managed.

Web- and cloud-based solutions

One way forward involves the replacement of out-dated windows-based applications (which in some cases are even locally installed) with web-based applications. The advantages are many: 24/7 accessibility and availability, cross-platform compatibility (work with any operating system), accommodate a range of devices (work from anywhere), and render unnecessary the installation of additional software (all devices have a web-browser!) and inconvenience of updates.

Cloud solutions also have the advantage of centralised data, allowing for direct access to the latest information. The result will surely be beneficial for collaboration. Cloud-based solutions are efficient and easily scalable to increased workload, while saving the costs associated with infrastructure.

The security concerns about web-based solutions should not be allowed to override the many benefits provided.

Customizable solutions

In addition to all the above, web-based solutions are easily customizable, while offering increased interoperability (exchange of information and data across different software). This capability is crucial, since each company has its individual forecasting needs. One-size FSS does not fit all.

Forecasting for retailers' demand, call centres, spare parts, or energy consumption involves different data streams (in terms of frequency, granularity and characteristics) and, as such, different forecasting processes and methods. This suggests that it does not make sense to create a *super FSS* able to accommodate all needs.

On the contrary, flexibility is key: the FSS should allow for a customizable presentation tier allowing different companies or even different managerial levels or work-groups within a company to maximize efficiency. The user-interface should be kept as clean as possible and thus easy to use and more acceptable by its users.

Mobile forecasting

A flexible user-interface makes forecasting possible through the use of mobile devices, such as smart-phones and tablets. The forecasting "in the pocket" concept was proposed in a recent *Foresight* article by Asimakopoulos et al. (2014) and colleagues (2014). They describe the multiple opportunities arising from mobile forecasting, including increased communication capabilities, instant access to forecasts and reports, and tracking of promotional events.

You could take advantage of the technical specifications of mobile devices and introduce additional features for a future FSS, such as the *click & forecast* concept (Skiada et al., 2013) that automatically digitizes a graph and produces forecasts.

Free, open-source software

Focusing on the logic tier, a way forward is the use of the free and publicly-available R statistical software. The numerous advantages (and two disadvantages) of R have been discussed in a previous article of *Foresight* (Kolassa and Hyndman, 2010). The enthusiastic and exponentially growing user base offers, without fee, state-of-the-art methods and invaluable advice. The functions are well-documented and open-source as well, encouraging user acceptability.

R offers excellent visualisations and is a good educational tool; however, it does require programming knowledge. Currently, it contains approximately 180 time series related packages including forecasting, univariate and multivariate modelling, decomposition, and dynamic regression models. These are freely available and ready to go: no need to reinvent the wheel!

Methodological dimension

State-of-the-art methods

In his keynote speech at the 33rd International Symposium on Forecasting (Seoul, 2013), Rob Hyndman discussed developments in automatic selection algorithms such as automatic exponential smoothing (ETS) and ARIMA methods. Despite these algorithms being freely available in the *forecast* package for R, the forecasting toolbox of many other forecasting software packages remains limited.

In addition, the Theta method (Assimakopoulos and Nikolopoulos, 2000), a relatively simple decomposition method that outperformed all competitors in the M3-Competition, has not attracted the attention of software vendors.

An FSS should include all methods that have been shown repeatedly to produce accurate and robust forecasts. Moreover, the performance of current automatic selection algorithms should be compared against benchmarks in the forecasting literature by exploiting publicly available data sets (such as the 4,000+ series of the Makridakis Competitions).

Forecasting for intermittent demand

Methodological limitations of current FSSs are especially apparent when faced with intermittent demands, the phenomenon that zero demand occurs during some time periods and, when a non-zero demand is occurred, its size varies.

While intermittent demand patterns are very common (for example in spare parts), current FSSs provide little to no support in handling such data. Worse, in some cases, the FSS fails to include any methods specifically designed for forecasting intermittent demand.

In other cases, only a basic Croston's method is available (using fixed smoothing parameters), without considering upgrades such as the Syntetos-Boylan approximation for bias correction. On the bright side, several inventory software packages include these techniques, as well as classification strategies suggested in the literature.

In contrast, the open-source and freely available *tsintermittent* package in R provides implementations of such methods and techniques. The future FSS should be enhanced to deal with intermittent demands.

Temporal aggregation

Temporal aggregation (Syntetos, 2014) refers to the transformation of the historical data from one frequency (e.g. monthly) to a lower frequency (e.g. quarterly) or higher frequency (e.g. weekly).

Originally, temporal aggregation was proposed as a way to deal with the intermittent demand data aggregating from monthly to quarterly time buckets likely reduces the prevalence of zero demand periods it has also been shown to be beneficial for fast-moving time series.

Essentially, viewing the data in different time buckets results in the amplification or filtering of time series components such as seasonality, which is easier to detect and model in monthly and weekly. Conversely annual time series smooth out seasonality making the long-term trend easier to capture. So, temporal aggregation acts as a lens on the data, in an attempt to extract as much information as possible.

Forecasting the data not simply at one but at multiple aggregation levels has been shown to increase forecasting accuracy for both fast- and slow-moving time series (Petropoulos and Kourentzes, 2014). The superior forecasting performance is coupled with the unique feature of automatically reconciling the forecasts across different frequencies and horizons, thus aligning operational, tactical and strategic decisions. In other words, the use of multiple temporal aggregation levels enables the decision making based on the "one-number" forecast.

A worthwhile enhancement of future FSSs would be the incorporation of approaches for temporal aggregations such as the Multiple Aggregation Prediction Algorithm (MAPA) now implementable through R.

Cross-sectional aggregation

Forecasts at different hierarchical levels (company-level, sector-level, SKU-level) can differ greatly and require reconciliation. Various statistical reconciliation approaches have been considered.

In the *bottom-up approach*, forecasts are produced at the lowest level of aggregation (SKU-level) and aggregated to create forecasts at higher levels. In the *top-down approach*, forecasts are made at a higher level and apportioned to the lower levels using historical or forecasted proportions.

The *middle-out approach* is a combination of bottom-up and top-down, where forecasts are produced at a middle level of the hierarchy and then are pushed upwards and downwards using bottom-up and top-down respectively. Finally, there is an *optimal approach* that reconciles by combining forecasts produced at all levels (Hyndman and Athanasopoulos, 2014).

In addition to reconciliation, appropriate grouping and aggregation of the data can help improve forecasting. A very interesting example is that of *product-group seasonal indices* (Mohammadipour et al., 2012). Instead of estimating the seasonal component per product individually, one could consider the seasonal patterns for analogous products. That would be extremely useful in cases of new products where the small sample size does not allow for robust individual seasonality estimation.

FSSs should allow for cross-sectional aggregation of the data as to enable automatic forecast reconciliation but also better modelling and estimation of the components such as seasonality.

"Is it safe to assume that software is accurate?"

No (McCullough, 2000). Even when it comes to the simplest methods, such as Simple Exponential Smoothing, the forecasts often differ across different software packages. Such differences may arise from over-simplistic assumptions in initializations or different optimizations or even (hopefully not!) bugs in the code.

McCullough suggests a number of ways to deal with this problem. Full documentation of the implemented algorithms as well as provision of simple code/examples would increase user's trust in software packages. Also, forecasting software reviews should be carried out and published in both academic and practitioners' outlets. Lastly, research on forecasting methods should be subject to standards of replicability and reproducibility (Boylan et al., 2015), which can be directly translated into better and more accurate software.

The judgmental component

Judgmental forecasting and adjustments

Statistical forecasts are usually adjusted by organizational experts. These judgmental adjustments serve a number of purposes, such as inclusion of the impact of a forthcoming special event or promotion. In other cases, however, revisions to the statistical forecasts are politically driven, often to meet budgetary targets. In some cases, users discard statistical forecasts for lack of trust (systems are regarded as "black-boxes") or because they believe that their judgmental forecasts can better capture the realities of the market, often confusing noise with signal.

Extensive research has been done on how to better integrate managerial judgment into an FSS. The researchers indicate that a forecasting *support* system should facilitate judgmental interventions and in a number of ways.

First, provide memory support, which would facilitate recall of relevant past events and what impacts they had on demand. This feature would also empower certain forecasting methods, such as structured analogies, that rely on past comparisons. Second, monitor and report the performance of both statistical and judgmentally adjusted forecasts. Third, provide note recording for the reasons behind judgmental interventions. That would build the means for a better understanding of market intelligence.

Despite the numerous studies that support these design strategies, current forecasting systems are only partly successful in adding the *support* term in the FSS acronym. However, such support should be provided from the system to the users in the form of guidance rather than restrictiveness (Fildes et al., 2006).

Judgmental model selection

The integration of managerial judgment should not be limited to the judgmental overrides of statistical forecasts. A recent study (Petropoulos et al., 2015) showed that humans can be as good (if not better) in selecting models than the automatic algorithms that are based on statistical criteria. While manual selection of forecasting models is not feasible when a company must forecasts thousands of SKUs, one could narrow the focus to the important products identified through the standard ABC classification scheme.

Judgmental selection of forecasting models is more efficient under a "model-build" approach where the problem of selecting a model is decomposed to the problem of judgmentally identifying the existence (or not) of the main structural series components, such as trend and seasonality. This is opposed to the standard design approach of a "radio-button" or "drop-down" style selection of one model over another.

Our study also shows that in situations where many experts are employed, weighted combinations of their individual selections can lead to significant improvement in forecasting performance.

Based on the above, an FSS should advise users that manual selection of the models has its merits, should provide the means for a model build (decomposition) approach, and should allow for grouped judgmental model selection (wisdom of crowds).

Judgmental hierarchical reconciliation

There are various hierarchical reconciliation approaches in common use as already described. A potential disadvantage of all these approaches is their full reliance on statistical weighting schemes that do not take into account the special circumstances of each case, thus lacking the judgmental component.

Consider a situation where different demand planners are responsible for the forecasts produced at the various levels of the company. It is possible that different qualitative information ("soft data"), such as promotional actions or rumours of a new competitive product, can be interpreted in different ways by planners at the different levels.

Worse, some information may not be available at some levels. In such cases, statistical reconciliation approaches, that take into account specific levels of aggregation or perform combinations, would effectively dampen or even discard the judgmental interventions made at only specific hierarchical levels, where managers have access to the information and incorporate this in the form of adjustments.

Different stakeholders should be able not only to share information, but also their views and opinions with regard to the impact of future special events. We need systems that would enable demand planners to judgmentally reconcile differences in forecasts at the various levels of the hierarchy. The benefit of this approach is consensus, not only in terms of numbers but, by allowing the forecasters to manually fix any differences in the forecasts, it fosters a sense of "collective ownership".

Forecasting & Foresight Support Systems

Foresight takes forecasting one-step forward by incorporating aspects of collaboration and networking and allowing for translation of the produced forecasts into decisions, while enabling for scenario planning.

A way to achieve judgmental hierarchical reconciliation is to audit and expand the means of communication and co-operation between demand planners of the various hierarchical levels. A recent article (Spithourakis et al., 2015) recommended the combined use of forecasting and foresight support systems (F^2SS).

Such systems should bring together common features of forecasting support systems with collaboration and interaction capabilities. A system that combines features of both should enhance user's satisfaction and experience.

When a prototype web-based F^2SS was introduced to a group of students as an elective exercise in a business-forecasting course, the results showed good levels of satisfaction and influence from team co-operation, and these increased further over time.

Ways forward

Here is my summary list of recommendations for improving the design and development of forecasting support systems:

1. Web- and cloud-based solutions
2. Customizable
3. Forecasting on-the-go
4. Use of open-source software
5. Implementation of state-of-the-art methods
6. Methods for intermittent demand
7. Temporal and cross-sectional aggregation
8. Full documentation of approaches and procedures
9. Better integration of managerial judgment
10. Support for judgmental model selection
11. Support for judgmental forecast reconciliation
12. Bring in foresight features

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