Expert Forecasting for Telekom Malaysia's Decision Support System

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Abstract: - Internet's growth over the last 20 years has been nothing short of phenomenal except more and more spectacular development witnessed. Living in the wired world together with rapid rise to prominence of using decision support system (DSS) in business, standalone systems are becoming obsolete. From layman to top management, the awareness of applying DSS in supporting them in making decision is becoming a apparent phenomena. With laurels of expert systems technology, researchers of Telekom Malaysia (TM) had developed an integrated expert system with forecasting decision support system, in assisting TM for forecasting, managing and monitoring TM employees' key performance indicator (KPI) which based on Balance Scorecard perspectives. This paper discusses, to name a few, about the expert forecast system's components, protocols and communication server, accompanied by its benefits to TM business operations and future related R&D works in planning.

Key-Words: - Decision Support System (DSS), expert system, forecasting, expert forecast, protocols, communication server

1 Introduction

The ubiquity of using Decision Support System (DSS) may be inevitable, either by savvy organizations or the small ones. Key achievements from the research and practice of DSS is about from 1981 and 2001, in some ways, have come from applied research and practice than from traditional academic research [7]. Keen & Morton [5] argued that a DSS is more a service than a product. It is because the most promising aspect of DSS is its ability to integrate data access and decision models [10].

Drummond [1] discovered that early economist applied scientific and mechanistic principles to decision making as they had witnessed the superiority of efficiency of machines over traditional way. The key of scientific approach is its reliance upon rationality, as distinct from instinct or superstition.

Forecasting support system is a decision support system meant for giving guidelines and a course of action to support decision in planning particularly for managerial and executive levels [7]. Also as discussed by Mohd Razilan et al. [7], the main concern in implementing a forecasting support system is first, how can changes in the user interface impact on the utility, perceived usefulness and effectiveness of the specific category of FSS? Second, how does the metadata available impact the usefulness of model-driven DSS like forecasting support system? Model management and model reuse remain as difficult tasks related to building model-driven DSS, particularly forecasting support system which mostly uses highly analytical models.

Probably no topic involving computer systems is more popular than that of expert systems. So, apart from the concerns above (or maybe some more others not mentioned here) and with the rapid rise of the Internet and web-based technology, expert system DSS seem more practical today then ten or twenty years back. In taking up this challenge, as a start, researchers of Telekom Research & Development (Telekom Malaysia Group) developed an expert forecasting DSS for its parent company.

Telekom Malaysia or TM is one of the largest group of telecommunication company in Malaysia. With thousands of its employees, managing each of their key performance indicator (KPI) is not an easy task. For the past few years, TM has been practicing Balance Scorecard (BSC) in evaluating its employees' work performance indicators. TM's Corporate Strategy division has been given the mandate of setting guideline and direction for TM Group BSC development, and also implementing and monitoring BSC within the TM Group.

With respect to the requirement in monitoring and forecasting the KPI based on selected BSC perspectives of TM and its Subsidiaries, an expert forecast system had been developed with the purpose of assisting TM to forecast the required each division/department's KPI. It is to fulfill the company's objective in carrying BSC assessment check at least once a year and ensuring that all corrective actions are executed necessarily, for future strategies and achievements. By providing expert forecast advisor in the tool, the management could use scientific results in making the decision for the company, with respect to monitoring and guiding the BSC for TM's employees.

1.1 Expert Forecast System

In previous years, forecasting systems developed for TM's market planners and network forecasters were in networked version and web-based basis, where users had to perform the forecasting analysis process manually. In other words, users (regardless with little statistical knowledge background) had to select what is the best model in fitting their data. The successful impact of forecasting is tied directly to the manager's need, understanding and involvement for forecasts [6]. However, few managers are familiar with the wide range of forecasting techniques. A crucial problem facing managers is the selection of an appropriate method for their specific situation [3].

Since the requirement of automating the forecasting process was high, we believed it was the right time to design and develop an expert forecasting system, to assist them in making decision for business operations.

Expert forecast system developed by TM Research & Development researchers features univariate forecasting models, and this system is part of the module used in TM's BSC system (also developed in-house) called COMPASS (Communicating and Managing Performance, Accountability and Strategy System for TM).

The expert forecasting capable of analyzing and selecting the best model fitted to data series used.



Forecast menu toolbar in main page of COMPASS.

Fig. 1: Forecast menu icon in main page of Telekom Malaysia's online Balance Scorecard system

2 The Design of Expert Forecast System

This system consists of three main programs, Web Interface, Communication Server and Engine (statistics models). Whereas its basic structure include these subsystems:

- 1. Database for system to extract data series for forecast modeling process (it is from existing COMPASS database).
- 2. An engine consists of curve fitting and time series forecasting models.
- 3. A knowledge base that serves for selecting the best forecast model, as part of the inference engine that provides advice and reasoning for the recommended model (using forward chaining).

Web Interface is the front-end for the end user to enter the data and get the results, the Engine is the main engine that receives data input from the Web Interface, and the Communication Server is the middleware for both Web Interface and Engine. The Engine responsible to compute the data based on the statistical models and the results will be sent back to Web Interface through Communication Server.

All of these programs communicate using TCP/IP socket to transfer the data. Figure 2 shows the communication between Web Interface, Communication Server and Engine.



Fig. 2: Main components of expert forecast for Telekom Malaysia Decision Support System

2.1 Web Interface

Web interface provides an interface to communicate with COMPASS system. This interface will query into COMPASS database and keep the data as actual data set to be forecast (i.e. to be displayed in Actual tab web page). User may select all the BSC index as stored in COMPASS database. The data is in monthly and quarterly basis.

Main features of the interface are forecast (actual data, scenario analysis results and view all reports), external file loading (with edit facility), graph, report and save file.

Some of interfaces of main features are displayed below:



Fig. 3:Data series loaded from COMPASS database is displayed in Actual tab web page.

			Data	Graph	Analysis		
ASTED DA	TA (A	CTUAL	1				
			50				
e: Monthly							
	la.	Date	Measure	Fitted	Lower	Upper	
1.17	1	01/2007	48.30	48 629266	39 949904	59 194271	
	2	02/2007	59.00	55.059463	47.091502	64 375618	
	3	03/2007	52.60	57.386543	49.222803	66 904262	
	4	04/2007	57.90	58 586709	50.206941	68.365100	
	5	05/2007	58.70	59.318824	50.769193	69 308229	
	6	06/2007	61.80	59,811976	51.132109	69 965282	
	7	07/2007	57.10	60.166735	51.385508	70.448580	
	8	08/2007	64.60	60.434185	51.572388	70.818724	
	9	09/2007		60.643023	51.715874	71.111170	
	10	10/2007		60.810613	51.829494	71.348000	
	11	11/2007		60.948077	51.921688	71 543670	
	12	12/2007		61.062867	51.997991	71.708036	
	13	01/2008		61.160166	52.062183	71.848043	
	14	02/2008		61 243689	52,116935	71.968726	
	15	03/2008		61.316168	52.164186	72.073824	
	16	04/2008		61.379657	52.205379	72.166170	
	17	05/2008		61,435731	52.241607	72.247951	
	18	06/2008		61,485618	52.273717	72.320879	
	19	07/2008		61.530288	52.302374	72.386318	
1	20	08/2008		61.570518	52.328106	72.445365	
1.1	21	09/2008		61.606940	52.351339	72.498912	
4	22	10/2008		61 640070	52 372420	72 547693	

Fig. 4: Forecasted data is accompanied with lower and upper values.

ACTUAL SCENARIO 1	SCENA	RIO 2	SCENARIO 3	VIEW ALL	HELP	
Data	Res	ults	Graph	Analysis		
DATA (SCENARIO 1)						
Measure:TM Group OPEX Efficiency (OPEX Data Monthly Type:	/Reven	ue) (%)	External File	Edit Forecasi	Piot Graph	Save As
	No.	Date	Measure			
	1	01/2007	48.30			
	2	02/2007	59.00			
	3	03/2007	52.60			
	4	04/2007	57.90			
	5	05/2007	58.70			
	6	06/2007	61.80			
	-	0710007	57.40			

Fig. 5: Scenario 1 tab web page shows that user is allowed to add external file data, edit the figures of data series used, forecast, plot and so forth to save the data.

2.1.1 Examples of output

Following are some example of web pages of expert forecast output in COMPASS.

Measurement of Errors

R-Squared	-0.036985
MAPE	51.602230
MSE	303.631555
AIC	209.769339
MdAPE	0.250037

Durbin-Watson statistic: 0.759152

Weight Functions

S1	46.681214
S2	42.610526
Constant	50.751902

Model's Estimates

Smoothing Constant			
α	0.100000		
Coefficient			
Linear	0.452299		

Estimated Model

Measure_{*T*+r}(*T*) = ((2 + $\frac{0.100000 \text{ r}}{0.900000}$)-45.681213) - ((1 - $\frac{0.100000 \text{ r}}{0.900000}$)-41.610527)

where,
$$\begin{split} \tau &= 1,2,...,lead. \\ T &= current number of observation \end{split}$$

Fig. 6: Example of statistics results

EXPERT ADVISOR

About the data

- · No missing data detected in the series.
- Kolmogorov-Smirnov analysis shows that your data is a normal data (therefore no transformation of data is required).
 Durbin-Watson statistic shows that no serial autocorrelation exists in the series and hence regression model is
- sufficient in modelling the data.

The model

Regression - Cubic Model estimated by the system is selected as the best model for the data.

R² statistic

- Also known as coefficient of determination. It is a statistical measure of goodness fit of the relationship between Fixed Line Revenue (RM Mn) (Measure) and Time variable.
- 100% of R² indicates perfect predictability.
- The Measurement of error results show that your model is 67.06% fit.

Fig. 7: Expert advisor provided for user



Fig. 8: Data series plot with zooming facility

2.2. Models' Engine

Expert forecast engine features curve-fitting models and time-series model (for seasonal and nonseasonal data). Models featured are:

1.Curve fitting models:

- Linear regression
- Quadratic
- Cubic
- Exponential
- S-Curve

Time series model includes:

2. Moving average

- Simple
- Double
- 3. Exponential Smoothing Brown (non-seasonal)
- Simple
- Double
- Triple
- 3.Exponential Smoothing Winters' (seasonal)
- With trend
- Without trend
- 4. Multivariate models:
- Multiple Linear Regression
- What-if Scenario Analysis

Apart from that, the statistical requirements, tests and diagnostics are based on methods of;

- F-test
- t-test
- Kolmogorov-Smirnov test

- Box and Cox power transformation
- Durbin-Watson test
- Dickey-Fuller test
- Correlation analyses Pearson, Spearman's r and Kendall tau b
- Missing values analysis Multiple Imputation
- Error measures R², MSE, MAPE, MdAPE and Akaike information criteria.

The engine is capable of differentiating raw data sent by the GUI, whether the data is a single dimension or multiple dimensions. If the data is a single dimension, the engine will execute the univariate forecast models featured, otherwise, it would perform multiple linear regression model.

2.2.1 Expert Inference Engine

This system is using CLIPS (C Language Integrated Production System) as an expert system inference engine. There are several ways of using CLIPS with applications, but for this expert forecast system it is embedded in the engine. All the CLIPS files, except the main.c files, are compiled with the other expert forecast engine files.



Fig. 9: Interaction of the expert forecast engine with the CLIPS engine.

Fig. 9 shows the interaction of expert forecast engine with CLIPS engine. The CLIPS engine source codes are compiled together with the e-expert forecast engine. After the completion of statistical tests/diagnostics/processes, expert forecast engine updates the Data Characteristics on the CLIPS inference engine. That is, if the data characteristics match the rules, the CLIPS inference engine will send the recommendation to expert forecast engine and lastly, it would send the recommendation together with recommendation results to the web interface.

The reasoning for advice or "consultation" purpose used in the inference engine is forward chaining rule. We have designed the expert forecast engine to utilize the CLIPS inference engine to give the expert forecast engine the right recommendation template. Before the rules are fired, we need to add the facts that will be matched with the rules. To add the fact to the CLIPS environment to the CLIPS memory, example of such a rule is as below:





2.3 Communication Server

Communication server acts as a middleware where it handles multiple connections from the clients. The communication server is required to be executed first before the whole expert forecast engine can entertain the request from the clients.

From the Communication Server, the expert forecast engine is forked or executed. It is called with several selected parameters which where the data is in form of one long string (separated by a semicolon ";" or a colon ":"in between the data). A colon is used to differentiate one dimension of data to another. Next figure shows the interaction between clientscommunication server-engine. The communication server can entertain multiple connections simultaneously.

In other words, the communication server could manage more than one connection (of client's request) at one time and fork expert forecast engine for each request (refer to Fig.11). Once the engine is forked, it would then be executed independently. It communicates with the communication server through TCP/IP. The communication server closes the connection once it receives signal to close the connection from either client or expert forecast engine.



Fig. 11: Overview of expert forecast system components.

2.3.1 Protocols

TCP/IP is used for the communication between the three components; client, communication server and the expert forecast engine. In addition to the TCP/IP protocol, additional protocols are created for the inter-process communication of the expert forecast engine components.

For this system, each block of data is set to 512 characters. Thus, if the data that need to be sent is more than 512, the data are sent block-by-block basis until all the data are sent completely. In order to control the number of characters in a block, we designed the communication control string to serve relevant type of string received from the client.

3 Benefits for TM

It is indeed useful to have a rule-based expert forecast system integrated with decision making purposes especially to assist non-statistical background/novice users in selecting the most appropriate model based on their specific requirements and pattern of data series.

In considering potential benefits of applying expert system technology in management's decision making process, we believe that the expert forecast module developed is capable of supplying them with useful guidelines in setting and monitoring the company's KPIs. First, faster understanding on current and as well as future pattern of KPI indices, based on information of forecasts, data analysis and graph provided. Second, evaluation, monitoring and setting of BSC development could be easier by performing the forecast analysis in systematic fashion (with the use of scenario analysis). Third, high-level non-technical/statistical management people find this system convenient enough in getting forecast results, i.e. without needing them to have in-depth knowledge of forecasting topic. Last but not least, with assistance of scientific models produced, the decision-making process can be made easier by incorporating judgmental knowledge into the recommended model which may make it useful in practice.

4 Conclusion

Current expert forecast module incorporated in internal TM's Balance Scorecard system is useful, convenient and helpful especially for management people who have least or no forecasting and/or computing background but yet wish to enrich their decision making via scientific method.

Future research and development would be firstly to add forecast models like Box-Jenkins ARIMA, spectral analysis, outliers analysis and some other non-linear forecasting methods. Secondly is to add dynamic graph function (as proposed by management). Thirdly, to produce a generic expert forecast system so that it can be benefited not only by business community but for public as well.

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