JURNAL PENGURUSAN PENGETAHUAN

JOURNAL OF KNOWLEDGE MANAGEMENT

Jilid / Volume 1 ISSN: 1823-1136 Edisi 2005

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A Framework for Development of Model-Driven Decision Support System

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Abstract

With expansion and growth in computing technology, systems for supporting decision-makers in planning can be crucial, either to expedite and enhance the work environment or to gain efficient and effective forecasting results, as to compete with other rivals in business war-gaming. In this article, we will explore the state-of-art in developing a Model-Driven Decision Support System (DSS) namely Forecasting Support Systems (FSS), via time series forecasting model which based on Box-Jenkins approach known as ARIMA, as the analytic model in model base; for managerial and executive level, dominantly who involves inforecasting field. The aim of this paper to discuss on how decision-making process (with respect to forecasting and planning) can have its computerized support by a DSS, also to understand the concepts of FSS component and its development via DSS technology levels, which may support managers in decision making process, emphasizing on concept and approach of Box-Jenkins.

Keywords: *Decision Support System (DSS), Model-driven DSS, Forecasting Support Systems (FSS), DSS Technology levels, Box-Jenkins ARIMA.*

Introduction

In today's exigency and competition, decision making which based or justified by scientific way may be crucial to organizations. From layman up to top management, the awareness of applying tools in supporting them in making decision is becoming apparent. Vis-à-vis a tool for assisting either managerial level or executives, everyone must be exposed, participated and divulged in this faddish kind of way for decision making purpose, in order to vie with other competitors in business world.

Tool is a system developed for those who have specific requirements to analyze data, with the objective that the tool may aid them making decision or in reporting-wise. The ubiquity of use of Decision Support System (DSS) may be inevitable, either by savvy organizations or the small ones. Key achievements from the research and practice of DSS in a about 20 years back (from 1981 to 2001), in some ways, have come from applied research and practice than from traditional academic research. For example, researchers at a number of universities made substantial contributions to the development of Group DSS and their research stimulated many studies related to the use of group technologies in organizations. Vendors have worked to implement DSS products using graphical user interfaces and this has increased the accessibility of query and reporting tools, decision models and expert system technologies. A Model-driven DSS use data and parameters provided by decision makers to aid decision makers in analyzing a situation, but they are not usually data intensive, that is very large data bases are usually not needed for model-driven DSS. Improved products have not however led to many new empirical studies related to how DSS impact decision behavior or decision quality. And, the application of such system that is for the purpose of for forecasting and planning is already widespread. Early versions of Model-Driven DSS were called Computationally Oriented DSS. Such systems have also been called model-oriented or model-based decision support systems

This paper will discuss on the state-of-art for developing a model-driven DSS, which can be used as a guide and so forth to appreciate the scientific way of performing the forecasting analysis, specifically by applying Box-Jenkins ARIMA method.

Decision Support System

Decision Support System (DSS) is a system designed to endow with information and decision techniques to analyze specific problems. Usually. DSS must be custom-tailored. DSS relies on model bases as well as databases as vital system resources. DSS software packages can combine model components to integrate models that support specific type of decision. In the purpose of developing forecasting software as planning tools, such model base would include various types of forecasting models, from the simplest like linear curve fitting models to the most advanced like ARIMA. The increasing interest in the development in decision support systems is actually being led by the growing popularity of Online Analytical Processing (OLAP) and data warehousing.

DSS use analytical models, specialized databases, decision-makers' own insights and judgments, and interactive computer-based modeling processes to support the making of semi-structured and unstructured decisions by decision makers. Structured decision involve situations where the procedures to follow when a decision is needed can be specified in advance. Structured decisions may involve, (i) *Deterministic or algorithmic decisions:* A decision's outcome can be determined with certainty if a specified sequence of activities is performed and, (ii) *Probabilistic decisions:* Enough probabilities about possible outcomes are known that a decision can be statistically determined with an acceptable probability of success. Unstructured decisions involve decision situation where it is not possible or desirable to specify in advance most of the decision procedures to follow. Many decision situations are unstructured because they are subject to too many random or changeable events or involve too many unknown factors or relationships.

DSS supports individuals, small groups and entire organization where users have more control on it. It may handle unstructured problems that cannot be easily programmed. Main roles of DSS are (i) to assist in approaching less structured problems and to provide facilities for creating and maintaining decision models, (ii) for OLAP - for specific databases and servers, OLAP is a software technology that enables users to access data interactively with wide variety of possible views of information that has been transformed from raw to real data, (iii) to assist in modeling where models are stored in suitable formats. According to Mohd Shanudin et al. (2000), input for DSS can be external data, data specific to user requirement, data from Transaction Processing System (TPS) or even from Management Reporting System (MRS).

For instance, Sprague & Watson (1993) give example of the GADS (Geodata Analysis and Display System) - a tool for police beat allocation system used by police in San Jose, California. It was written in FORTRAN, using dialogue handling software, a laboratory-enhanced raterscan color monitor, and a powerful interactive data extraction and database management. The other example is Cognos Powerhouse QUICK, which is a tool for accessing and manipulating data in modeling framework (Turban & Aronson 2001). Keen & Morton (1978) argue that a DSS is more a service than a product. Since the problem can only partially be structured, and since managers grow in their understanding and needs over time, a DSS must constantly grow and evolve as the user adapts and learns. This is its very nature and implies much for the construction of such a system, the kind of software used, and, more importantly, the way it is implemented and maintained in the organization itself.

Criteria for Evaluating DSS Software Package

Users must be circumspect in selecting DSS for their organizations so that it would meet or comply with their needs. It is very important to recognize and identify comparable "off-the-shelf DSS software packages system in the market. "Off-the-shelf is often appropriate for task specific DSS software like healthcare scheduling software, collaboration and groupware software, Web-based reporting software, enterprise portal software, data mining software and competitive intelligence software. Then, one must determine which products might meet the need.

In evaluating DSS software, several criteria must be considered. Although these factors are important and need to be considered in most situations, this question should be framed more broadly and some other issues should be addressed before specific criteria are discussed. Approximately six major criteria should be identified and weighted for evaluating the comparable DSS packages:

1) **Capabilities:** Examine the functions that a DSS product can perform and how important they are to the decision support need of targeted users. Determine if the package can be customized and in what ways. Does it meet the need? Does it provide the desired support?

2) **Cost of the Package:** Examine the total cost of ownership including acquisition costs, implementation and training costs, maintenance costs, and any annual software license costs.

3) **Ease of use:** The ease of learning and using the capabilities of a product to accomplish tasks. Ease of use is in the mind of the user so ask users to assess this criterion.

4) **Ease of installation and operation:** How easy is it to configure, deploy and control use of a product? Is it easy to transfer information to and/ or from other company information systems? Are there potential technical implementation problems?

5) **Performance:** What is the speed or capacity of the product when performing its functions? Also, part of the performance criterion should be software reliability.

6) **Vendor reputation and reliability:** The vendor matters, but in emerging product areas this criterion can be difficult to assess. What kind of vendor and technical support is needed and is available?

Model-driven DSS

As software products that help users to apply analytical and scientific methods to decision making, they work by using models and algorithm such as mathematical programming, stochastic modeling, simulation and optimization. Building a DSS require significant expertise in decision analysis, programming and user interface. Forecasting Support System is a Model-Driven DSS, others are like the ones linked to Decision Analysis, Operations Research and Simulation. Model-driven DSS emphasize access to and manipulation of a model, e.g. statistical, financial, optimization and/or simulation. Simple statistical and analytical tools provide the most elementary level of functionality. Some OLAP systems that allow complex analysis of data may be classified as hybrid DSS systems providing both modeling and data retrieval and data summarization functionality. In general, model-driven DSS uses complex financial, simulation, optimization or multi-criteria models to provide decision supporting the users.

Forecasting Support Systems

In practice, the forecasting software being built is still remarkably depending on the final decision by forecasters or planners, rather than letting the software itself produce the decision-making. Forecasting Support Systems (FSS) is a tool meant for giving guidelines and a course of action to support decision in planning particularly for managerial and executive levels. End user of FSS software is mainly executives or forecasters/planners, and also managers in planning the production or marketing.

The main problem especially in implementing FSS are how can changes in the user interface impact the utility, perceived usefulness and effectiveness of a specific category of FSS and how does metadata available to user impact the usefulness of Data-driven DSS and Model-driven DSS like FSS Also, managing and creating large decision support databases remains a difficult task. Model management and model reuse remain difficult tasks related to building Model-driven DSS, particularly like FSS which is using highly analytical models.

In respect with the forecast values produced, despite of being analyzed in statistical way, individual knowledge, judgment and experience on data must be taken into account in setting final decision so that the forecast figures are representative enough for the real world scenario. Of course, representing knowledge and capturing knowledge from experts in useful domains for decision support is certainly not a trivial task but through practice, one may gain enough experience to customize to FSS, which tailored to organization's need. Specific forecasting model in FSS i.e. only ARIMA (Box-Jenkins or B-J) methods will be considered as this method has been adopted by many academics since 1970 and has also been used by practitioners (Mentzer & Cox 1984).

Components of Forecasting Support Systems

A decision support system will have its own components based on the type and objective of building it. In any forecasting software, besides data and models, the architecture of a FSS includes networking, software and hardware, and users are also important components. In specific, the main components of FSS consist of Database Management System (DBMS), Model Base Management System (MBMS), Dialogue Generation Management System (DGMS) and Report Generator System (RGS).

When a data warehouse is included as a component in a Data-driven FSS (like FSS for specific requirements tailored to user customization), an FSS analyst or data modeler needs to develop a schema or structure for the database and identify analytic software and end user presentation software to complete the FSS architecture and design. Data-driven DSS is a type of DSS that emphasizes access to and manipulation of a time-series of internal company data and sometimes external data. Simple file systems accessed by query and retrieval tools provide the most elementary level of functionality. Data warehouse systems that allow the manipulation of data by computerized tools tailored to a specific task and setting or by more general tools and operators provide additional functionality. The FSS components need to be linked in an architecture that provides appropriate performance and scalability. In some Data-driven FSS designs, a second multidimensional database management system (MDBMS) will be included and populated by a data warehouse built using a Relational Database Management System (RDBMS). The MDBMS also provides data for OLAP where, Data-driven DSS with OLAP provides the highest level of functionality and decision support that is linked to analysis of large collections of historical data. Executive Information Systems (EIS) and Geographic Information Systems (GIS) are special purpose Data-Driven DSS. Displayed below are the components of FSS tools.

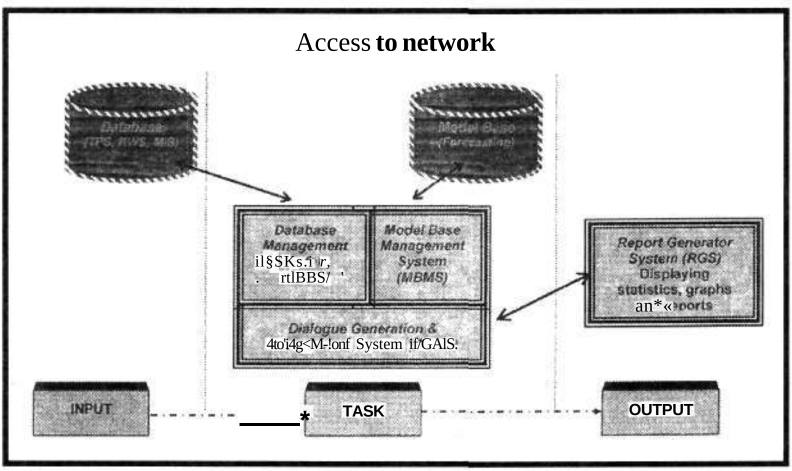

Figure 1:
Components of the Forecasting DSS Tool

From Figure 1, data extracted from database need to be validated from time to time (for the purpose like updating any recent relevant data and others) and must be in the form of operational data. This task is performed under the DBMS module. This means, prior to analyzing process, all data (or observations) must be in the form of data that can be read by processor, in order to analyze it. In other words, the data format should comply with the processor as programmed in the system. MBMS acts as modeling or analyzing data according to type of model requested. This module responsible of reading the operational data and model it. Each of FSS tool components has its subsystems which will be discussed in developer's point of view only.

Database Management System

It is essential to have internal and as well as external data. The main reason is because decision making especially for the upper management levels is heavily dependent on external data sources. It is common to build a data warehouse using an RDBMS from Oracle or IBM and then use query and reporting and analytical software from available vendor as part of the overall Data-driven FSS design. What some vendors call "business intelligence software" often provide the analytic and user interface functionality for a Data-driven FSS built with a data warehouse component.

Among significant capabilities of DSS tool are it is capable of combining a variety of data source through a data capturing and extraction facility, able to add and delete data quickly and easily, and able to manage wide variety of data with full range of data management functions. Hence, an FSS should be able to support data management systems like from TPS, Knowledge Work System (KWS) or Management Information System (MIS). Figure 2 exhibits the data of subsystem components in DBMS.

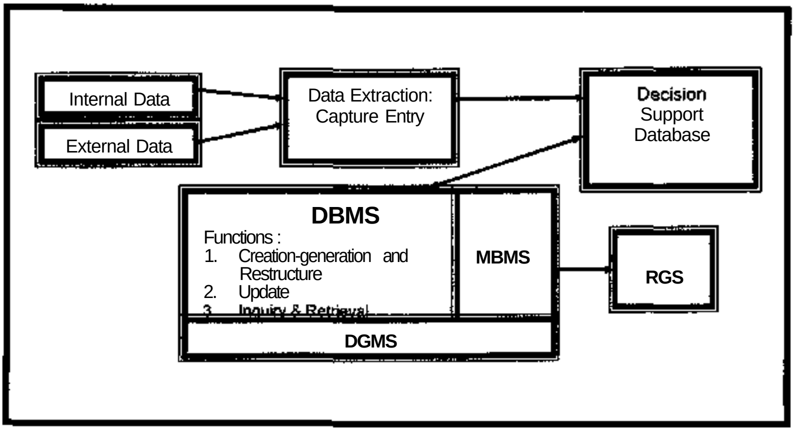

Figure 2:
The Data of Subsystem in Database Management System

Either internal or external data would be captured via data extraction facility provided by Forecasting Support System, in order to ease the process of analyzing. User may also to key-in manually if they wish to model any data which are not related to specific requirements as programmed in database. Data from database should have facility of editing, updating, inquiring, retrieving, and other features.

Model Base Management System

The most promising aspect of DSS is its ability to integrate data access and decision models (Sprague & Watson 1993). In general, a DSS model can be in the form of Strategic Models, Tactical Models and Operational Models. In FSS, the model creation process should be flexible, with a strong modeling language and should have a set of subroutines which can be assembled to assist the modeling process (for more routine and subroutines in ARIMA model, it will be discussed in Forecasting Methodology Section). Subsystem in MBMS is shown below.

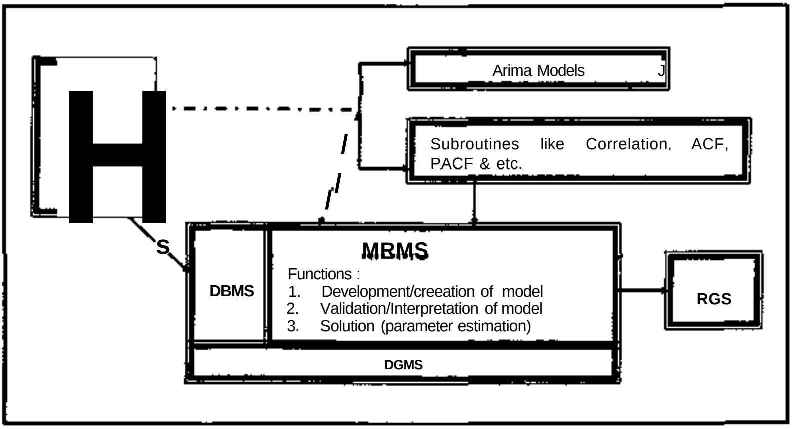

Figure 3:
The Subsystem in Model Base Management System

Data stored in database would be used as observations for models of ARIMA or other subroutines like Correlation, Autocorrelation Function, Partial Autocorrelation Function, Plotting and other functions covered in exploratory data analysis (EDA). MBMS functions would include the generating, updating and also manipulating model built. Model-driven DSS like forecasting models incorporated in Box-Jenkins approach involve particular tasks. The tasks in general modeling life cycle can be categorized in 8 categories (i) Problem identification, (ii) Model creation, (iii) Model implementation, (iv) Model validation, (v) Model solution, (vi) Model interpretation, (vii) Model maintenance, and (viii) Model versions or security. Listed in table below are the aims and mechanisms for each task mentioned.

Table 1: Task in Modeling Life Cycle

Task	Goal	Mechanism
1. Problem	Clear, precise problem statement Identification	Argumentation process
2. Model creation	Statement of the model (s) required to mathematically describe the problem	Formulation Integration Model selection and modification (if necessary) Composition
3. Model implementation	Computer executable statement of the model	Ad hoc program development Use of high-level specialized languages Use of specialized model generator programs
4. Model validation	Feedback from validator	Symbolic analysis of attributes such as dimensions and units syntax rules
5. Model solution	Feedback from solver	Solver binding and execution Solver sequencing and control script execution
6. Model interpretation	Model comprehension Model debugging Model results analysis	Structural analysis Sensitivity analysis
7. Model maintenance	Revise problem statement and/or mode] to reflect changes/insight	Symbolic propagation of structural changes
8. Model versions/security	Maintain correct and consistent versions of models. Ensure authority to access.	Versioning Access control methods

Dialogue Subsystem

Dialogue subsystem is also known as software for managing the interface between the user and the system. It is the key to information. Among good characteristics of a DSS is the one that has easy-to-use interface. User, terminal and software system are identified as the components of the interface system, which comprise of the action of language (i.e. what user can do to communicate with system), display or present the language (what user actually sees) and also knowledge base (what user must know). Figure 4 below displays the user interface system.

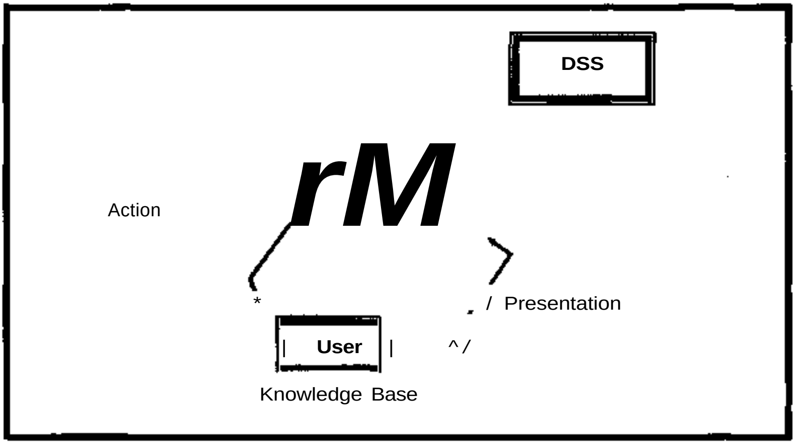

Figure 4:
User Interface System in Dialogue System

In this subsystem, among key elements to support user or system interface are data presentation in variety of formats, dialogue styles and flexibility in supporting for user's knowledge base.

Report Generator System

FSS should have its own specific forecast report that complies with user's requirement on report format. Therefore, it should provide the following capabilities:

- Statistical graphics, including time series plots and plots of functions related to ARIMA models.
- Specialized graphics for depicting the results from analytical models and sophisticated statistical techniques together with statistics results produced from model developed.
- Full range of tabular reports normally associated with each of the above.
- Reports customized to users' need.

Integration of these four systems is the foundation for the development of FSS, which based on three technology levels in DSS.

DSS Technology Levels

Sprague & Watson (1993) breaks DSS out into three levels of technology that are used by different levels of technically competent groups of people. Sprague (1993) breaks DSS out into three levels of technology that are used by different levels of technically competent groups of people, Specific DSS (IS systems application or the final product that actually accomplishes the work, it refers to the final application used by the end user to accomplish decision making in his/her environment), DSS Generator (package of related hardware and software which provides a set of capabilities to quickly and easily build a Specific DSS, for instance MS Excel) and DSS Tool (fundamental technology, consists of programming languages, graphics and editors). DSS Tool is actually a technology that has seen the greatest amount of recent development where it refers to the most basic set of technology or software methodologies available that allow the development of a specific DSS or more importantly the DSS tools. Here is where new conversational languages, voice command systems, color graphics, and simulation or animation tools come into the arena. As it is based on three distinct technology levels, illustration on the relationships among Specific DSS, DSS Generator and DSS Tool are displayed in Figure 5. It can be seen that, Specific DSS may be constructed either from DSS Tools and DSS Generator or, directly from DSS Tools. Most early DSS were developed without generators, while new ones are almost exclusively developed with them.

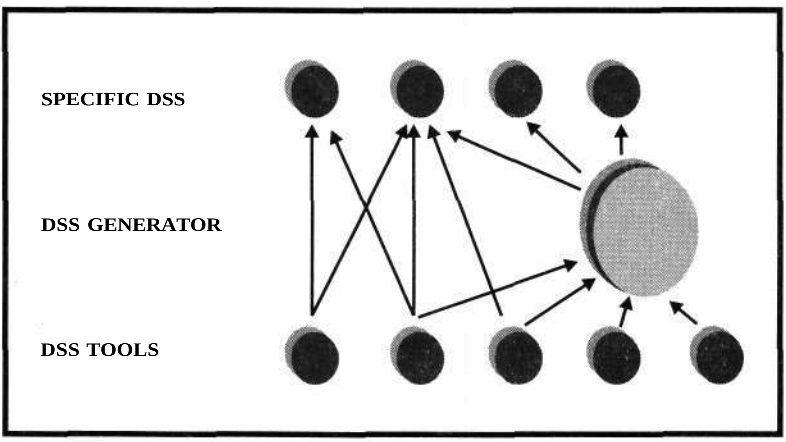

Figure 5:
DSS Technology Levels

Based on DSS technology levels (as shown in Figure 5), FSS can be developed via models available for forecasting in level of DSS Tools. DSS Tools acts as the processor for any current or future development of FSS. This processor consists of models' algorithm and techniques and also, these models can be re-used for any DSS Generator and/or Specific DSS which of course depends on users' needs and custom tailored to their requirements. Developers need to consider the aspect of user-friendly system interface as they should expect the various levels of end users of FSS.

Fitting an ARIMA Model

The main process flow of *Task* stage (Figure 1) will perform much of the computational work. FSS would guide its end users to perform all stages in performing ARIMA models and what model is actually fitted the time series data analyzed. Towards the end, it would eventually give the forecast results which may can be used to support users in presenting reports, business planning or other business activities. For larger databases, user must take precaution in providing high-end computer, with high-capacity and memory, as the ARIMA process for large data may consume more speed and memory.

Observations used (referring to internal or external time series data) for ARIMA model must be in time series basis. Time series is a sequence of measurements, typically taken at successive points in time. In simpler definition, time series data is a type of data which requires the time sequence for example in hourly, daily, weekly, monthly, quarterly or yearly basis. Time series analysis includes a broad spectrum of exploratory and hypothesis testing methods that have two main goals: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described.

ARIMA Models

When discussing on B-J process, we are actually concerning on a group of models. The three models are Auto Regressive model (AR), Moving Average model (MA) and, Mixed Auto Regressive Moving Average model (ARMA). Where, B-J method is more commonly known as Auto Regressive Integrated Moving Average, or simply ARIMA (Bowerman & O'Connell 1987). B-J approach considers for seasonal and non-seasonal time series data. Time-series model is generally expressed either as multiplicative model (where the value of the time series at time *t* is specified as y_t = Trend, x Cyclic, x Seasonal, x Random,; or additive model (where the value of the time series at time *t* is specified as y, = Trend, + Cyclic, + Seasonal, + Random,). The trend, cyclic, seasonal and random variations are four components of time-series model.

(i) AR model

For discrete time series data Y, = Y,, Y_2,..., Y_k, its general form of AR process withp order (written as AR(p)) is :

$$Y_t = 8 + \$_I Y_{t-1} + fe Y_{t-2} + ... + <(>_p Y_{t-p} + a_t \qquad p]$$

where at is a current noise (shock) with a_t ~ NID(0, af).

In backshift notation*, [1] can be written as,

•p(B)Y,= 6 + a,.

where,

BY, = Y „

<|>p (B) = 1 - <|>,B - <|>2B ^{2} -... - (|>pB ^{p} is the AR(p) operator with assumption Y_t is stationary.

This model has p+2 unknown parameters, i.e. 8,4>i, ^. . . . .<|>p and <a^2 - which needs to be estimated.

(if) MA model

MA(q) model is in the form of

$$Y_t = n + a_t - bflt\text{-}i - ... - 0_q a_{t-q} \qquad [2]$$

where is a_t is also normally distributed with mean zero and constant variance. Again, with backshift notation, [2] can be written as

Y, = n + e (B) a,

where,

6(B) = 1 - 6 , (B)-6_2(B)^2-... -9_q(B) "is the operator of MA(q).

This model too has q+2 parameters to be estimated from the observations i.e. H, 9i,e_2, ...6_q, and <jf.

A general model for non-seasonal ARIMA(p,d,q) data is :

$$OpCB^{\wedge}Zt = 0_q(B)e_t \qquad [3]$$

where,

z, is data in series

<Þ$_p$ is auto regressive with order *p* or AR(p), where $*_p(B) = 1 - \sum_{i=1}^{p} I>,5'$

&$_q$ is moving average with order *q* or MA(q), where $®_q(B) = 1 - \sum_{i=1}^{q} 1 \wedge$

(B)V^d is backshift notation for differencing *(V^d* = (1 - *B)^d)*

e, is the error term (white noise or shock).

Model [3] is for non-seasonal data. For seasonal data, it can be noticed from time plot that the variability of time series increases as time advances, which implies that the time series is nonstationary with respect to its variance). Therefore, for seasonal time series data, [3] will become,

$$\Phi_p(B)\Lambda_P(B^s)\nabla_s^D\nabla^d z_t = \Theta_q(B)\Gamma_Q(B^s)a_t\,,$$

where,

$V® = C\backslash\text{-}B^S)^D$, $AJB^S_P) = 1 - \sum_{i=1}^{P} K,.B^{s'}$ and $T_n(B^s)_U = -\backslash\text{-} \sum_{i=1}^{Q} (p.B^{5'}$

$$\Theta_q(B) = 1 - \sum_{i=1}^{q}\theta_i B^i$$

which is a more complex model.

Model in [4] is a multiplicative* seasonal model of order (p,d,q) x (P,D,Q) s, where the small letter p, q and d represents the order of AR, MA and differencing, respectively, for the non-seasonal part; and capital letter P, Q and D are the order of AR, MA and differencing, respectively, for the seasonal part.

In parallel with this model development cycle, seasonal factor cannot be taken lightly. Seasonal auto regressive and moving average parameters are added or dropped in response to the present of a seasonal (or cyclical) pattern in the residual terms or a parameter coefficient approaching zero. Also, care should be taken to insure that the parameters are uncorrelated and significant, and alternate models should be weighted for these conditions as well as for overall correlation (R^2), standard error, and zero residual.

Stages of ARIMA Process

In FSS, results of processed (analyzed) data will be displayed either in the form like graphical presentation, forecast values, or statistics results, and also customized report for summarizing the results produced. B-J model emphasizes on recent past rather than distant past and therefore, it is suited to short-term forecasting. It matches to data measured at equally spaced, discrete time interval. The B-J methodology consists of a four-stage iterative procedure where it will be programmed in MBMS. Figure 6 below displaying the process flow for Box-Jenkins approach, in specific task of analysis involved.

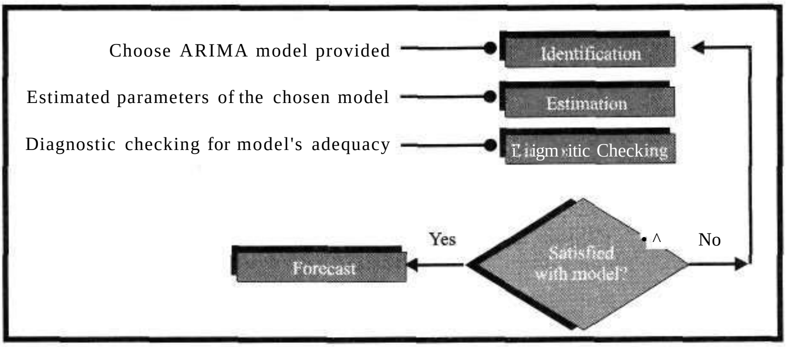

Figure 6:
Stages of performing B-J ARIMA method

The steps involve in B-J process are as elucidated below:

Stepl. Tentative Identification

Prior to identifying model, historical data are used to tentatively identify an appropriate B-J model by observing the stationarity aspect (mean and variance are constant through time). If otherwise, differencing should be performed to make the data stationary (Pankraz 1983). To determine the data is stationary, plotting it against time should be sufficient. If the data seem to fluctuate with constant variation around a constant mean m, then it is reasonable to believe that the time series is stationary. Also, it can be done by looking at Autocorrelation Function (ACF) and Partial Autocorrelation

* Time-series model is generally expressed either as multiplicative model (where the value of the time series at time t is specified as $y_t = Trend_t \times Cyclic_t \times Seasonal_t \times Random_t$; or additive model (where the value of the time series at time t is specified as $y_t = Trend_c + Cyclic_i + Seasonal_t + Random_T$). The trend, cyclic, seasonal and random variations are four components of time-series model.

Function (PACF)[1] of time series values. ACF measures linear relationship between time series observations, which being separated by *k* time units (often known as at lag *k).* Whereas for PACF; it is quite difficult to give a precise interpretation at lag *k.* Nevertheless, it can intuitively be thought of as autocorrelation of time series observations separated by a lag ofA units with the effects of the intervening observations eliminated. In general, for non-seasonal data and if the ACF of a working series of z_t, if it;

1. Either cuts off fairly quickly or dies down fairly quickly, then the time series values should be considered stationary.

2. Dies down extremely slowly, then the time series values are considered as nonstationary.

Type of models to be identified in this stage is based on ACF and PACF plots, which shows whether or not the time series data is stationary.

Step 2. Estimation

Historical data are used to estimate the parameters of the tentatively identified model.

Step 3. Diagnostic Checking

To ensure the model specification is adequate before performing the forecast. Test commonly applied are c^2 and t-test (to ensure error term at time *t* is independent with error term at time *t-1).*

Step 4. Forecast

Use the selected model to forecast, with forecast horizon according to interest.

Knowledge of using ARIMA is highly important in order to perform this analysis. ARIMA is the most advanced forecasting model compared to other models like linear curve fitting models (like simple regression), moving average and exponential smoothing[2]. It is a sensible practice to do preliminary analysis prior to model building. One important issue to remember is the influence of outlier data, which may lead to serious biases in parameter estimates in time series models. ARIMA will generally produce superior results as it incorporates and handles the problem of violating the independence assumption (most time series data face the problem of autocorrelation).

If observed closely Figure 6 and flow of B-J ARIMA modeling approach (in Appendix A), clearly this B-J ARIMA model involves an iterative process. Usually in FSS, the ARIMA process has to be performed step-by-step, where user must has knowledge what to perform and how to interpret the outcome (in each stage). As fitting the ARIMA model entails tedious process, algorithm in FSS tools should be translated in the GUI in as simple as possible. In other words, the GUI in FSS ought to be user-friendly enough in producing the results or outcome in each stage of ARIMA process. Next will be discussed tasks in each stage of ARIMA process in FSS, based on the process flow displayed in Appendix A.

Identification Stage Routines

This stage consists of three distinct routines.

- To determine whether the data is stationary, i.e. for both mean and variance: The easiest way to identify the variance is stable is by plotting the observations. For this purpose, FSS must have GUI for graphical presentation for plotting data. If variance is stable, user may proceed to check the mean if otherwise, data should be transformed to natural log or base 10 log. Feature should be considered to include in forecasting tool is facility to transform observations into function like logarithmic or reciprocal.

- To do differencing (if necessary): If mean is stationary (i.e. by looking at the behavior of ACF and PACF plots of the time series values or the transformed ones), differencing is not needed. Time plot (which refers to the plotting of the time series data), ACF and PACF plots are essential features in FSS to guide end users to accomplish this stage. Both ACF and PACF plots are obtained from calculation based on models for ACF and PACF, as calculated by the system. If the lower and upper bounds of ACF plots show shapes like sinusoidal (dies down extremely slowly), then, it means that data need to be differenced. The hint here is if ACF of the time series either cuts off or dies down fairly quickly then, it should be considered as stationary. Otherwise (if it dies down extremely slowly), then it is nonstationary (need to be differenced). First differencing for a time series data $y, ,y_0,\dots ,y_n$ is $z_t = y_(- y_M$, where t = 2,3,.. .,n. If first difference is not suffice (meaning the data is still not stationary), user may have to go for second differencing where the $z_t = (y_(- y_M) (y_{(:} - y_{i,2})$ for t=3,4,.. .,n, until the data becomes stationary (usually, second differencing would achieve the stationarity of time series values). For this purpose, FSS should provide feature whereby user may enter the value for differencing.

- To identify what B-J model is appropriate: Behavior of ACF and PACF plots would reflect what ARIMA process it follows together with what order is has. To identify whether the model is AR(p), MA(q), and ARMA(p,q) or ARIMA(p,d,q), user has to observe the plots and then to compare it with theoretical plots, so that he enables to identify which process is actually his data follows. The guide for this identification is as listed in table below.

Table 2:
Characteristics of ACF & PACF for processes in Box-Jenkins approach

Process	Characteristic of ACF	Characteristic of PACF
AR(p)	Tails off (decaying)	Spike at lag *p*
MA(q)	Spike at lag *q*	Tails off (decaying)
ARMA(p,q)	Tails off (decaying)	Tails off (decaying)

This identification stage can be made easier if users have great knowledge in interpreting the results (usually based on experience) plus with user-friendly system interface.

Estimation Stage Routines

This stage would require system in computer to perform lots of computational work. MBMS of an FSS is expected to be intelligent enough to cater models incorporated in ARIMA process. In this stage, user input is important, which all the relevant parameters used in this model should be entered by user in manually basis.

- Besides defining what variable to use, user must aware parameters required to perform ARIMA that he has to enter information like p, d, q (these are obtained from Identification stage), length of season (for seasonal data, for non-seasonal data the length would be zero), lags and number of observations. This stage is actually stage that would represent the ARIMA model apparent to end users and the GUI should embody parameters required for this model via lucid and simple interface so that it would not confuse the users especially for non-statistical ones or with little knowledge in statistics.

An FSS should keep the estimation values of the fitted, lower and upper bounds (optional), and also the residuals. The reason why residual values should be saved by the system is they would be used for diagnostic checking stage.

Diagnostic Checking Stage Routines

Once model is selected and parameters are being estimated by the system, it is important to diagnose whether the model is an accurate one. When we are dealing with issue related to the accuracy of a model, it means we are looking at the residuals (white noise or shock or error). In any methods, all we wish is to reduce the error terms (something that unobserved) so that our model is fit enough in describing the data that we have in hand. The routines to be performed under this stage are as follows:

- User needs to plot for ACF and PACF, but for this one, the variable is the residuals (errors) and not the original observations. The desired plots are, the ACF and PACF plots (values) must lie within the lower and upper limits for both plots, to make the model is the satisfied one. If the patterns exist then, user may be content to use the developed model to forecast, according to forecast horizon of interest.

- If the patterns do not show the desired one then, it indicates that the model is not accurate and user must go back to the Identification stage and re-model the data by following the step-by-step procedure in ARIMA.

Forecasting

The final stage in ARIMA process is of course forecasting. Forecasting can be done according to user's forecast horizon. In SPSS version 9.05 (as well as other software), user has the freedom to have his own forecast horizon, which has to be entered in GUI provided. B-J model is used for short and intermediate term forecasting. End users are also encouraged to monitor the forecasts accuracy in real time. It is mainly because as time progresses, the accuracy of the forecasts should be closely monitored for increases in the error terms, standard error and a decrease in correlation. When the series appears to be thus changing over time, recalculation of the model parameters should be undertaken. This B-J approach is translated and programmed in MBMS, DGMS and RGS. Integration of DBMS, MBMS, DGMS and RGS is actually the final product of FSS where aspects like forecast values, plot, report or summary of analysis, can be customized with accordance to users' requirements, which tailored to their specific needs.

Conclusion

In the presence of model-driven DSS especially forecasting tool as a decision support, researchers, practitioners (managers, executives), decision-makers (forecasters, planners) or even educators, may find them useful in assisting them in making decision with respect to forecasting, planning, education and as well as for reporting purpose. This so-called expert system is not only helping in terms of producing forecast values but may reduce the operation time - meaning that less time could be spent compared with manually basis. This system was developed based on how the experts think. Non-statistical or non-mathematical background users easily adapt the techniques introduced in FSS since the system eventually able to decide what forecasting methods is appropriate, in a given situation and how it should be used. Furthermore this program is a scientific program which may guide its end users to forecast in scientificcally and accurately without any basis or support from any of statistical forecasting approach. The key of scientific approach is its reliance upon rationality, as distinct from instinct or superstition. Drummond (1993) discovers that early economists applied scientific and mechanistic principles to decision making as they had witnessed the superiority of efficiency of machines over traditional way. Currently, it is hard to deny that the evolvement of computing technology like development of FSS (and as well as other types of model-driven DSS), has ameliorated the way of managers,as well as executives work, especially in the area with respect to forecasting and planning, and also decision-making. This improvement would of course ease the neophytes in adapting themselves to computing world.

A DSS project is actually a strategic decision and should financially be supported from the top management and aware the benefits to the company and as a viable project. Besides Model-driven DSS, the DSS research directions in general are more towards Communications-Driven

DSS, Knowledge-Driven DSS and Document-Driven DSS. Swanson & Ramiller (1993) suggest contrasting the processes and outcomes of computer-supported and conventional interaction. More efforts is being put through to learn about the management of models and most of us need new model components to advance the state of the art. The behavioral issues associated with Model-driven DSS have often been avoided by relying on specialists and intermediaries to use complex models for analyses. Most of us aware that models still need to be distributed more widely in organizations and they need to be packaged as model-driven DSS used by managers and also executives or relevant employees with non or little statistical/mathematical background. The understanding of how that diffusion of technology can happen is based more on personal experience that is through empirical research.

Consiquently, more examinations on the effects of various conditions on the use of and outcomes of using Communications-Driven DSS technologies have to be undergone, especially the Internet and Web technologies. Knowledge-Driven DSS and Management expert systems applications seem more practical today than ten years ago. Field studies of emergency management personnel or medical doctors using handheld computers with Knowledge-Driven DSS can be explored. Document-Driven DSS is a reasonably new frontier to many, but they have been used for more than 25 years (Swanson and Culnan 1978). What has changed is that document-driven DSS are now more accessible, more powerful and less expensive to develop and deploy. We still have many of the same questions to answer that we were struggling with 25 years ago.

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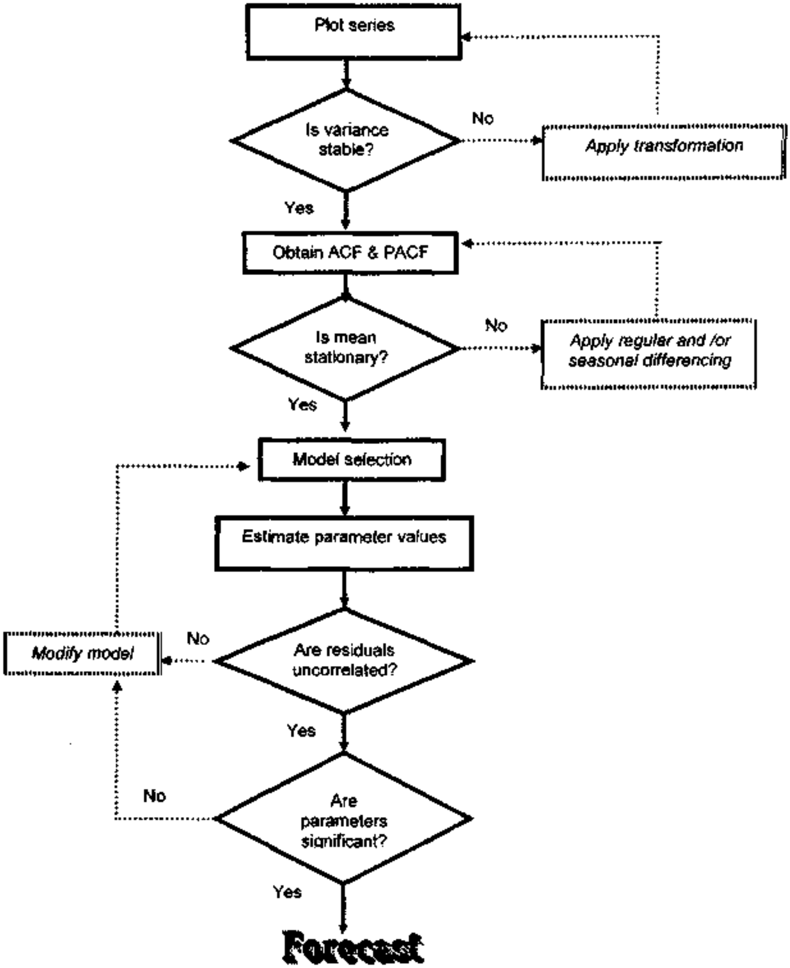
AppendixA



Source: Arsham (1984)