A Decision Support System for Subjective Forecasting of New Product Sales

Mohamed Hassan
CIS Dep., Sadat Academy for Management Sciences

Abeer Badr Eldin
CIS Dep., Sadat Academy for Management Sciences

Alaa El-Ghazali
CIS Dep., Sadat Academy for Management Sciences

ABSTRACT
Launching new products is risky by nature. As demand for an older product decreases, a company is forced to make a risky unavoidable decision of launching a new product. With the lack of historical data or sales records of the new products, the company has to make difficult decision to avoid failure of the new product. In this research paper, the research proposes procedure for new product sales forecasting and guides the calculation of new product sales forecasts based on accusation, evaluation and choice of subjective forecasts provided by executives and salespeople for new products which don’t have any historical data.

General Terms
Decision support Systems, Sales forecasting

Keywords
DSS, Sales Forecasting

1. INTRODUCTION
There are many reasons why new products may fail. New product failure can be the result of poor marketing, poor product design, or even bad timing of launching the new product. Regardless of the reason of failure, if the company had accurate forecasts, such failure products wouldn’t be marketed in first place. This creates the necessity of having forecasting decision support systems capable of forecasting the sales of new products.

2. DECISION SUPPORT SYSTEMS
The process of decision making, concerned with deriving the best options from feasible sets is present in every business. Consequently, the study of decision making is necessary not only in decision theory, but also in research areas such as management science, operations research, politics, and so on. It’s obvious that the comparison of different actions according to their desirability in decision problems can’t be done by using a single criterion or a unique person in many cases. Thus, the decision process has become a major concern of research in decision making.

A Decision support system (DSS) is “computer-based system that enables management to interrogate the computer system on an ad hoc basis for various kinds of information on the organization and to predict the effect of potential decisions beforehand. [1]

A DSS is a set of computer-based tools which are used to support complex decision making and problem solving.[2] Decision support systems are interactive systems that aid users in judgment and choice activities. [3] Decision support systems are designed to help managers and business owners in the process of decision making.

2.1 Structure of DSS
Decision support systems is normally consist of three subsystems which are used together to form a complete Decision support system (DSS). These three components are a database, a model base and a user interface. Each of these three subsystems has a different role. Database management subsystem is used for managing the data, model base management subsystem is used for managing the models to perform algorithms and quantitative analysis, and the graphical user interface is used for enabling interactive queries, reporting, and graphing functions of decision solutions.

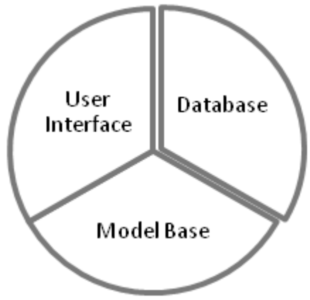

Figure 1 : Components of DSS

2.1.1 Database
For the improvement of decision-making process in companies, decision support systems are built from sources (operational databases). These dedicated systems are based on the data warehousing approach. [4] An important process in data management subsystem is Extraction, Transformation and Load (ETL). Extraction means to reading data from one or more data sources. Transformation is converting the extracted data from its previous form into another form fitting different databases. Load means putting the data into its target database.

In some situations, difficulty in decision making is because of the lack of data. But in other situations, decision making can be difficult because there is too much data to handle. Data mining helps overcome this problem by finding patterns from large sets of data. Data Mining helps in discovering previously unknown relationships among the data by using pattern recognition technologies and statistics.

On-line Analytical Processing (OLAP) is used for querying and analyzing data. Usually OLAP includes some activities as generating and answering queries, requesting ad hoc reports and graphs and executing them. [5] OLAP tools enable users to analyze multidimensional data interactively from multiple perspectives, conducting traditional or modern statistical analysis and building visual presentations.

2.1.2 Model Base
Models use mathematical and statistical techniques to describe the real world, and apply these models to the task at hand, allowing the operator to receive recommendations or what-if scenarios. [6] The model management subsystem includes all models which use mathematical techniques to perform algorithms for advanced calculations and quantitative analysis.

These models allow the decision support system to not only supply information to the user but aid the user in making a decision. [7] In addition to including mathematical calculations and techniques, the model management subsystem is expanding to include business models such as Enterprise Resource Planning (ERP), Supply Chain Management (SCM) and Customer Relationship Management (CRM) [8]. Models apply quantitative analysis and mathematical calculations to the real world tasks at hand.

2.1.3 Graphical User Interface
The graphical user interface (GUI) is in charge for the information visualization. It provides the user with control over the model management subsystem to making changes in model base and database, and presents desired information and possible courses of action for the user.

2.2 Types of DSS
Types of decision support systems include data driven DSS, model driven DSS, knowledge driven DSS, document driven DSS, group DSS, function specific DSS and web based DSS.

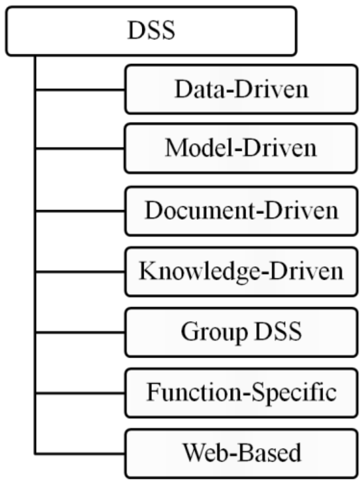

Figure 2 : Types of DSS

2.2.1 Data-Driven DSS
Data-Driven Decision support systems provide tools for access and manipulation of large databases or data warehouses storing large amounts of data. Relational databases accessed by query and retrieval tools provide a high level of functionality of the decision support system. A higher level of functionality is provided by data warehouse systems allowing manipulation of data and online analytical processing (OLAP)

2.2.2 Model-Driven DSS
Model-Driven DSS include computerized systems that use accounting and financial models, representational models, and/or optimization models to assist in decision-making. [9] Model-Driven decision support systems don't use much data. Instead, they mainly rely on using mathematical techniques, algorithms and quantitative analysis to provide help in the process of decision making. The main component of a Model-Driven DSS is the model-base used for providing support for decisions which require mathematical calculations more than data

2.2.3 Knowledge-Driven DSS
Knowledge-Driven DSS Sometimes described as a "Suggestion DSS" or as an "Expert System" provides recommendations for the course of action to be taken.[6] Knowledge-driven DSS can store and apply knowledge for a different problems and tasks which are normally resolved by a human expert.

2.2.4 Document-Driven DSS
This type of DSS assists in knowledge categorization, deployment, inquiry, discovery and communication. [10] Document-Driven decision support systems are used for management, retrieval and manipulation of unstructured information in a variety of electronic formats. Document-Driven DSS can be useful for handling documents such as catalogues, historical documents.

2.2.5 Group DSS
Group decision making involves series of interactions, communication, deliberation and other activities such as among a group of individuals. [11] A Group Decision Support System (GDSS) is "an interactive computer system. It is conducive to solving structured or semi-structured problems by way of group decision making". [12]

Group Decision support systems support the use of communications and decision models to facilitate the solution of problems by decision-makers working together as a group by supporting communication, document sharing and other group activities.

2.2.6 Function-Specific DSS
Function-Specific decision support systems accomplish a decision task which is specific to the environment in which the DSS will be used. [6] A function Specific DSS is made to handle a specific reoccurring task which needs to be handled regularly.

2.2.7 Web-Based DSS
Web-Based DSS implement any of the other types of DSS with web technologies and they become a web-based DSS.[13] A Web-based DSS is a complex software system. It may integrate different data sources and related tools to generate information to support decision-making. [14] Web-Based DSSs use thin clients such as web browsers and load processing to web servers which handle requests and return the results.

3. SALES FORECASTING
Sales forecasting is the activity of predicting the future level of demand of products. It's vital for developing sales programs and budgets, setting up territories and evaluating sales performance of sales people.

Sales forecasting plays a significant role in making decisions regarding new products and older products. For older products, there are several quantitative methods for sales forecasting such as moving average, percent rate of change, unit rate of change, exponential smoothing and line extension. For new products, with the lack of historical data, a few simple routines can be employed, requiring more creativity in order come up with useful predictions of the future level of demand.

3.1 Product Life Cycle

A company wouldn't know how the sales of a product will change in the future from one period to the next. However, the sales of any one product to some extent will normally follow the product Life Cycle curve. A product's life cycle includes four distinct stages such as Introduction, Growth, Majority and Decline.[15]

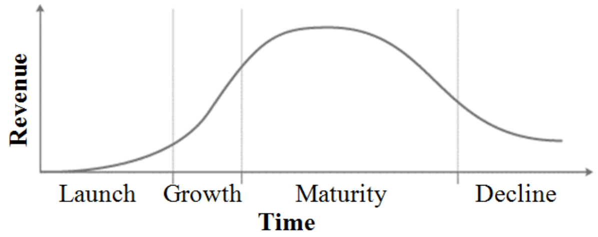

Figure 3 : Product Life Cycle

3.1.1 Launch

During the first stage, Because of some conditions such as technology limitations and high promotion costs, low production output and low market recognition could persist, leading to limited sales, thin profit or maybe even loss.

3.1.2 Growth

During the second stage, the product is accepted in the market and sales grow rapidly. When a product has won customers' favor by technology improvement, advertisement and sales promotion, it has entered a period of growing demand.

3.1.3 Maturity

During the third stage, as the product has achieved acceptance by most potential buyers at this stage, the sales reach peak and growth slows down.

3.1.4 Decline

During the final stage, when sales fall off and profits stop. Any product would one day face its end: being eliminated by the market. When a product cannot meet customers' demand anymore, eventually production will stop and the product will become history.

3.2 Subjective Forecasting Techniques

An important advantage of subjective techniques is that they take into account the key personnel experience and require little formal data. They can be very valuable when little or no historical data is available, such as for new product introductions. [16] Subjective forecasting techniques are procedures that turn the predictions of experienced personnel such as corporate executives, outside experts and salespeople, into formal forecasts.

3.2.1 Face-to-Face Meetings

With the advance in technology, most business meetings can be held virtually. However, face-to-face contact still matters and is considered the most effective way of doing business.

Face-to-Face meeting has always been believed to be the most effective way of contact for business. This is mainly because face-to-face contact enables a person to send information, give immediate feedback and generally maintain a trust worthy, personal and friendly atmosphere which could be much harder if done using communication technologies.

Decision support systems which are facilitated for meetings may not apply to spatially distributed groups, which may require replacement of business travel with communication technologies such as videoconferencing.

Increasingly, companies have access to multiple computer-mediated systems to organize business meetings. These meetings have several objectives and choosing the suitable meeting mode is considered important to effectively accomplish their objectives.

3.2.2 Delphi Method

Using Delphi method, experts do not meet directly. So they will avoid such possible negative influences within the group such as, fear of the superiors, seizure of discussion from the dynamics and experts anger. [17]

Numerical estimates or forecasts are made by experts in at least two phases. The first phase is sometimes called the phases of definition and the next phases are called phases of convergence. The questions are about the same in each stage, but before completing the questionnaire, the opinions of experts are presented to their colleagues. So the questionnaire may include or exclude certain sections depending on the results of certain phase. The moderator or the leader of the group processes the responses to the questionnaires. Filling of the questionnaire will continue at least two times and it will keep repeating until no new estimates are occurring.

4. CALCULATION OF SUBJECITVE FORECASTS

To calculate the sales forecasts of jury of executives weights are assigned to each member of the jury based on the count and accuracy of forecasts of the member. Forecasts of each executive for each product are saved in the forecast table in the database.

Table 1 : Sample of Executives' Forecasts for Sales

Product	Month	Executive 1	Executive 2	Executive 3
Product 1	May-15	1454	1293	1131
Product 2	May-15	5376	4778	4181
Product 3	May-15	630	560	490
Product 1	Jun-15	2880	2560	2240
Product 2	Jun-15	9054	8048	7042
Product 3	Jun-15	1141	1014	888
Product 1	Jul-15	423	376	329
Product 2	Jul-15	1496	1330	1163

The system counts the number of forecast of each member of the jury of executives and the accuracy of forecasts. A rating is given to each member of the jury of executives and then weights are assigned to members based on their ratings

Table 2 shows different possible scenarios for executives' forecasting performance. It show executives who have:

- High count of forecasts and high accuracy
- High count of forecasts and low accuracy
- Average count of forecasts and average accuracy
- Low count of forecasts and high accuracy
- Low count of forecasts and low accuracy

Table 2 : Executives Accuracy and Count of Forecasts

Executive ID	Count of Forecasts	Percentage of Total Count	Accuracy of Forecasts
Executive 1	1309	100%	90%
Executive 2	1309	100%	80%
Executive 3	1309	100%	70%
Executive 4	1309	100%	50%
Executive 5	988	75.5%	90%
Executive 6	988	75.5%	80%
Executive 7	988	75.5%	70%
Executive 8	478	36.5%	95%
Executive 9	478	36.5%	85%
Executive 10	478	36.5%	50%

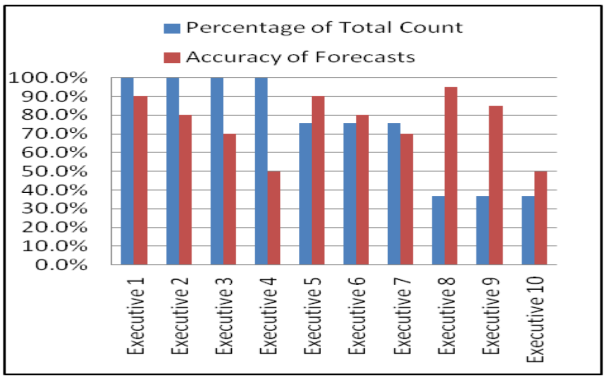

Figure 4 : Executives Accuracy and Percentage of Total Count

Executives' ratings, which are used for assigning weights to them can depend on accuracy, count of forecasts, or both of them. Table 3 shows assigning weights to executives based on their accuracy of forecasts. Different weights of executives depending on accuracy are shown in figure 5.

Table 3 : Executives Weights Based on Accuracy

Executive ID	Accuracy	Count	Rating	Weight
Executive 1	90	100	90	0.11842
Executive2	80	100	80	0.10526
Executive3	70	100	70	0.0921
Executive4	50	100	50	0.06578
Executive5	90	75.5	90	0.11842
Executive6	80	75.5	80	0.10526
Executive7	70	75.5	70	0.0921
Executive8	95	36.5	95	0.125
Executive9	85	36.5	85	0.11184
Executive10	50	36.5	50	0.06578

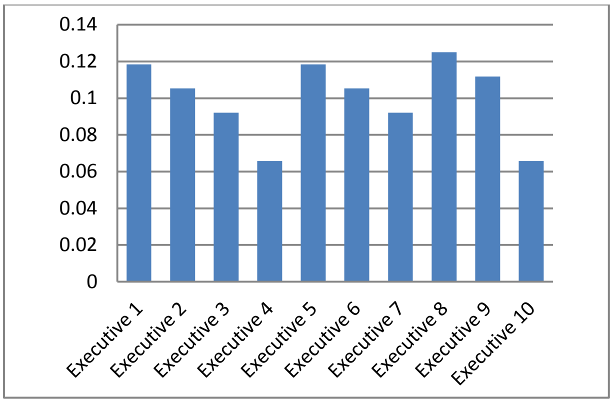

Figure 5 : Executives Weights Based on Accuracy

Table 4 shows assigning weights to executives based on their percentage of the total count of forecasts. Different weights of executives depending on percentage of the total count of forecasts are shown in figure 6.

Table 4 : Executives Weights Based on Percentage of Total Count of Forecasts

Executive ID	Accuracy	Count	Rating	Weight
Executive 1	90	100	100	0.13587
Executive2	80	100	100	0.13587
Executive3	70	100	100	0.13587
Executive4	50	100	100	0.13587
Executive5	90	75.5	75.5	0.10258
Executive6	80	75.5	75.5	0.10258
Executive7	70	75.5	75.5	0.10258
Executive8	95	36.5	36.5	0.04959
Executive9	85	36.5	36.5	0.04959
Executive10	50	36.5	36.5	0.04959

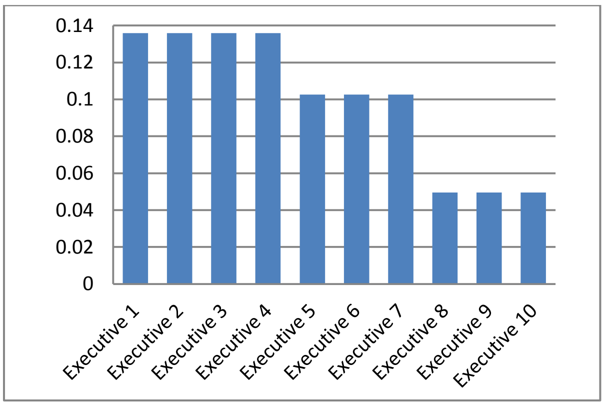

Figure 6 : Executives Weights Based on Percentage of Total Count of Forecasts

Table 5 shows assigning weights to executives based on their accuracy and percentage of the total count of forecasts. Different weights of executives depending on accuracy and percentage of the total count of forecasts are shown in figure7.

Table 5 : Executives Weights Based on Accuracy and Percentage of Total Count of Forecasts

Executive ID	Accuracy	Count	Rating	Weight
Executive 1	90	100	95	0.127
Executive2	80	100	90	0.12032
Executive3	70	100	85	0.11363
Executive4	50	100	75	0.10026
Executive5	90	75.5	82.75	0.11062
Executive6	80	75.5	77.75	0.10394
Executive7	70	75.5	72.75	0.09725
Executive8	95	36.5	65.75	0.0879
Executive9	85	36.5	60.75	0.08121
Executive10	50	36.5	43.25	0.05782

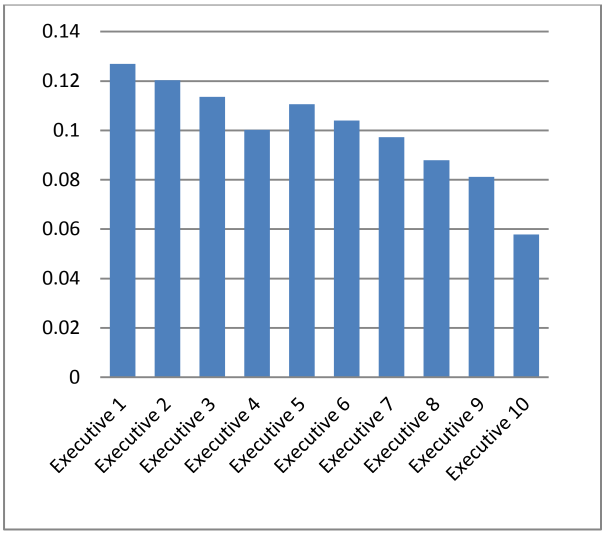

Figure 7 : Executives Weights Based on Accuracy and Percentage of Total Count of Forecasts

Given several forecasts of several executives, the average of given forecasts can be used to calculate the jury of executives' forecast. But since executives have different weights assigned to them depending on their accuracy of forecasts, count of forecasts or both, the management can use theses weights to calculate more reliable forecasts.

After calculating the subjective forecasts of the new product sales, the results are displayed for the sales management to choose which forecasts to rely on. Table 8 shows different subjective forecasts displayed for sales management.

Table 6 : Calculating Jury of Executives' Forecasts

Executive	Forecast	Weight	Forecast * Weight
Executive 1	1050	0.1270	133.35
Executive 2	940	0.1203	113.082
Executive 3	820	0.1136	93.152
Executive 4	590	0.1002	59.118
Executive 5	1050	0.1106	116.13
Executive 6	940	0.1039	97.666
Executive 7	820	0.0972	79.704
Executive 8	1110	0.0879	97.569
Executive 9	990	0.0812	80.388
Executive 10	590	0.0578	34.102
Forecasted Sales			904

Sales force composite is an easily calculated forecasting method. With this procedure, forecasts are calculated by aggregating the forecasts of sales people in their own territories.

Table 7 shows the calculation of sales force composite forecasts by aggregating the forecasts of sales force.

Table 7 : Calculating Sales Force Composite Forecasts

Product	Sales Force 1 Forecast	Sales Force 2 Forecast	Sales Force 3 Forecast	Sales Force Composite Forecast
Product1	200	100	100	400
Product2	500	400	500	1400
Product3	350	150	150	650
Product4	300	300	600	1200

Table 8 : Different Subjective Forecasts

Forecasting method	Forecast
Jury of Executives Sales Forecasting	1200
Sales Force Composite	2500
Willing to buy survey results	1800

With no data available, depending on human skill and experience can be the best possible way to forecast the sales of new products. A decision support system can use different subjective forecast of executives and salespeople to help management make more reliable forecasts. However, management still has to make important decisions using the decision support system. Management has to choose a basis for the evaluation of executives which changes the weights assigned to each of them. Management also has to decide which forecast to rely on, jury of executives forecast, sales force composite forecast or willing to buy results.

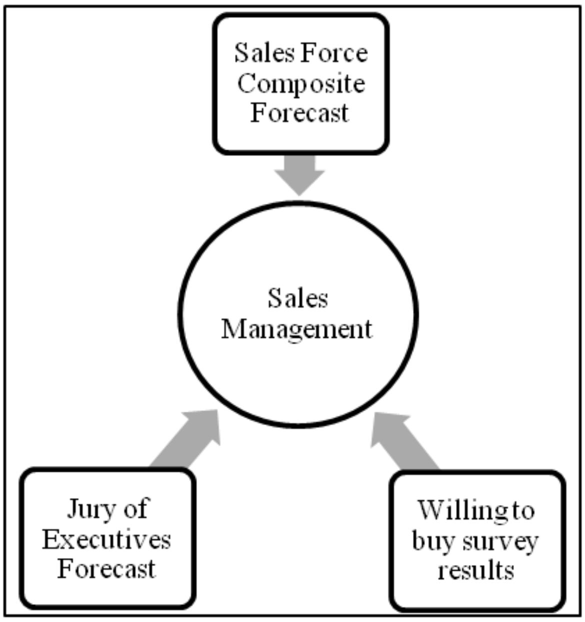

Figure 8 : Forecasts Received by Sales Management

5. CONCLUSION

This paper has demonstrates the decision support systems and their importance in new product sales forecasting. Components of decision support systems have been reviewed. Different types of decision support systems have been clearly identified. In addition, sales forecasting and product life cycle stages have been clearly identified. This paper shows the subjective forecasting techniques and presents the calculation of new product sales forecasts based on subjective forecasts of executives and salespeople and survey results. For the future work the researchers intend to conduct an experiment using decision support systems with subjective forecasting methods to achieve an enhancement in new product sales subjective forecasting. The researchers intend to apply the research on jury of executives for forecasting new product sales. This may be a good start for new product subjective forecasting in the future. The future scope includes using product evaluation in terms of reliability, services, operation costs and customer satisfaction and comparing them to older products to be able to use the sales records of old products for forecasting the sales of new products. Sales records of older products and comparison between old products and new products can be used together to increase accuracy of new product sales forecasting in the future, using quantitative methods in addition to subjective methods.

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