

Forecasting of new products in the ECLIPS research project

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SUMMARY

The objective of the ECLIPS research project is to provide breakthrough solutions to companies facing ever more complex supply chains, product diversification and shortening life-cycles. One of the key research topics of ECLIPS is the forecasting for new products. Today, the current forecasting models for new products are insufficient because they still rely largely on time consuming qualitative techniques. ECLIPS uses the aid of artificial intelligence to improve and streamline the forecasting for new products.

PRESENTATION OF ECLIPS

ECLIPS is a three years research project, started second quarter 2006 with funding of the European Commission, aimed at extending the state-of-the-art in Supply Chain Management. ECLIPS is the acronym for Extended Collaborative Integrated Planning System.

The project consortium is composed of experts from the industry and from the academic world. The six members of the project consortium are:

- MÖBIUS (Fr, Be, UK) - consulting
- Riga Technical University (Lv) – academic partner, specialized in artificial intelligence
- Eurodécision (Fr) – optimization experts
- LoQutus (Be) – software partner
- Pliva-Lachema Diagnostika (Cz) – industrial partner / pharmaceuticals
- Huntsman (De) – industrial partner / chemicals

By combining their individual strengths in this project, the consortium partners are committing to **answer today's major supply chain challenges**.

The industry will monitor the relevance of the work to its business environments through an **Advisory Board**. The initial members are: Hansen Transmissions, Tate & Lyle, Agfa Gevaert, Associated Weavers, Thales Electronic Devices, Alcatel, Arcelor and Solvers. **The Advisory Board is open to all interested industrial parties.**

Visit the website www.eclipsproject.com for more details.

OBJECTIVES OF ECLIPS

Globalization, more complex and longer supply chains, ever increasing product diversification and

shortening life-cycles, these are the challenges posed to companies today. These challenges require to be faced with solutions from breakthrough innovation. The members of ECLIPS believe that these breakthroughs will allow **global supply chain inventory reductions of 30%**. The objective is the translation of academic level concepts into a robust software package that can **easily be added on existing ERP and APS packages**. The add-on concept will assure the broad applicability and exploitation of this development. This generic set up of the project make it a very promising element in **enhancing the competitiveness of the European Industry**.

ECLIPS TO IMPROVE ALL PRODUCT

LIFECYCLE PHASES

The following figure represents the simplified lifecycle of a general product. We can see 3 phases:

- The introduction phase
- The maturity phase
- The end of life phase

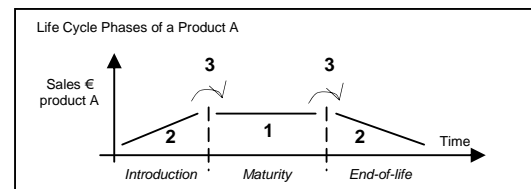


Fig.1: Simplified Product Life Cycle

To improve Supply Chain performance, the ECLIPS project has 3 Key Research Topics

- Maturity phase: Multi-Echelon Cyclic Planning
- Introduction / End-of-life: Improved Statistical Forecasting
- Lifecycle Integration: Automated switching of Supply Chain Control

A key problem is forecasting. Current forecasting techniques work well for the mature phase but poorly support the introduction and end-of-life phases. For mature products, we believe that using optimization for multi-level cyclic planning will strongly improve current operations. Multi-level cyclic planning is the cruise control in planning the different levels in the supply chain. By using this pragmatic approach, all echelons in the supply chain can be brought to a certain rhythm. The complexity of it does not lie in the execution of such a plan, but merely in finding the optimality of it. As the pace of product introductions increases and life cycles shorten, an automated switching

between the optimal supply chain control mechanisms is also a key challenge for the supply chain systems of the future.

In this article, we will focus on the introduction phase and more specifically on the forecasting part. ECLIPS will use Artificial Intelligence techniques to improve the forecasting for new products.

FORECASTING OF NEW PRODUCTS: WHY IS IT NECESSARY?

The **introduction and end-of-life phases of products are hardly described in literature** or supported in commercial software packages. In many cases the same methods and tools are used as for the mature products. Historically, the issue of introducing and phasing out articles has been less important. However as lifecycles shorten because customers want ever-more customized and up-to-date products, this problem becomes ever bigger. Today, many companies are struggling to manage product introductions and the end-of-life stages.

Planning an efficient supply chain starts with a good forecast. This holds even more true for the introduction of new articles. A good forecast here is crucial, but that good forecast is equally elusive due to a lack of historic data or market knowledge.

But even more often the forecast for new products is just a manual one, which is static and, certainly when driven by an aggressive marketing plan, mostly optimistic. This static approach is a source of either unused inventories or in the other case of unmatched demand. Neither of these results is satisfactory, so other techniques must be explored.

The advanced company has already experienced with certain statistical or qualitative techniques to forecast the demand for new products. The frequent disappointment with these **“traditional” techniques is very often caused by a misunderstanding of the assumptions of these models**. In other words: a forecasting technique is used for something it was not intended to do.

We will first give an overview of the usability of currently known techniques, their applications and limitations.

We will finally conclude on how we can improve the forecasting of new products by the incorporation of artificial intelligence. The academic tone of this section will be balanced with **practical comments** on how these advanced forecasting models are planned to be used by two industry partners of the research consortium.

WEAKNESSES OF CURRENT TRADITIONAL FORECASTING MODELS FOR NEW PRODUCTS

All the described types of models can be divided into three major classes:

1. Statistical models require a statistical sample related to the historical behaviour of the product. Statistical models include multivariate or other types of regression with optional use of:

- ARIMA / Box Jenkins or spectral analysis
- Exponential smoothing
- Linear and nonlinear econometrics

For example, R.Neelamegham and P.Chintagunta (*ref.1*) examine sales of new movies in domestic and overseas markets by using an elaborated, solution specific model. The number of viewers of a movie in a given week and the number of screens, distribution strategy, movie attributes such as genre and presence/absence of stars are among the factors analyzed to influence viewer-ship. **The methodology provides forecasts under a number of information availability scenarios**. Thus forecasts can be obtained with information from a historical database containing data on previous new product launches in several international markets.

2. Approximation models including:

- Bass model
- Rogers model

These so-called diffusion models need making preliminary assumptions and hypotheses about the character of the product's behaviour. For example (*ref.2*) an attempt can be made to connect the results of a monthly forecast with the inventory level. From an exact theoretical point of view, these models only apply for the forecasting of new product families and they are often criticized for their rough and ramshackle assumptions. Still, they are the most frequently (mis)used models for forecasting new products!

3. Judgemental models including:

- Expert judgements, Delphi and alike methods
- Looks-like or analogous analysis
- Behaviouristic models

K.B.Kahn (*ref.4*) makes an overview of those models that require judgements of a sales manager or other persons involved in the organization and statistical approaches. He concluded that qualitative methods are used more frequently but mostly because of convenience and not for some clear added value.

R.J.Meyer and A.Sathi (*ref.5*) present the multi-attribute analysis of customer's judgements. The model makes a hypothesis about how a population of consumers makes brand choices while learning during a series of successive shopping occasions.

The model is defined only within a limited domain. The main assumptions are:

- On each shopping occasion a single choice is made of one brand in each desired product class. No attempt is made to represent decisions related to purchase volume.
- Each successive decision is made independently. Hence, we assume that the product is fully consumed between shopping occasions.

A forecast is then made based on the probability of a buyer choosing a product within a product class. Behaviouristic models are related to this approach. For example, PC Wilton and EA Pessemier (*ref.6*) take into consideration the behaviour and psychology of buyers in choosing the product they will buy. The preferences are evaluated with respect to many parameters of the product. Customer's preference, however, depends on how much they are informed about the merits and demerits of the product. Researches of this kind are conducted using large sets of respondents. It is assumed that it is possible to determine the initial structure of the product perception of a new product. **The robustness and reliability of such researches is of great doubt.** Works of this kind are of pure research nature.

This analysis of traditional forecasting methods shows that in order to use them sufficiently, **a large amount of historical or qualitative information is needed or a solution specific approach should be followed.**

ADDED VALUE OF ARTIFICIAL INTELLIGENCE IN FORECASTING NEW PRODUCTS

In this part, we will not describe in detail the academic background of the existing Artificial Intelligence methods that will be used for forecasting a new product. We refer to standard literature for that purpose, as we focus here on the applicability of AI, rather than on AI itself.

To carry out forecasting of new product demand in the introduction phase, it is planned to divide the work into three stages, all of which employ existing Artificial Intelligence techniques. It is however the first time that these techniques are used for this purpose and in this combination.

In the first stage, the historical demand that is available at the time of analysis is summarized for those products that have already passed the stage of their introduction on the market. The second and the third stage are activated just after the new

product is introduced. The different stages are called as follows:

- A. Clustering – using cluster analysis for summarising the data about introduction phases of different products.
- B. Identification – ascribing a new product to one of the identified clusters using similarity measures of the product to products in the clusters.
- C. Forecast– forecasting product demand level according to its cluster as well as correcting that forecast in respect with time.

Thus, the forecast of new product demand is only possible after the historical demand information of previous product introductions is pre-processed. It should be noted that for this purpose no historical demand of the new product itself is required, which is in sharp contrast to the few existing quantitative techniques for new products.

As can be understood from this research strategy, we will focus on the forecast of large numbers of **individual** products. Each forecast will make a statement on the demand level of a **number of periods** out in the future. The added value lies in the automated “ab initio” calculation, without qualitative manual input, of these forecasts and in the fact that these forecasts are **updated automatically** each time new demand data becomes available. This approach can however equally be applied to the forecast of new product families, as long as the relevant data on that level is available.

A. Clustering

Cluster analysis applied on forecasting new product:

Stage one starts by summarizing, with cluster analysis, the existing historical demand information regarding different products in the phase of their introduction. This is obviously only done for products whose phase of introduction already completed. The level of demand for a product can be represented as a time series. Cluster analysis is one of possible techniques for generalizing time series on the basis of their similarity. The process of combining data in groups is called clustering.

After the clustering of available pre-histories of different product introduction is completed, a list of characteristic groups of the corresponding time-series is obtained. Each of the groups will be represented by a group prototype, like the most representative object of that group or by the averaged time series of that group. Each of the products used for clustering will be assigned to the cluster to which it belongs.

An example of clustering methods:

Different clustering methods are available, but in order to give some clue on what the results look like, we give an example in Figure 2 of a partitioning and hierarchical method.

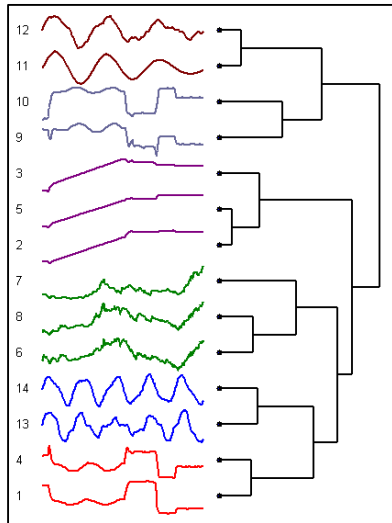


Fig.2: The hierarchical dendrogram of the combination of 14 different time series

Crisp clustering unambiguously ascribes an object to a single cluster. In clustering time series a situation might occur when such a partitioning of product introduction histories is not acceptable because the similarity degree between different time series can be too high provided that two or more clusters are located close to each other. In cases of that kind, the final membership in a cluster can either be determined by an expert or the object will be considered lying in two clusters at once. To solve the above situation, one may use fuzzy clustering methods.

An example of fuzzy clustering is shown in Figure 3. The rectangles enclose “hard” (traditional) clusters in the data, H1 and H2, whereas a fuzzy clustering algorithm might produce the two clusters F1 and F2 depicted by ellipses.

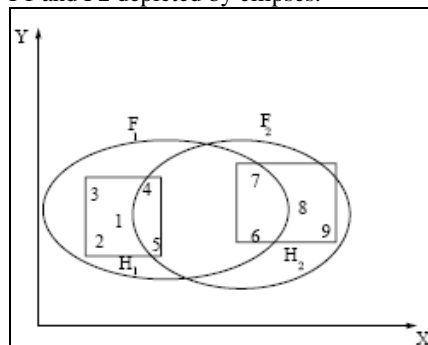


Fig.3: Two types of clustering, “hard” and fuzzy, of nine two dimensional objects

B. Identification

Every new product must be assigned to one of the clusters found at the stage of clustering. In other words, it is necessary to identify to which cluster (i.e. the corresponding group of time series) that new product might belong. The process of identification is only possible if the similarity measure between the different products is crisply defined. Similarity calculation means manipulating quantitative and qualitative features describing an object, in this case the newly introduced product. These sets of features are attributes that assume particular values for each object.

The most complete list of attributes describing the products is necessary. The list must be common for all the products; it can be conditionally divided into several groups of attributes as follows:

- 1. Physical and technical parameters of the product, e.g. the weight and dimensions of the product packing.
- 2. Qualitative indicators, for example, ingredients (components) of the product and its belonging to specific class of products.
- 3. Economical parameters, for example, the cost price of the product and the type of market on which it will be sold.
- 4. Other groups of attributes – the complete and concretely defined list requires to be clarified.

A more precise specification of the list of attributes is a key factor of further successful calculation of similarity of different products.

C. Forecast

If a product is ascribed to the corresponding product cluster, the demand for that product in the phase of its introduction can be conditionally assumed to be identical to the demand level in that cluster. In this case, the most trivial model could be to assume the demand level of the representative product of that cluster as the searched demand level. After some time, when the data about the real level of product demand become available, it is necessary to associate the product with a cluster whose characteristics represent the real demand curve with the smallest deviation. More complexity will be added here as the model can also learn about the correctness of its previous decisions and the constraint of the trivial model can be relaxed.

CONCLUSION

The forecasting for new products is one of the key research topics of ECLIPS. We have seen how to use Artificial Intelligence techniques to improve the forecasting of new products. Clustering methods are used to summarise the data about introduction phases of different products. Subsequently a new product is ascribed to an existing cluster and a forecast is made.

Tests will be done on real data from the industry partners of the ECLIPS research consortium and we hope that those results can be presented next year.

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Alex Waterinckx is a supply chain management consultant at MÖBIUS specialised in Multi-Echelon supply chain optimization. Furthermore, Alex is the architect of the advanced forecasting functionalities offered in the software package Atomium/M that MÖBIUS uses to support its consultancy in the field of forecast process support, demand management and S&OP. Alex is a steering member of the ECLIPS supply chain research project, sponsored by the European Commission.

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Yuri Merkuryev is a professor in the Riga Technical University. He was graduated as an engineer in “Automation and Remote Control”. He has a doctorate of Engineering in Identification of Control Objects (1982, “Minimax estimation of control objects model parameters under interval uncertainty of initial information”). He is habilitated Doctor of Engineering in Systems Simulation (1997, “Methods for discrete-event systems simulation under limited resources”). He manages the Department of Modelling and Simulation in Riga Technical University.

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