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L 2 INTEGRATED FOOD PRODUCT DEVELOPMENT

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Rationale/Introduction

Multivariate statistical techniques and machine learning tools are rapidly finding their way into sensory and market research applications. In the process of developing a product these methods help to decide which of numerous new or improved products should be introduced to the market and provide valuable information about market positioning, segmentation and consumer preferences. Despite the greater than before recognition of computer-aided techniques in the process of New Food Product Development, their utilisation in industrial practice is rather limited.

Marketing experts say 80 percent of all new products fail on introduction and another 10 percent disappear within five years. In the food industry, the rate of failure on introduction is even higher and only one in ten products survives for longer than a year. On the other hand the rate of turnover of food products in supermarkets reaches 10% per year (Grunert, 1995) and food products have to be modified as the market and consumer requirements change. Development and improvement of meat and meat products is probably more difficult than development of any other food. The meat industry has to respond to bad publicity caused by recent health scares and epidemics. These underline the need for effective quality assurance attributes of a product as the effect of media induced panic is difficult to overcome by generic promotions (Verbeke, 2000). Nutritional concerns and world-wide condemnation of animal fat contribute to more and more selective purchase patterns, which can change tastes and preferences via acquired taste. Other factors influencing consumption and popularity of meat involve increasing consumption of fish and broadening range of low-cost meat substitutes. Expanding vegetarian tendencies amongst younger people as well as red meat avoidance are other reasons why meat producers and processors have to stay extremely alert and provide an existing consumer base with products of first-rate sensory quality corresponding fully with consumers' requirements. Consumption trends also indicate that there is a shift from meals prepared at home to meals eaten away from home or purchased fully prepared for use at home. This means tight production specification, portion control and emphasis on consistent sensory quality. New product and process development has to be more closely co-ordinated with the retail and catering sector partners who have better contact with consumers. In consequence, greater flexibility is required to meet changing consumer demands and to react quickly to changing conditions in markets. As product cycles are becoming shorter the time required to identify trends as they develop and to communicate the changes is crucial. Responsiveness is required both with respect to timing and provision of products that meet customer specifications fully.

Unfortunately, tastes and preferences of contemporary consumers are whimsical and difficult to predict. Moreover, marketing strategies move into satisfying smaller and smaller market segments, which does not always bring a benefit of premium prices required to cover costs incurred while reducing economy of scale.

The ultimate test for each new product introduced to the market is its consumption. Although the perception of a product can be greatly influenced by what consumers expect (e.g. see description of food quality perception process by Oude Ophius and Van Trijp, 1995 applied by Steenkamp and van Trip, 1996), flavour is typically the most important determinant influencing overall level of food product acceptance (Moskowitz and Krieger, 1995). Many meat products are in the mature stage of product life cycle with their consumption levelling off or declining. Improvement of these products and their repositioning is a difficult task which require involvement of many participants and has the high risk of failure which can cause a decrease in sales of the core product. In order to achieve maximum consumer acceptability, the hedonic evaluation of a product has to be taken into account and incorporated into the process of development. The use of descriptive sensory analysis only might have a negative impact on development as results could indicate the need to change product to improve attributes further, even if this may not actually improve consumer preference.

It is difficult to describe the exact nature of the relationship between product characteristics and consumer preferences, especially when large amounts of data have to be processed, hence the need for fast and user friendly data processing applications. Therefore, the tools and techniques that make possible to fulfil the demanding requirements of modern product development process are urgently sought.

Product development is a process characterised by activities carried out by people from different functional areas of a firm. Given the broad scope and complex nature of the processes associated with product development, there is no single software package that supports all these activities. Instead, there are numerous packages that are potentially useful for supporting specific stages and aspects of the process. Also the software solutions have to be customised and take into account specific characteristics of food products, as opposed to other fast moving and durable consumer goods. However, in the industrial practice of product development, technologists require an easy-to-operate and robust tool which can integrate the different processes taking place during product development.

This paper is organised as follows. The next part presents computer aided analytical methods and their applicability in (New) Food Product Development. The use of multivariate and machine learning based techniques is described. Part 2 contains a modelling framework constructed for improvement of ham which illustrates the application of the integrated model. Part 3 suggests a way of combining different techniques with an interactive interface to support the process of integrated food product development. This section also summarises possible benefits to the food industry resulting from New Product Development (NPD) Workbench application and indicates its future role in stimulating product development progress.

2) Computer-aided product development – tools and techniques.

This part of the paper gives an introduction to statistical and machine learning techniques available to the product developer, food engineer, food scientist or technologist. The theory is presented with the minimum of mathematical detail. The intention of this section is to make the audience aware of the fundamentals of these methods and to demonstrate their possible applications in product development.

Once good quality data, computational power and analytical expertise are available, it is possible to build models with high predictive accuracy. The need for such models in consumer studies is underlined by the fact that preference scores are difficult to relate to product characteristics *en mass* as post-modern consumer markets become more and more fragmented. On the other hand, development teams consisting of people representing very diverse functions of an enterprise demand precise, quantified product attributes. These attributes should fit into market structure and fully correspond to consumer requirements whatever segment or niche they belong to. Product development on a trial and error basis is no longer an option in an environment of an ever-escalating competition and shortened time to market. The criteria of the success is applying the technology and product knowledge in the process of application development.

Identification and description of relationships which influence consumer preference formation are difficult as they require correct choice of variables which describe the physico-chemical profile of a product (McFie and Hedderley, 1993) and high reliability of sensory analysis (comprehensiveness of product profile, reliability of measurement, consistency of individual scores on attribute intensity). Hence numerous efforts to adopt and successfully apply various data processing methods in the process of systematic food analysis.

Some multivariate statistics and machine learning techniques that can be used for analysis of diverse food product data are described below.

Analysis of Variance - ANOVA is used for evaluation of attribute significance changes for different product formulations, verification of panel reliability, discriminative ability of the whole panel and consistency of scoring by individual panel members. It helps to describe variability of product sensory characteristics and identify attributes with satisfactory disciminative power, before including them into further analysis (Ellekjaer et al. 1996). The application of ANOVA in sensory data processing was described in details by Powers (1988).

Principal Component Analysis - PCA and also *Factor Analysis*, are used mostly for data reduction purposes and can be applied to all variables describing properties of food products. PCA results are especially useful in graphic form which summarises investigated variables in 2 or 3 dimensional space defined by loadings (loading is a correlation between a variable and a factor/component). Individual observations can also be represented in such a space as they are defined by scores – component values for an observation. In the market place, PCA can be then used for purposes such as comparison and identification of products of superior sensory quality (Ellekjaer et al. 1996).

In order to relate results of PCA performed on instrumental data to sensory profiles, *Principal Component Regression* (PCR) can be applied. However, as in the case of multiple regression, PCR does not identify internal correlations between variables. *Principal Component Correlation* can overcome this problem by supplying information on how instrumental variables explain variability of sensory attributes. (MacFie and Hedderley 1993). PCC involves carrying out PCA on sensory variables and then calculation of correlation coefficients between instrumental variables and PCA results.

The differences between products have to be analysed in relation to individual consumer preferences by contrasting sensory profiles with sensory liking. This problem is usually tackled with *Preference Mapping*, a PCR based technique, widely recognised and popular method in sensometrics in recent years. *Internal preference mapping* identifies consumers of similar preferences (Schlich, 1995; Schlich and McEwan, 1992) and places products and consumers in common space defined by components, loadings and scores. *External Preference Mapping* is used when the sensory profile of a product is available and describes consumer preferences as a function of product sensory properties (after reduction of sensory variables to components). Very often Preference Mapping is used together with cluster analysis and preference models are built for each of the identified clusters (Arditti, 1997). Other method used to relate sensory profiles to its acceptance is Partial Least Squares, (PLS). This method is similar to Preference Mapping as it reduces sensory variables to few selected linear combinations, which then are used to predict directions of preference changes. (Helgensen et al., 1997). The difference is that PLS produces linear combinations from both sensory profile and sensory liking data sets. Then for each of the components, PLS maximises covariance between linear combinations of sensory and preference data. Helgensen et al. (1997) suggest that Preference Mapping and PLS yield similar results.

Cluster analysis is commonly used for group identification within large sets of data. Clustering in integrated product development can be used for grouping consumers, products and other kinds of variables (Quannari et al., 1997) which describe product characteristics. With a wide array of clustering algorithms available (see for example Tabachnic and Fidell, 1996) this technique places objects in groups in such a way that variance within clusters is minimised and variance between clusters maximised. As consumer markets are becoming more fragmented, clustering is very often seen as a routine approach in consumer studies. Verification of cluster analysis can be carried out with ANOVA or by application of Internal Preference Mapping (Helgesen i in., 1997).

Amongst other methods used to relate different sets of data is Structural Modelling which tests numerous hypothesis on existence of linear relationships between variables by comparing their variances and covariances (correlations) (Duncan, 1975, for application in meat science see Steenkamp and van Trijp, 1996).

Symmetrical method of Generalised Procrustes Analysis (GPA) compares sets of data using isotropic scaling and rotations. Its methodology and its application to relating sensory and instrumental measures was described by Dijksterhuis and Gower (1991) and

Dijksterhuis (1994). Application of multivariate techniques (PCA, PLS) specifically in meat quality analyses was presented by Naes et al., 1996).

An increasing number of publications report on applications of neural networks and other machine learning techniques[1] in management science and practice across different branches of industry. These techniques are very often compared with more traditional statistical methods such as multiple regression, discriminate and cluster analysis (Venugopal and Baets, 1994), factor analysis related techniques (Wilkinson and Yuksel, 1997) or structural modelling (Davies et al., 1999). Depending on the nature of the investigated process, machine learning tools can be more or less successful than statistics based tools.

Neural networks and other machine learning systems analyse large sets of data and decide what information is most relevant. This information can then be used to make decisions faster and more accurately. This machine learning technique has been shown to produce a useful set of quality characterisation models for consumers. These have easily interpretable decision trees which are built on the objective attributes measured. The techniques help to provide an insight into the complex decisions made by consumers considering the purchase of, for example, mushrooms. (Bollen et al., 2000). When machine learning algorithms are used for product development modelling, the adjustment of product attributes can be carried out without direct consumer participation. (Wilkinson i Yuksel, 1997).

Artificial Neural Networks (ANNs) is a machine learning technique inspired by biological neural nets: ANNs nodes correspond with neurones and connections between nodes relate to synapses. The simplified mechanism of ANNs can be described as follows. The artificial neurone receives a number of inputs (either from original data, or from the output of other neurones in the neural network). Each input comes via a connection which has a weight and single threshold value. The weighted sum of the inputs is formed, and the threshold subtracted, to compose the activation of the neurone (also known as the post-synaptic potential, or PSP, of the neurone).The activation signal is passed through an activation function (also known as a transfer function) to produce the output of the neurone. The ANNs consists of large number of interconnected neurones. Most ANNs are feed-forward structures in which input variables are passed through input, hidden and output layers of ANNs nodes. The input layer introduces the values of the input variables. The hidden and output layer neurones are each connected to all of the units in the preceding layer. When the network is used, the input variable values are placed in the input units and then the hidden and output layer units are progressively executed. Each of them calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer, and subtracting the threshold. The activation value is passed through the activation function to produce the output of the neurone. When the entire network has been executed, the outputs of the output layer act as the output of the entire network.
Neural networks rely on training data to program the system. Individual applications are developed by establishing a training set that the ANNs learn and generalise. Then the future input data (e.g. instrumental and sensory profile variables) can be processed and the output can predict (liking scores) according to patterns in the new data as recognised by the ANNs.

There are many types of ANNs, which have different applications and are suitable for processing specific data inputs (see e.g. Fausett 1994). In food industry, neural networks have primarily engineering-related applications such as process control and steering. To a limited extent, they were also used for prediction of sensory properties and preferences on the basis of instrumental data (Zhang and Chen 1997). ANNs can also help in determining sensory properties responsible for product quality without carrying out sensory analysis each time the quality estimate is required (Takahashi et al., 1998). ANNs are able as well to predict improved product sales forecasting or perform classification tasks. (Venugopal and Baets, 1994).

A relatively simple approach to linking techniques which are required to run an integrated product development is establishing a loose structure in which statistical and machine learning tools can function independently. One way is they can interface with each other via communication lines (data transfer). Some of the tools can be coupled more tightly with other software to provide specialised functions or subroutines to the overall system. The system should be adjusted and customised according to specific product and company characteristics and requirements.

Product Development framework: Developing tastier ham

This section of the paper proposes an integrated approach to an improvement of cooked ham as a response to changing consumer preferences and increasing popularity of traditional hams, produced on a small scale. This framework was used in a research performed on the set of products available in British market; however, the scope of this paper does not allow for full presentation of the obtained results.

The rationale – market push:

In recent years, a revival of traditional food products[2] can be observed (Mintel, 1999). This trend could be used to restore creditability of red meat and generate more consumer interest in meat products. However, as traditional products have different sensory profiles, a question arises as to what extent the traditional taste of a product is going to influence consumer preferences and to what extent product modifications should progress. Some of traditional, artisanal hams have a strong taste, which could be difficult to accept for some consumers. Moreover, traditional or speciality products even if produced on a bigger scale can induce additional

[1] Machine Learning is the study of computer algorithms that improve automatically through experience. Applications range from data-mining programs that discover general rules in large data sets, to information filtering systems that automatically learn users' interests.

[2] According to Mintel definition traditional (artisanal) food can be described as "foods based on traditional craftsmanship, usually but not necessarily made on a small scale. (...)Prepared foods, such as conserves, bread and other baked goods, may also fall under this heading if prepared to traditional recipes using all natural ingredients"

costs. To control product development from that point of view, some application of product formulation optimisation would seem necessary.

The objective:

The framework was designed under assumption that changing consumer preferences have to be incorporated into development process in a such a way they could be translated into physico-chemical and sensory descriptors of a product. In order to account for all possible stimuli to which the consumer is exposed in the market place, the most representative industrial and artisanal hams available in both mass outlets (supermarket own brand premium and standard hams) and in speciality butcher's delicatessen should be included in the investigation. These have to include: 1) Traditional ham with no added water, either dry or immersion cured (no brine injection) 2) Premium ham - premium muscles -- semimembranosus-adductor and bicepsus femoris- semitendinosus. 3) Chopped and reformed ham.

The model

The integrated approach to product development was built on three sets of data: physico-chemical, sensory profile and hedonic level of consumer liking. As the model was constructed bearing in mind its applicability, the analyses aimed to provide product development oriented information rather than detailed investigation of individual relationships between measured describing product characteristics.

While developing the framework, the following aims were taken into account:

1) selection of instrumental variables (possible to measure in the industrial environment in the company laboratories);

2) verification of sensory data accuracy (analysis of variance);

3) indication of product formulation directions (preference mapping);

4) construction of a predictive model allowing for prediction of consumer preferences from the set of instrumental and sensory variables (ANNs and clustering).

Taking into account the rule of parsimony prerogative, complexity of structure and model operations was minimalised.

The model describes variables within the groups, defines relationship between the groups (e.g. preference mapping) and regresses chosen variables from all the groups onto consumer preferences for individual clusters.

The structure of the modelling approach is presented in Figure 1.

The integrated product development was design as follows: after data input and verification, all three sets were analysed with descriptive statistics. Analysis of variance was carried out on sensory data, the reliability of the panel and attributes was checked. Then the multivariate analysis was carried out – clustering and PCA on sensory scores. Finally, after Preference Mapping which indicated directions of development, the neural networks models for each identified cluster were developed. The choice of variables, network training and verification was carried out for each cluster separately. In the process of product development, such an approach allows for early selection of the target market and concentrates efforts on a very specific product profile.

Model evaluation is a vital stage in development of an integrated system. This can be done by various methods e.g. use of training and verification data sets. If the predictive part of the model is being tested, the percentage of correct predictions for the verification set can be easily interpreted. In the proposed model, evaluation was done for each part separately i.e. sensory data was statistically verified for panel reliability, discriminative power of attributes and repeatability. The results of preference predictions with Generalised Regression Neural Networks were assessed against test data, error values, error standard deviations and ratio of error/data standard deviation ratio. Below, a brief summary of results that can be supplied to a product developer is presented.

The results

The greatest variation in sensory profiling of traditional ham is through the flavour of the product, then texture, and the least variability can be ascribed to the appearance of the products. Variability in composition of traditional hams is greater than amongst industrial hams. Industrial hams have a sensory profile with the following differentiating features: softer texture; less intensive odour or colour, lower flavour intensities, tend to be less salty, and have leaner appearance. Traditional hams are: harder and more rubbery in texture, have strong flavour, have more 'ham-like' flavour, and have more 'bacon-like' flavour (apart from organic ham which has strong "pork" flavour).

There is a significant variability in consumer liking of hams. Clustering analysis identified a group of consumers who appreciate traditional hams and especially hams with strong flavour (22% of the sample). There is a group of consumers accepting only industrial products and rejecting traditional hams (15%). There are two groups displaying reverse preference patterns: one prefers products of distinctive flavour, the other rejects them (13 and 11 % respectively). There is a group that can be described as the ham lovers cluster scoring all products above 7 using the 9-points acceptance scale. Remaining groups are characterised by very diverse patterns, which correspond with specific product characteristics.

Preference mapping carried out according to the methodology proposed by Danzart and Heyd (1996) has revealed the eclectic character of the overall consumer liking. Unrelated attributes such as "bacon-like" and "ham-like" have proven to influence directions of consumers' preferences. On the other hand, some texture-related descriptors had a strong impact on the preference scores for individual products. Consumers have two strong pools of rejection and two surfaces of acceptance. Neither reformed bland ham nor strong, traditional product of distinctive flavour got accepted. These two products are characterised by average intensity in terms of important texture attributes. They are neither hard nor soft and neither dry or juicy.

The second area of acceptance relates to the appearance and texture descriptors – "wet" and "juicy". As the "positive poles" lie symmetrically to each other, the preference for the hams of similar flavour will probably be determined by texture features. Ham has to be then either "hard and dry", or "soft and juicy" to achieve maximum acceptance.

Once the direction of development is established, the product can be reformulated to achieve the desired sensory profile. The reformulation can be cost controlled by application of the Least Cost Formulation approach (see for example Bender et al., 1992). Once the new version of the product is tested and its characteristics known, the consumer preferences can be predicted by an ANNs based module. The preference for such a product can be predicted for each of the previously identified clusters separately.

The results obtained for ANNs based consumer preferences forecasts (not presented) suggest that ANNs can be successfully used in product development. Application of ANNs is especially justified in case of enterprises which have to handle a broad assortment of food products, subject to modifications due to changes in market place and supermarkets' requirements. The worst ANNs performance was recorded when clusters of low level of preference variance were analysed. In such cases, however, product development can be based on less elaborate multivariate analysis such as PCA, which can link consumer preferences directly to physico-chemical characteristics. When there are differences in preferences of similar products, ANNs give a possibility to account for non-linear relationships which are difficult to identify and incorporate into traditional models. As the proposed model differentiates between clusters, identification of variables important for given clusters is possible. In consequence, the technologist can concentrate specifically on these physico-chemical parameters which are important for a given target market.

The NPD Workbench

In the food industry, technologists who are involved in product development are computer literate and work with modern computer applications. These people use various computer platforms and need a tool that will assist them through all phases of the development process. In order to construct such a tool, an interface can be designed to incorporate all necessary modules in one to provide an easy-to-use development environment.

The interface looks like a typical Windows based software and has a number of "states" through which a user works, corresponding to stages in the product development. The interface could link different analytical and database applications depending on the needs and specific requirements of a user. However, the core modules of the NPD Workbench should correspond with the proposed integrated model:

1) Sensory Profiling Module: Describing and identifying essential sensory attributes of a new product. The module will represent and analyse sensory profiles of individual product versions.
2) Preference Mapping Module: Sensory profiles of products and consumer preferences will be used to indicate the sensory characteristics of the most preferred products. This preference mapping allows for identification of a set of attributes for the "ideal product", which sets a target for product developers. Subsequently, by relating the attributes of a product to its sensory characteristics, an indication of a technological specification for a product can be obtained.
3) Consumer Preferences Forecasting Module: Another NPD module, based on Artificial Neural Networks (ANNs), allows for an estimation of a consumer preference score in relation to the product being developed, without carrying out consumer taste tests. The input data for the ANNs consists of the full physico-chemical and sensory profile of a product. It can be customised and its parameters adjusted according to the specific properties of a given product.
4) Product Formulation Module: As a product has to be developed within certain cost and technological constraints, the optimisation module of the NPD model allows for least-cost formulation (using mathematical programming) of the product. The product then can be balanced against pre-specified, technological, financial and operational parameters.

The example of an interface that could incorporate all above-mentioned modules is given in the Figure 2.

NPD Workbench – Concluding thoughts

The NPD Workbench can be customised and adapted to the needs of an individual company. Modular construction could permit the design of different versions of the Workbench, according to the scope of NPD activities in a given enterprise by the incorporation of additional modules. The system could be particularly helpful in handling composite food products, such as ready meals. Packaging and other non-core product features can be also included in the process. Most of the available tools for the Food Industry concentrate on only some of the aspects of Product Development, e.g. recipe formulation. The Workbench concept allows simultaneous consideration of many NPD process functions: starting from minimum cost optimisation and ending with consumer preference forecasting through the development of product attributes according to a given market segment's requirements.

The data input and the results of analysis will have to have simple forms and be easy to interpret. The user-friendly operating environment could be accessed by everybody involved in the NPD process.

The success of the integrated approach lies in bringing the knowledge of food technology and business management to the process of application development. The Food Industry faces extreme competition, especially with regards to the introduction and sustainability of new products. The Workbench tool can be set up for use in small and medium size companies, and as such can pioneer the use of a "mini expert system" in a business environment, which normally has restricted skills and experience. The target market for introduction of the Workbench would be then medium-size businesses especially, which have a broad portfolio of products under development. These enterprises have very limited resources that can be deployed in the process of NPD, yet costs of these activities are high in relation to their net profits. The application of the Workbench can give food manufacturers a shorter time to the market for new products, can decrease the cost of development and increase the success rate by fully meeting consumer requirements and satisfying the ever-increasing demands of the multiple retailers.

The Workbench can enhance the competitiveness of the enterprise by providing a powerful tool for integrating of all functions of an enterprise in the process of NPD. As some of the companies are well renowned for their excellence and specificity, the NPD Workbench tool can extend these assets by uncovering unknown aspects of product data and combining the skills of human user and analytical capabilities of the NPD tool. Pencil and paper procedures can be eliminated, number of trials reduced, and some consumer tests eliminated. The least cost recipe formulation would control production costs. All this would boóst efficiency in NPD in small and medium food processing enterprises. The use of the Workbench should stimulate development of staff skills and should facilitate ICT (Information and Communication Technology) penetration across the food supply chain.

The specific character of food and especially meat products influences all links across the supply chain. Present tendencies in development of NPD tools and methods suggest that in future this process (which in the past went through technology and later marketing domination stages) is going to be in parallel and co-ordinated across all food chain stages. It will remain focused on both manifest and latent consumer needs. Due to competitive pressure and advancement in managerial technology, NPD will become more and more specialised, quantitative, fast and based on high level of interdisciplinary knowledge.

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Figure 1. Schematic representation of integrated product development modelling.

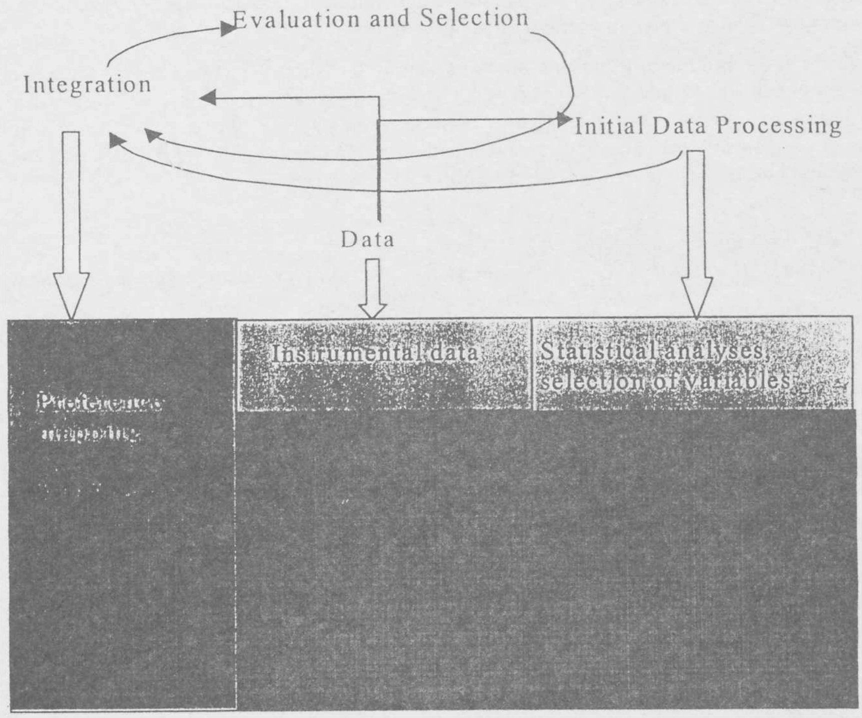

Figure 2. An Example of an Interface for Product Development Workbench.