

# A Heuristic Based Conceptual Framework for Product Innovation

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**Abstract**—This research elaborates decision models for product innovation in the early phases, focusing on one of the most widely implemented method in marketing research: conjoint analysis and the related conjoint-based models with special focus on heuristics programming techniques for the development of optimal product innovation. The concept, potential, requirements and limitations of conjoint analysis and its conjoint-based heuristics successors are analysed and the development of conceptual framework of Genetic Algorithm (GA) as one of the most widely implemented heuristic methods for developing product innovations are discussed.

**Keywords**—Product Innovation, Conjoint Analysis, Heuristic Model, Genetic Algorithm

## I. INTRODUCTION

THE incorporation of customer preferences for development of product innovation is essential for successful product innovations in a competitive environment [38]. Consequently, measuring customer preferences among multiattribute alternatives has been a primary concern in marketing research. Among many methodologies developed, conjoint analysis [23] has turned out to be one of the most widely implemented preferences-based methods for identifying and evaluating new product concepts [8]-[11], [23]-[27], [38]. Conjoint analysis provides a structured framework to incorporate the “voice of the customer” into product innovation, enabling customer expectations to be met within shorter time frames. Nevertheless, the challenge is those high technology products with high degree of product complexity will generate a very large number of possible combinations within conjoint analysis. In this case, to obtain a realistic solution in a reasonable amount of time, literature proposes the use of conjoint-based heuristic methods.

This research work analyses the performances of several conjoint-based heuristic methods for developing product innovations and specifically the role of conjoint based Genetic Algorithm for product innovation development at two multinational enterprises in Germany.

## II. THEORETICAL BACKGROUND

### A. Conjoint Analysis and Optimal New Product Design

Conjoint analyses have been carried out on a very broad scale over the past three decades in order to analyse customer trade-offs and to develop new products, as well as solving decision making problems. Nevertheless, to shorten life cycles, new methodologies are needed to address the complexities related to conjoint analysis’ designs [23]-[25].

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One of the first steps in designing a conjoint study is to develop a set of attributes and corresponding attribute levels to characterise the competitive domain. Focus groups, in-depth customer interviews, and internal corporate expertise are some of the sources researchers use to structure the sets of attributes and levels that guide the rest of the study. Within the framework of conjoint analysis, a small number of different product profiles are tested, and the specific preferences of individuals are determined for each of the various levels of the different attributes. In the next stage, these individual preference measures (part-worths) are utilised to predict the valuation for any new product profile which had not originally been evaluated. By combining these results from all customers, a complete enumeration procedure to identify a single product profile that results in the highest share-of-choices may be undertaken. However, as the number of attributes and attribute levels increases, the number of possible product profiles increases exponentially and, consequently, makes it infeasible to obtain a realistic solution in a reasonable amount of time with the conventional conjoint analysis. Consequently, a number of conjoint-based models with special focus on mathematical programming techniques and efficient heuristic models for optimal product design have been proposed [8]-[13], [23]-[27], [38]-[40].

### B. Conjoint-based Heuristic for Product Innovation: Selected Methods and Comparisons

Belloni et al. [12],[13] analysed and benchmarked in their study the performance of several conjoint-based heuristic methods with regard to the case of finding optimal or near-optimal new product design solutions. The scope of the study was 9 product line optimisation methods and the results were that 4 methods consistently find optimal or near-optimal solutions: Simulated Annealing, Divide-and-Conquer, Product-Swapping and Genetic Algorithms. Referring to this finding, the author focuses on analysing these selected 4 methods in order to find the most appropriate method for product innovation development.

#### 1. Simulated Annealing

Simulated annealing is a popular algorithm for difficult discrete optimization problems [1]. The name of the method is derived from the physical process of annealing, in which a liquid is slowly cooled in a heat bath in order to form a solid in a low-energy state. Simulated annealing starts with a randomly chosen solution and proceeds to test random feature changes to the current solution and the simulated annealing algorithm sometimes accepts feature changes that reduce the fitness value. The probability of accepting such a negative change depends on the magnitude of the drop in earnings and also decreases over time as the algorithm progresses through a pre-set “cooling” schedule. Because simulated annealing sometimes accepts feature changes that reduce the fitness value, it has the ability to escape from a locally optimal solution in the perspective of finding a better solution.

## 2. Divide-and-Conquer

Green and Krieger [27] suggest applying a “divide and conquer” heuristic to the optimal product line design problem. This method divides the product line into groups of attributes and completely enumerates all possible combinations for one group while holding the other groups fixed. In Belloni’s [12]-[13] study, they treat each product as its own “group” of attributes and they start with a random product line, and then optimise the choice of the first product, holding all other products constant, and then move on to the second product, and so on. This process continues until it is impossible to improve earnings by changing any single product. This heuristic is guaranteed to find a locally optimal solution, with the local neighborhood defined to include all solutions that differ from the current solution by a single product attribute.

## 3. Product Swapping

The product-swapping heuristic refers to the interchange heuristics proposed by Green and Krieger [24], begins by choosing a random product line and evaluating the earnings level produced by this solution. It then tests each candidate product that is not part of the current solution to see if there is a product in the current solution whose replacement by the candidate product will increase the results. If such a swap does improve earnings, then the candidate product is added, and the current product is removed from the current solution. This process continues until it is impossible to improve earnings by swapping in any single product. Like the divide and conquer heuristic, the product-swapping heuristic is guaranteed to find a local optimum, with the local neighborhood defined to include all solutions that differ from the current solution by a single product.

## 4. Genetic Algorithms

The biological process of natural selection provided the original inspiration for genetic algorithms. Genetic algorithms have been applied to a wide variety of problems in the operations research literature and were first applied to the optimal product design problem by Balakrishnan and Jacob [9]. Alexouda and Paparizzos [3], Steiner and Hruschka [38], and Balakrishnan, Gupta, and Jacob [10] have also used genetic algorithms on product line design problems. The GA searching process operates from a population of points rather than a single point, which increases exploratory capability. The objective function is used directly for evaluation rather than derivatives used by gradient search techniques. GA performs a complete evaluation of specified candidate solutions, as opposed to building profiles one attribute at a time. GA also works with a direct coding of parameters, rather than parameters themselves. The “fittest” members of the initial population survive and move on to produce the next generation of solutions. New solutions enter the population through a process of reproduction (in which pairs of product lines “mate” to produce offspring that inherit attributes from each parent) and mutation (in which product lines undergo random changes to individual product features). This process continues until a given stopping condition is reached. This optimisation problems for product design which is characterised as discontinuous, high dimensional and

multimodal, should be especially suited for GA as opposed to gradient or random search techniques [5], [36]-[38].

## C. Results Analyses with Real and Simulated Data

Table I and Table II present results from simulation with real data and simulated data for ten trials of each optimisation method analysed by Belloni et al. [13]. For each method, the table reports the average performance shown as a percentage of the optimal solution which is determined by the Lagrangian relaxation method. Lagrangian relaxation method relaxes some of the constraints in a problem in order to create a new problem that is easier to solve. For example, one of the constraints relaxed says that each consumer purchases at most one product. In the relaxed problem, consumers can purchase any number of the available products. For any solution in which a consumer purchases more than one product, the Lagrangian relaxation method subtracts a penalty from the earnings of that solution. Likewise, the method adds a reward to the solution’s earnings when a consumer purchases less than one product. The solution to the relaxed maximization problem then provides an upper bound on the optimal earnings in the original problem. The key to the success of this strategy is finding tight upper bounds in order to rule out portions of the feasible set as quickly as possible. The method searches for the tightest possible upper bounds by varying the penalties that are applied to the objective function when a solution violates the relaxed constraints [13].

The next two columns in both Tables show the percentage of trials for which each method finds the optimal solution and a solution greater than 95% of the optimum, respectively. The CPU time was measured while running the methods in Matlab on an IBM Thinkpad laptop with a 1.7-GHz Pentium processor and 512 MB of RAM.

TABLE I  
SIMULATION RESULTS WITH REAL DATA  
[13, modified]

Methods	Av. Performance	Finds Optimal Solution	Finds solution > 95% of optimal	Av.CPU time (sec)
Simulated Annealing	100%	100%	100%	128.7
Divide and Conquer	99.6%	100%	100%	12.5
Product Swapping	99.9%	99.9%	99.9%	14.1
Genetic Algorithms	99%	100%	100.0%	16.5
Coordinate Ascent	91.7%	98.3%	98.3%	302.8
Greedy Heuristics	98.4%	98.4%	98.4%	3.5
Dynamic Programming (DP) Heuristic	94.4%	97.4%	97.4%	5.5
Beam Search	93.9%	98.6%	98.6%	1.9
Nested Partition	96.7%	98.4%	98.4%	8.4

As seen in Table I, among the practical methods in analysis, the genetic algorithms, simulated annealing, divide and conquer, and product swapping perform best, reaching solutions that are, on average, within 1% of the optimum.

TABLE II  
SIMULATION RESULTS WITH SIMULATED DATA  
[13, modified]

Methods	Av. Performanc	Finds Optimal Solution	Finds solution > 95% of optimal	Average CPU time (sec)
Simulated Annealing	100%	100%	100%	131.8
Divide and Conquer	98.7%	45.8%	97.5%	0.7
Product Swapping	98.5%	39.2%	95.8%	0.8
Genetic Algorithms	99.9%	81.7%	100.0%	11.8

Focusing on the best 4 methods, Table I and Table II also show while simulated annealing and the genetic algorithm perform on average at least as well on the simulated data as on real dataset, the divide and conquer method (98.7% simulated data vs. 99.6% real data) and the product-swapping heuristic (98.5% simulated data vs. 99.9% real data) now produce average solutions that are slightly further from the optimum. Belloni et al. [13] conjecture, that this is because the optimal solution for the real data set, included two products that were identical to the competing products but priced slightly lower. Methods searching in product space could easily identify these two products. In the simulated problems, all attributes are “fit” attributes, so that different customers prefer different levels of these attributes.

Regarding the simulation time, while simulated annealing finds the optimal solution for all 120 datasets, it also has a running time that is one or two orders of magnitude larger than other methods. From the perspective of a computation time vs. performance trade-off, it could be argued that simulated annealing is less efficient than genetic algorithm and others.

There have been previous comparisons of selected pairs of these methods. The findings reported by Belloni et al. [13] are consistent with these comparisons. For example, Balakrishnan and Jacob [8] present results comparing genetic algorithms and the Dynamic Programming heuristic. Their findings also favor the genetic algorithm. Similarly, Alexouda and Paparizzos [3] finds that genetic algorithms outperform beam search, while Steiner and Hruschka [38] report that genetic algorithms outperform the greedy heuristic.

Referring to the above mentioned findings which have shown the superiority of genetic algorithm in case of solving new product design in a large search-space which represents the high-technology and complex products, this research work proposes a GA based conjoint for the development of product innovation. Referring to the conjoint based Genetic Algorithm (GA) from Steiner and Hruschka [38], the input data of customer preferences on product characteristics, technology feasibilities and market segments serve as input parameters for finding optimal product innovation candidates. This is done by representing the combinations of product characteristics and relevant technologies in the specified markets at their best possible levels. These input data should be provided by internal subject matter experts and the customers who defined the utility values of product characteristics, technology and markets to reveal their preference structure. In this context, GA will help to process the input data with high degree

complexity in a more efficient way and provides realistic solution in a reasonable amount of time.

### III. THE DEVELOPMENT OF A HEURISTIC BASED CONCEPTUAL FRAMEWORK FOR PRODUCT INNOVATIONS

As already explained in the previous chapters, a clear distinction between the terms and, accordingly, concepts of product innovation process and genetic algorithms are of paramount importance for deriving a meaningful and relevant contribution to product innovation. By crystallising the core elements and mechanisms of complex interactions between organisational entities in the product innovation process on a strategic corporate level, it becomes apparent that the involvement of all stakeholders (subject matter experts, users, and customers) will be of benefit in the creation of a reliable product innovation process. These core elements and their interactions are illustrated as the reference framework in Fig. 1.

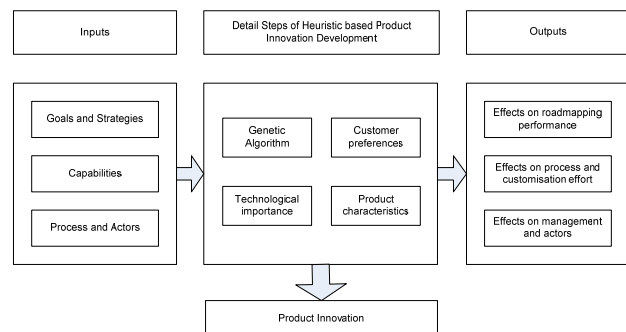


Fig. 1 A Heuristic based Conceptual Framework for Product Innovation

The reference framework illustrated in Fig. 1 comprises the specific conditions and challenges of the different aspects and process steps of a heuristic based product innovation process.

The purpose of the empirical study was to test the practicability of the method developed. Two multi-national companies were used as study cases. They share the same industry background related to the development of high-technology oriented products (automation technology) and the importance of customer oriented product innovations.

In order to commence the empirical study the research idea was presented to the Chief Technology Officers (CTOs) from both companies, and followed by initial data gathering in form of explorative interviews with the CTOs concerning product characteristics, technological importance and company objectives. Following these interviews, the data gathering was continued through other interviews and e-mail correspondences with the CTOs.

In case of Company A, the CTO provided all data concerning customer preferences on product characteristics and also technological importance, as no direct access to customers existed to gather data directly. On the other hand, data provided by Company B come from several sources. The CTO provided the technological importance and marketing provided input on customer preferences based on historical

data from questionnaires. Furthermore, the study relies on extensive literature research and the analysis of company documents.

Selection of the focus of this empirical study was influenced by the observable phenomena and analysis of the relevance of different input parameters (for example: product lines, market segment, technology lines). All of the data collected from both companies were used as input parameters for conducting the simulation.

#### *A. Product Innovation Process and Alignment of Goals and Strategies*

Alignment of goals and strategies with the product innovation process is one of the starting points of successful product innovation process. The successful achievement of an organisation's goals begins with a clear definition of the objectives and well-structured strategy formulation which is one of the prerequisites of product innovation process [2],[14],[15].

An important objective in product innovation process is to help to identify those areas that seem to have high potential, and to accelerate the transfer of technology to actual products. For strategic product innovation planning, incorporation of business objectives and constraints enables economically meaningful responses to potential threats and opportunities to be developed [6],[7]. This enables a company to downsize its development organisation and use the savings for such purposes as marketing initiatives and strategically critical acquisitions. Thus, the product innovation process not only yields better results in final products but also eliminates wasted efforts that distract an organisation from more important work. In the best performing companies, the product maps and the processes used to be created at the centrepiece of the entire product development process [14]. Related to this, the results from both companies have shown that the better the alignment of product innovation process with an organisation's goals and strategies, the better will be the quality of product innovation.

#### *B. Resources Capabilities and Actors in Product Innovation Process*

The process of the product innovation development itself and the subsequent integration of it into an ongoing business process is considered complex issues [16]. Therefore, the implementation needs to be carefully planned, especially in aligning the right people and resources into the process to guarantee success because one critical factors to the successful implementation of a product innovation process are the competencies of the human resources [17]. Referring to this, it is critical for individuals and teams within a company to align their roles and responsibilities with the dynamic activities of product innovation process [15],[18],[41]. Only with correct understanding of own roles and responsibilities the individuals and teams can perform their best in achieving company objectives. There are several key players which hold important and influential roles to ensure the successful implementation of product innovation process. They are innovation promoter, subject matter experts (SMEs), and management.

The innovation promoter is the one who acts as a motor of the product innovation process, has the knowledge of product innovation process in the company, and has the drive to organise the interactions between departments in the company. The emergence of the innovation promoter is an indispensable ingredient in the process of innovation and strategic change. A innovation promoter sees not only the needs and benefits for innovation, but also provides transformational leadership throughout the product innovation implementation process [41]. The main role of the innovation promoter is to guide the other product innovation process key players through the process and mitigate constraints along the way.

The next key players are the subject matter experts who have the vast knowledge and expertise of their areas such as R&D, technology and marketing and contribute with those knowledge and expertise during the expert convention to identify the product innovation requirements and provide input for its development. Finally, the last key player in product innovation process is management, whose involvement is required through the process and especially during the initiation process of product innovation (scope definition, objectives) and the evaluation of product innovation [16],[17].

Related to this, the results from both companies have shown that the competent resources contributed significantly to the success of product innovation. Moreover, the good information flows and interactions among the key players have contributed positively to the success of product innovation.

After having analysed the critical success factors of the product innovation process, this section discusses in detail the next steps for a heuristic based conceptual framework implementation which comprises the design of GA and its integration into product innovation process.

#### *C. Design of Genetic Algorithms as The Heuristic Method for The Development of Product Innovation*

As discussed in previous chapter, GA has been proven useful to solve complex problems which have large sets of input data (search space). Furthermore, as prerequisites for a proper implementation, the input data should be translated into input parameters, with specific measurement scales in order to be evaluated quantitatively by a defined fitness function. In the end, the fitness function acts on behalf of such criteria in evaluating the input data by the predefined requirements for a sufficiently good solution. Hence, referring to these potentials, GA is a suitable option to optimise the development of product innovation [8]-[13],[23]-[27],[38]-40].

In GA based product innovation process, the objectives of a company should be reflected in a GA fitness function in form of a mathematical model. The fitness function in turn mirrors the vision of a company regarding innovation, serving as acceptance criterion for an innovation.

The most appropriate combinations of innovation are selected and filtered by the fitness function to finally come to the predefined sufficiently good solution. The fitness criteria continually change as creatures evolve, so evolution is searching for a constantly changing set of possibilities through

cross-over and mutation processes to ensure that the most optimal solution for the situation at hand is achieved. The data input consists of the chromosomes that represent arrays of parameter values. As seen in equation 1 and 2, if one chromosome has a set of  $N$  parameters given by  $p_1, p_2, \dots, p_N$ , then the fitness function transforms the input parameters into the fitness value of the chromosome [9], [20]-[22]. The mathematical formulation is illustrated in the following equation:

$$\text{Fitnessvalue} = f(p_1, p_2, \dots, p_N) \quad (1)$$

$$f: X \rightarrow R, X = p_1, p_2, \dots, p_N \quad (2)$$

The fitness function processes the parameters and evaluates every chromosome of the initial population and finds the fitness values through the fitness function. Several publications state that GA performs well in the presence of medium or high parameter interdependencies [20],[21]. On the other hand, years of practice in GA have led many researchers to propose the abstract assumption of the parameter interdependencies, since such a supposition simplifies the matter of concern. The formulation of a relevant function to the problem is a difficult task. Balakrishnan [9] stated that the definition of a suitable fitness function is essential to the successful use of GA. Consequently, the company needs a clearly defined optimisation objective and to articulate the notion of an optimum into the fitness function.

In literature, profit maximisation is the most widely implemented fitness function for generating new product development with genetic algorithms [9],[10],[12],[13],[38]. The author refers to Steiner and Hrushcka's idea [38] and deploys conjoint based GA approach with regard to the optimisation of product innovation process. Steiner and [38] considers the calculation of a fitness function with profit maximisation as the organisation's objective:

$$\text{PROFIT} = \sum_r \left[ (\text{PRICE}_r - \text{VC}_r) \cdot \sum_i S_i \text{PROB}_{ir} \right] \quad (3)$$

Where  $r=1, \dots, R$  are the items (proposed products with set of characteristics) of a new product line that a company wants to launch and  $i=1, \dots, I$  are the target market segments of the company.  $\text{PRICE}_r$ ,  $\text{VC}_r$ ,  $S_i$  and  $\text{PROB}_{ir}$  denote the calculated price and variable cost of item  $r$ , the size of target segment  $S_i$ , and the probability that a consumer of segment  $i$  will choose item  $r$  respectively. Thus, total profit contribution of the product line results from the sum of individual profit contributions of each of the new items across the target segments. The fitness function could be customised to accommodate other company objectives such as maximising market share and sales volume. In order to accommodate those objectives, the price and variable cost setting should be set to 1 and 0 for all  $r$ , as well as for individual instead of segment level consumer preferences. To calculate  $\text{PROB}_{ir}$  for item  $r$ , the multinomial logit model [33] model can be used:

$$\text{PROB}_{ir} = \ell^{\mu_{ir}} / \sum_r \ell^{\mu_{ir}} + \sum_j \ell^{\mu_{ij}} \quad (4)$$

Where  $j=1, \dots, J$  denotes the status-quo (ideal) product which the customer wished for,  $\text{U}_{ir}(\text{U}_{ij})$  is the total utility of item  $r$  (ideal product  $j$ ) to a consumer in segment  $i$ , and  $(\mu > 0)$  is the scaling parameter of the multinomial logit model [33]. Referring to this rule, the probability that a consumer in segment  $i$  chooses a new item  $r$  is a function of the utility (attractiveness) of item  $r$  relative to the sum of utilities of all relevant (existing and ideal) products to the customer in that segment [34]. The composite utilities  $\text{U}_{ir}$  (and  $\text{U}_{ij}$ ) are usually obtained from an additive part-worth function:

$$\text{U}_{ir} = \sum_k \sum_l \beta_{ikl} x_{klr} \quad (5)$$

Where  $k=1, \dots, K$  are the attributes (including price) and  $l=1, \dots, L_k$  the corresponding levels of attribute  $k$  used in the conjoint study.  $\beta_{ikl}$  denotes the estimated part-worth utilities (respectively for level  $l$  of attribute  $k$  in segment  $i$ ), and  $x_{klr}$  is a zero-one variable indicating the presence or absence of level  $l$  of attribute  $k$  for item  $r$ . The latter is essential, as not all levels might be available for all attributes. The variable costs  $\text{VC}_r$  are typically modelled as a linear function of an individual attribute level cost data [27]:

$$\text{VC}_r = \sum_k \sum_l c_{kl} x_{klr} \quad (6)$$

where  $c_{kl}$  denotes the organisation's variable cost for level  $l$  of attribute  $k$ .

In the proposed conceptual framework, GA works as underlying solver for the product innovation problem of high-technology products with high degree of product complexity and helps to process conjoint data in a more efficient way and provides realistic solutions in a reasonable amount of time. The fitness function works as the driver of the heuristic search process for optimal solutions. The clear formulation of this function is the prerequisite of a reliable product innovation process. The fitness function processes input data such as customer preferences on product characteristics and technology feasibility to calculate the most preferred and feasible product to be depicted as the next product innovations. Furthermore, the standard GA operators, such as selection, cross-over and mutation operator, are applied during the simulation to ensure that the simulation process is working properly and will generate a reliable product innovation.

#### D. Integration of Customer Preferences

One of the key questions of this research is the integration of customer preferences into the conceptual model. The incorporation of customer orientation into the product innovation process increases the success rate of product innovation [6],[7]. Furthermore, literature and some studies indicate strongly that the inclusion of customer preferences in the product innovation process strengthens its reliability for

generating successful product innovations in the market [6],[7],[14],[15],[41]. A product innovation process describes, to some extent, customer requirements and market orientation, and thus supports the anticipation of those requirements and their development in a timely manner. Product innovation process illustrate the development paths of present and future product concepts, in so doing enabling the definition of essential product functions. An appropriate definition of customer needs enables the salient information for successful planning of product innovation to be gathered and lays the groundwork for long-term management of time to market [15]-[18].

Referring to the concept of intelligence generation and intelligence dissemination delineated in section 2.1, customer needs will be translated to customer preference data which should be gathered through a well-structured market research method, e.g. explorative interviews, conjoint analysis or lead-user method. The direct input from customers as a result of primary market research method should help to avoid the bias of data solely provided by the internal marketing department. Furthermore, since this research aims to provide a metric to increase the reliability of evaluation, this conceptual framework proposes to quantitatively deploy customer preferences in the simulation process for calculating the best potential product innovations. Related to this, customer preferences will be provided in the form of a utility value (rating) on an interval scale which indicates the importance of available product characteristics from the customer's point of view. Furthermore, a customer should also be allowed to write down their wishes for product characteristics not yet available. This is a means of generating feedback for the company in order to plan for future product innovation.

The results from empirical studies from both companies have shown that the integration of customer preferences into product innovation process has a positive influence on the success of product innovation.

#### E. Evaluation of Technological Importance

Beside customer preferences increase the potential of market success of a product innovation, technological advancement is another of the key requirements of high-technology oriented product innovation [14],[15]. In order to avoid the stagnation of technological development, companies should pay more attention to potential new technologies and be concerned with their relevance for their product innovation development. Thus, the ability to profit from technological advances or technological breakthroughs often leads the company to successful product innovations and ensures its position in the market [16],[17],[41].

Through the integration of technological perspectives into product innovation process, product and technology gaps with inconsistent timing can be defined and bridged systematically. This integration process typically is an iterative and cross-functional process which results in the elimination of irrelevant technologies and infeasible product concepts. Furthermore, the initiation of technological cooperation and the acceleration of time-critical technology and product development, and eventually supplying the necessary additional capital or human resources can be achieved.

Hence, the integration of technological advances into this conceptual framework is essential to ensure that the proposed product innovations are aligned to technology trends and its development. To ensure quality, data gathering on technological importance is performed through workshop sessions attended by internal and ideally also external subject matter experts (SME), e.g. Chief Technology Officer (CTO), representatives of industry experts, representatives of research institutions, etc. Feedback from external SMEs will enrich the technology facets to be considered for product innovation development. Underlining its importance to successful product innovation, the role of technology importance data in supporting successful product innovation has been proven in the both companies product innovation process.

#### F. Evaluation of Product Characteristics

In the context of product innovation, the product profile in GA is represented by chromosomes, which in turn are composed of genes (product characteristics) each of which can take on a number of values (levels of the characteristics) [9],[20],[21],[38]. This encoding step is crucial as the appropriateness of the product characteristics determines the performance when solving real-world problems. The binary encoding method is being widely applied by GA literature, and several examples of its application will be discussed in the following [9],[20],[21],[38].

In binary encoding method, every chromosome string consists of  $P$  bits, and a particular number of  $P$  bits constitute a substring. Such substring  $j$  is associated with a possible product attribute setting and  $L_j$ , defines its length. Balakrishnan and Jacob [9] use the design of a soap bar as an example (see Fig. 2). The soap bar  $v_i$  has three distinct attributes  $k = 1, \dots, K$ . The first attribute is the shape of the soap bar, which is assigned the following settings: rectangle, square, and spherical. Further, the soap's colour is the second attribute, which assumes the settings as follows: red, green, yellow, and white. The third attribute is defined by the soap's scent, which is set to: fruity, flower, and antiseptic. Within the context of binary encoding, each position  $P$  contains either the digit one or the digit zero.

The digit one indicates the presence of a particular attribute setting, and the digit zero denotes the absence of a particular attribute setting. One possible instance of a string is related to a spherical shaped soap bar with green colour and an antiseptic scent, see Fig. 2.

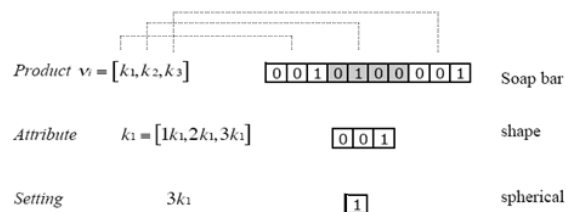


Fig. 2 Binary Encoding

As seen in Figure 2, if a product profile features  $k$  attributes,  $k = 1, \dots, K$ , and each attribute  $k$  assumes  $j_k$  level

settings,  $j_k = 1, \dots, j_k$ ,  $C_{ijk}$  is the setting of attribute  $k$  at level  $j_k$  selected by consumer  $C_i$ ,  $i = 1, \dots, N$ . Consequently, a particular product profile  $V_i$  consists of  $k$  attributes each assigned to the setting  $j_k$ . Consumer  $C_i$  selects the particular product profile with defined attribute values  $V_i$  over his consideration set product. Taking into account its simplicity and flexibility of product characteristic representation, the binary encoding ensures the consideration of relevant issues like technological feasibility and the interrelationships among the product attributes because of the presence and absence of the characteristics and its value determines the presence and absence of others [9].

The binary encoding method is used for this conceptual framework. Literature emphasises the necessity of decoding the binary strings (1 or 0) of the chromosomes back into the continuous parameter (calculatable parameter) before evaluating the chromosomes, because many fitness functions demand the continuous nature of parameters in order to evaluate chromosome fitness [10]. Underlining the importance of the encoding step, hence, the product characteristics should be defined as clearly and as detailed as possible for the sake of a reliable recombination (cross-over) and mutation process.

In this conceptual model GARAM, the information of product characteristics comes from an internal subject matter expert (SME), e.g. CTO, production manager or R&D manager. They provide the information of product lines and their respective characteristics in detail for the contact customers, so that the customers in the end can give the preferences to the products and their characteristics, accordingly. If the data is not complete or lacks sufficient detail, the quality of input parameters concerning product characteristics and related customer preferences will suffer. To avoid this and ensure the quality of results, it is important to maintain the quality of data on the product characteristics. The results from both companies have also shown that the better the quality of data on product characteristics, the more successful the product innovations generated.

#### *G. Effects and Results of the Heuristic based Product Innovation Process*

The implementation of heuristic based product innovation process in an organisation will affect the flow of the company's business process [2],[4],[5]. As the process involves key players including management, it will occupy their capacities and thus, the time allocation for product innovation development, meaning the related tasks and responsibilities, should be carefully planned to ensure the effectiveness of the process and, on the other hand, the company's day-to-day tasks. Focusing on the integration of the conceptual model into a company's strategic planning for product innovation, it will have particular impact on the business process, especially given that the genetic algorithm is deployed as a quantitative optimisation method. Any deployment involving an automatic simulation process for generating product innovation alternatives will have its own effects and results, and these must be carefully considered to ensure the successful generation of a reliable product innovation.

#### *H. Effects on Processes and Customisation*

Given the importance of alignment of the product innovation process with strategic planning as described in literature [6],[7],[14],[41], a likely effect of employing this conceptual model will be a necessary level of product innovation process customisation.

As discussed earlier, this conceptual model requires an integration of a well-structure market research method to gather the data on customer preferences. In addition, a company should strengthen its cooperation with industry experts and research institutes to ensure the incorporation of appropriate technology into its product innovations. This should be coherent with the process functions and tasks to ensure complementary support for successful product innovation [14].

Moreover, this conceptual model involves an automatic simulation process for generating product innovation alternatives which requires a careful consideration in the simulation's design process. The objectives and related input parameters should be determined accordingly by management and internal subject matter experts, because the success of the product innovations will depend very much on the good definition of objective function and input parameter settings. Hence, the customisation of the product innovation process especially calls for proper coordination and organisation in a company. The key functions in a product innovation process such as R&D, technology, engineering and marketing department will provide their input based on their perspectives of the prospective product innovation candidates. With this particular focus the deployment of this conceptual model increases the necessity for customisation of the current product innovation process.

#### *I. Effects on Management and Key Players*

The key players including senior management involvement in product innovation process is very critical in order to promote cohesion, commitment, and clarity throughout the organisation regarding the sequence and timing of new products. In that setting, all managers, regardless of their function, begin to grasp the significance of the new products for the organisation. In this way, the product innovation process forces senior management to make necessary but tough choices, whether to increase funding for a product line in order to become a market leader and how to tackle the inevitable trade-offs between promising individual projects and overall strategic direction [14].

To support customisation of the required innovation process, the tasks and roles of management and key players should also be properly adapted to the deployment of the model. As the product innovation process tasks and functions are affected by the key players and management who originally involved in the day-to-day business process, their allocation to the tasks should be carefully planned in order to avoid overloading of resources for specific functions and responsibilities [16],[17],[41]. In this regard, the management and key player's involvement and commitment should be performed consistently and in a balanced manner to both processes: day-to-day tasks and the product innovation process.



The results from both companies have also shown that the deployment of the conceptual model has an influence on the commitments of management and key players.

#### J. Effects on Performance of Product Innovation Process

One of the key research objectives is analysing the contribution of GA as an optimisation method for product innovation development. As described earlier, GA should offer quantitative solutions for delivering the best and most precise prediction for future product innovation candidates [5],[9],[10],[15],[16],[20],[21],[38]. The candidate innovations which are originally proposed by the subject matter experts will be evaluated by GA on the basis of a predefined mathematical model reflecting the company's objective (fitness function). This model also includes input parameters that represent the importance of the product characteristics from a customer's point of view, as well as technology advances and their feasibility for implementation. These input parameters will be processed by means of recombination (cross-over) and mutation processes to produce the next generation product with better characteristics according to the fitness function. Accordingly, the product innovation alternatives will be generated automatically to depict the product innovation candidates in specified timelines. These alternatives serve as decision support tool for management for strategic product innovation planning.

#### IV. CONCLUSION

Effectiveness and efficiency are aspects which should be considered in an optimisation process. As this heuristic based conceptual model involves a computer simulation process, the quality of its output strongly depends on the quality of its input parameters. Hence, as described earlier, the quality of these inputs parameters hold a pivotal role in determining the success of product innovation. In addition, this model offers added value from the time perspective because it saves time by directing the expert discussions towards a specific topic, objectives, relevant requirements and expected solutions.

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