TOWARDS PRODUCT PLATFORM INTRODUCTION: OPTIMISING COMMONALITY OF COMPONENTS.

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Abstract

Companies that design and manufacture products for a wide range of related applications need to offer the right product for each use. A platform design strategy allows designing the product range based on product platforms, where some of the components and systems are common across the range whereas other components are individual for each product variant. This paper presents the problems that a company faces when trying to introduce a platform strategy and outlines a method to find suitable components to be made common. The method is shown with a simple case. The approach uses fuzzy logic to obtain a suitable criterion to assess the overall value of the product line and a genetic algorithm for finding the set of components to be made common.

Keywords: Platform strategies, Optimisation, Product families, Simulation, Early design phases

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1 INTRODUCTION

Suppliers need to continuously adapt their products to meet the specific needs of their industrial customers. To get economy of scale, it is beneficial to have shared components across all or most products, and this concept of sharing components is often referred to as product platforms. It is common for companies to produce variations of products within product families, but developing a platform requires rethinking the wider product offering. This paper analyses the problems associated with this transition from a focus on product variations to a focus on product platforms. It is based on the author's experience in industrial vehicles product development.

1.1 Background

In the early 20th Century, Ford started mass-producing their model T using a system that has become one of the most cited examples of modern manufacturing. All the cars coming out of the production line were built to the same specifications, to the extent that they were all painted the same colour. Ford sold millions of virtually identical units of the model T to customers of all kinds. However, by the 1960's, the American automotive market was very different. Each car producer offered many models and each model was updated every year. Customers were also offered a wide range of options from which to choose the specification of their purchases. This made it theoretically possible for a company to manufacture millions of cars without repeating the same exact configuration twice (Wilson 1997). The automotive industry was a pioneer in this approach which, since the 1990s, has been referred to as mass customization (Silveira et al. 2001). In the current market, it is often expected that companies producing consumer goods are flexible enough to offer a range of products that appeal to a wide market, by satisfying the particular requirements of different kinds of customers without severely increasing the costs. For companies that produce goods destined for industrial use, personal preferences are less important because the products are mainly perceived as tools. But, the applications in which the products are going to be used can vary widely, and the implications for the manufacturer are still the same, i.e. they need to offer a wide range of different products at a competitive price to satisfy their customers.

With mass customisation in mind, companies aim to offer a wide variety of products while at the same time using the minimum number of different parts and systems (Nelson et al. 2001). This approach has several advantages: economies of scale and reduction of parts inventory (Martin and Ishii, 1996); shorter lead time and easiness to design new product variants (Ulrich, 1995); and reduction of manufacturing tooling and processes (Siddique et al. 1998). The concept behind this approach is product platform design (PPD). A product platform largely defines the design space, i.e. the space of possible designs from which a subset could be used for a specific design, potentially supplemented with specific components. Product platforms are usually organised into product families, i.e. *'sets of products that share a number of common components and functions with each product having its unique specifications to meet demands of certain customers'* (Pirmoradi et al., 2014).

1.2 Industry case

An example of the challenges faced by companies competing to meet customer requirements is presented by the materials handling vehicles industry, which produces a wide variety of different products for the purpose of lifting and transporting goods. Customers all have a common high-level requirement; they want vehicles that can pick up a load, and move it from one location to another, but the range of detailed requirements is very broad. The loads to be moved can range from 20 kg to 52 tons; the heights to which they need to be picked up range from ground level to 19 m; the environments range from well prepared warehouses to timber yards or cold stores; the loads can be arranged on 800 mm pallets or can be 40 ft (12 m) shipping containers, etc. This vast range of applications results in an equally vast product portfolio, if the target customers range across the whole market, which is not the case for all companies. An example of the configuration of different vehicles is shown in Figure 1. This data is a sample from specification sheets available from www.hyster.com and www.yale.com.

For a machine with the purpose of 'moving a load of up to 2500 kg from point A to point B', Figure 1 shows that, there are 107,712 possible different trucks. When other options are added such as rotating beacons, cold store versions, explosive atmosphere versions, additional hydraulic functions, types of brake system, tyre sizes and compounds, seat and trim materials, lights, seat suspensions, heating

systems, CCTV, etc., the total number of possible configurations easily rises into the tens or even hundreds of millions. These numbers refer only to 2.5 ton counterbalanced trucks, and that type of truck is offered with capacities ranging from 1 ton to 45 tons. Figure 2, shows the full range of truck designs including reach trucks, pallet stackers, very narrow aisle trucks, pallet trucks, reach stackers, etc. Typically, such vehicles are manufactured to order, and the manufacturer needs to be able to accommodate the customers' specific requirements and provide a vehicle that meets all of their needs. Sometimes this means explicitly designing new features not offered in the regular price list.

Power source	Type	Wheel base (mm)	Track width (mm)	Fuel	Engine	Mast type (All)	Mast lifting height (mm)	Forks (mm) (All)	Carriage type (All)	Cab (All)
Electric	DBB	1230	905, 1035			LFL	2090, 2490:100:3790, 3930:100:5130	760 900 1000 1100 1200 1400 1500 1800	Std	No cab
	DBB	1377	905, 1035							
	CBB	1606	938, 1054							
	CBB	1750	938, 1054							
ICE	Pneumatic tyres	1623	960	Diesel	Y2.6 Y3.0 Y3.3	2FFL	2500:100:3800, 4020:100:5320		ISS	Std cab
		1700	1025	LPG	M2.0 M2.2 M2.4	3FFL	3750:150:7800			
	Cushion tyres	1430	929	LPG	K2.4 P2.5					

Figure 1. Different options for a 2.5 tons forklift truck

This research is funded by the materials handling company NMHG as part of PhD research concerned with establishing a strategy for increasing the number of parts or solution principles that are shared across product families. It is a challenge to re-think a product line in terms of platforms because different vehicles are traditionally designed independently. Part of the challenge lies in identifying the components that could potentially be made common across a platform, while at the same time balancing the unavoidable losses in performance that can result from reducing the variability in components. One of the difficulties lies in the fact that important decisions need to be taken during the early design stages when there is a high degree of uncertainty around the consequences of decisions on the final product. Methods for making decisions in these circumstances exist, such as the Method of Imprecision (Scott and Antonsson, 1998) based on fuzzy sets assessment of performance and preference aggregation. This has also been proposed for platform design (Dai and Scott, 2006). The purpose of the research outlined in this paper is to use a similar approach to identify components common across designs and use these to explore different platforms that could support a product line. Exploration is based on simulation of the performance of each product variant, which is assessed against a value model without any preconceived idea of what the platforms may look like. Preference aggregation is part of the value model and is also incorporated into the results of the platform strategy.

Figure 2. Left to right: VNA truck, reach truck, ICE counterbalanced, Electric counterbalanced, reach stacker

2 PRODUCT PLATFORMS

The concept of platform design has been defined in a variety of ways, among them:
- '*A product platform is the collection of assets, including component designs, shared by otherwise different products.*' (Eppinger & Ulrich, 2012)
- '*The platform is the maximum level of standardization with which it is possible to meet all the requirements for all the products.*' (Nayak et al. 2002)
- A group of related products that share common components and/or subsystems. (Simpson and Souza, 2004)
- '*A platform strategy is essentially an effective and deliberate program of component reuse which takes advantage of the economies of scale across the product family, while minimizing the negative impact of reuse on individual product variant distinctiveness and performance.*' (De Weck et al., 2003)
- The concept of platform also includes the people involved and their relationships. (Robertson & Ulrich, 1998)

Although these definitions differ in scope, the essence of platform design can be summarized as the idea of developing several product variants based on both a set of common components and individual components to provide the necessary differences so that each variant can serve its particular purpose.

The development of a platform can be divided into seven phases (Primoradi and Wang, 2011):
1. Product family and platform configuration
2. Product family modelling
3. Product portfolio positioning
4. Design optimization
5. Metrics and indices
6. Design support systems
7. Supply chain management issues

This paper is mainly concerned with the fourth phase, i.e. the optimization of the platform design. This is because the motivation for the research results from a real industry problem of how to re-design and improve an existing product line by considering a platform-based strategy. Optimization involves finding a solution or set of parameters that will result in the best outcome for a defined problem. For problems where the best outcome cannot be simply defined because of the number of parameters involved, a key difficulty lies in identifying how to measure the 'best' outcome. This paper explores an approach for optimizing the performance of a materials handling truck, by identifying a measure of fitness of a product line.

An important part of platform design optimization is to decide which components will be part of the platform and which components will be individual for each variant. Several methods have been proposed for accomplishing that task, which have been developed independently and are therefore difficult to combine and synthetize (Otto et al., 2013). Methods include the Product Platform Concept Exploration Method based on a decision support problem (Simpson, 1998); vector modelling and comparison to market leader (de Weck et al., 2003); iterative processes (Gonzalez-Zugasti et al., 2000); and methods based on comparison of potential platform based products with individually designed products to identify the best platforms (Nelson et al., 2001). Other methods are based on defining indices of commonality (Martin and Ishii, 1996). Platform optimization is typically a multi-objective multi-variable problem, and a recurrent technique for such problems is the use of evolutionary or genetic algorithms (Simpson and Souza, 2004), (Antonsson et al., 2001). However, although genetic algorithms are a powerful tool for addressing these problems, there is still a bottleneck in how to suitably encode the problem itself. The concept of Value-Driven Design, is of potential use since its objective is to achieve a best possible score instead of meeting a list of requirements (Collopy et al., 2009). The score is obtained by assessing products against value functions, which ideally need to take into account all the factors that contribute to the value of the product. Defining such a function is necessarily a complex task.

3 THE PROBLEM OF INTRODUCING PLATFORMS IN INDUSTRY

A company that designs and manufactures consumer or industrial products needs to sell their products in a competitive environment where other companies also offer similar solutions. There are many factors that affect the sales of each product. Some of these are of a psychological or sociological

nature such as brand image, pre-conceptions, marketing, etc. But there are two factors that depend heavily on the design and engineering process; these are performance and cost. In this research, these factors are analysed and described for the case of materials handling industrial trucks, and they will be the main drivers for the introduction of a platform design strategy.

3.1 Performance

The Oxford English Dictionary defines performance as '*the capabilities of a machine, product or vehicle*'. For machines, such as the industrial trucks in this case study, there are lists of attributes, including pure performance figures and relevant parameters, that are described in a specification sheets and performance sheets, and are used by potential customers to assess and decide which particular product they will buy. Depending on the machine complexity, the number of these attributes or capabilities can range from just a few for a simple product like a hammer (length, material, mass) to several hundred for complex products like cars. While individual parameters can be quantified, the problem is how to combine these to quantify and compare the overall performance of products with many attributes. Designing a product that is better than any other for every attribute is rarely possible, especially because high performance in some attributes results from low performance in others, e.g. power vs fuel consumption in a car. Designers need to balance these attributes when making decisions on how to produce designs that satisfy their customers' requirements (Otto and Antonsson, 1991).

Consider the case of an engineering team designing materials handling vehicles, selecting which concept to pursue. In a very simple scenario they may consider two different designs for a new truck, such as those shown in Table 1. Here, 'loads per hour' is a measure of the amount of work a truck carries out in a standardised duty cycle, with the loads prescribed according to a truck's rated capacity, and the fuel consumption is a measure of the cost of carrying out this work.

Table 1. Attributes of two different fictional truck designs

	Truck A	Truck B
Loads moved per hour (loads/h)	*45*	*52*
Fuel consumption (l/h)	*4.1*	*4.3*

The traditional approach to selecting a concept is to define a set of product requirements and ensure that the design meets them. In this case, if the requirements specification sets the minimum loads moved as 45 and a maximum fuel consumption of 4.2 l/h, it seems clear that truck A would be appropriate since it meets both requirements while truck B does not meet the required fuel consumption. However, truck B moves many more loads than truck A for very little cost, so, unless the 4.2 l/h requirement is rigid and unnegotiable, for example due to legislation, it is beneficial to consider both concepts. In this situation, engineers would not discard truck B immediately. They may take notice of the particularities and revisit the requirements.

This is an overly simple example with only two attributes; in a realistic scenario there would be more design options and more performance attributes. In practice, it is rarely so easy to identify which is potentially the best design, and common practice involves 'satisficing' (Simon, 1956), or choosing an option that meets the requirements, even though it may be far from ideal. A robust method to assess the overall performance of a concept and compare different designs would be a valuable tool for engineering, and it is a challenge to accurately and unambiguously define one.

3.2 Cost

Design is one of the major influences on the cost of a product since it has a direct effect on the price of components and subassemblies, the development costs and the useful life of the product. A product platform has an immediate effect on the component or system costs and potentially development time. Most products will experience changes and redesigns during their life cycle, and the costs incurred depend heavily on how the original design is capable of accommodating the changes. A well thought out product platform with appropriate margins for future change will lower the redesign costs in the long term and will delay the necessity for a completely new design (Eckert et al. 2012).

3.3 The problem of a balanced platform strategy

The problem of introducing a platform strategy can be divided into stages, as illustrated in Figure 3:

- Target applications: identify the applications for which the company wants to offer a product.
- Product clustering: decide on the number of products and types necessary to cover all the target applications.
- Find suitable platforms: once the product variants are known, there is a very large number of combinations which they can be designed and built. Figure 4 illustrates some examples.
- Design variants: all the variants are designed based on the selected platforms and by adding all the necessary individual parts.
- Assess value: check the validity of the obtained product range. If the value matches the desired one, then the product range goes forward, otherwise the process is reiterated. This stage depends on the design philosophy, whether the goal is to obtain a good enough product range or the optimum product range. The dotted line means that product clustering can potentially be fed from the assessment, although it will not be in this example.
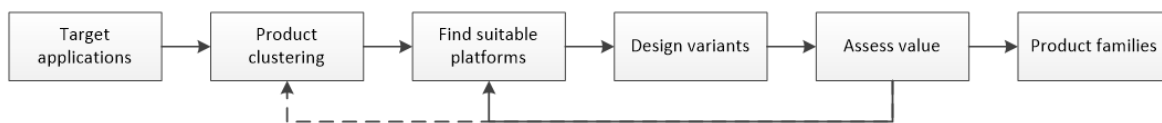- Product families: the range of products to be designed based on the platform decision process.

Figure 3. Diagram of the process to design a platform based product range

The illustrative example of Figure 4 shows option A in which the platform is the chassis and the transmission whereas the engine is chosen individually for each vehicle. Option B shows two vehicles based on a platform composed by the engine and transmission. The chassis is not part of the platform. The third vehicle is a stand-alone design. Both options are possible but engineers will be interested in finding which one better suits their criteria.

The question is how to balance the advantages and disadvantages of a platform based family and what components should be in the platform or individual for each variant. In all the reviewed literature, the elements that compose the platforms are defined in a step, and then both the platforms and the variants are optimized in one or two further steps. The main novelty of the method outlined in this paper is that the components of the platform are chosen and the product optimized at the same time.
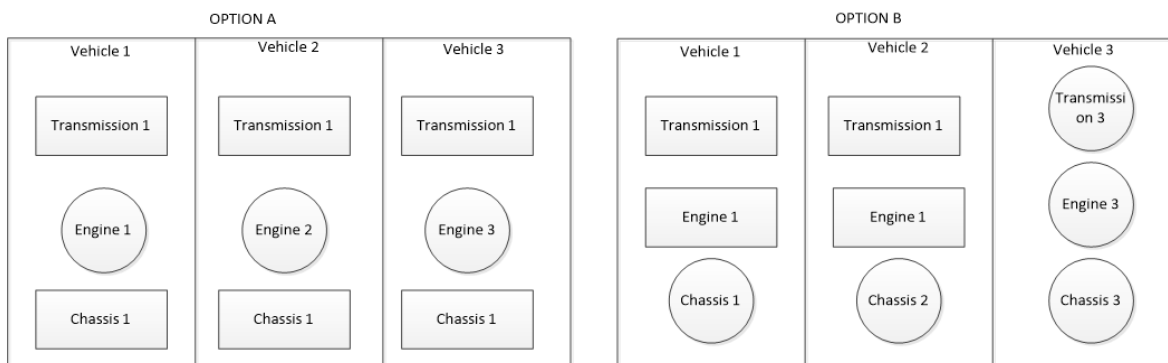

Figure 4. Illustrative example of two different options to design three different vehicles. Rectangles represent parts of a platform whereas circles represent components individually designed for each vehicle

4 SELECTING A POSSIBLE PLATFORM

This paper focusses on computational methods to select a suitable product platform, which is illustrated with a simplified problem. The method will consider the design as a combinatorial problem in which there is a set of available components that describe the design space, and a set of products based on some combinations of those components. A search will be conducted to find combinations that score high against a defined criterion.

The intended product family is composed of three materials handling vehicles for three different capacities: 3 tons, 6 tons and 9 tons. The objective is to find a platform for the driveline of those three vehicles based on the components available and a defined value for the product family. The components under consideration are the engine, gearbox and tyres. There are three engines available, three different tyres and eight gearboxes. The performance attributes considered are maximum speed, acceleration time from 0 to 10 km/h and fuel consumption during a defined one hour cycle. The performance of each potential configuration was calculated with a model of the vehicle dynamics, implemented with Matlab/Simulink.

4.1 Fuzzy logic assessment of performance

In this case study the performance is defined by three different attributes, and it is anticipated that no combination can maximize the three parameters at the same time. Maximum acceleration and speed is obtained with the biggest engine, but this will result in high fuel consumption. Similarly, maximum acceleration is obtained with the shortest gearbox, but this will make the maximum speed low.

Fuzzy logic is used in engineering for tasks such as translation of customer wishes into requirements or multi-attribute decision making (Agard and Barajas, 2012), and it is particularly suitable for problems in which opinions and preferences need to be put into a mathematical form. The goal of this method is to assess how suitable a range of vehicles is for a specific set of customers, and fuzzy logic is used to model the reasoning of those customers as they decide which vehicles are best for them.

The approach is to consider the performance in each measurable attribute as a degree of membership of a fuzzy set. The sets are designed with a process of 'fuzzification' of the available information about how the performance is perceived (Zadeh, 2001), which translates human opinions and perceptions into quantifiable sets. As a guide, a membership of 1 means that the performance is as perfect as it can be, membership above 0.8 should be considered as very good, between 0.5 and 0.8 is good, less than 0.5 is poor and 0 is unacceptable. Both 0.7 and 0.6 mean a good performance in general, but 0.7 is better than 0.6. The sets used are shown in Figure 5. In practice, these values could either be elicited directly from the customers or obtained from sales engineers.
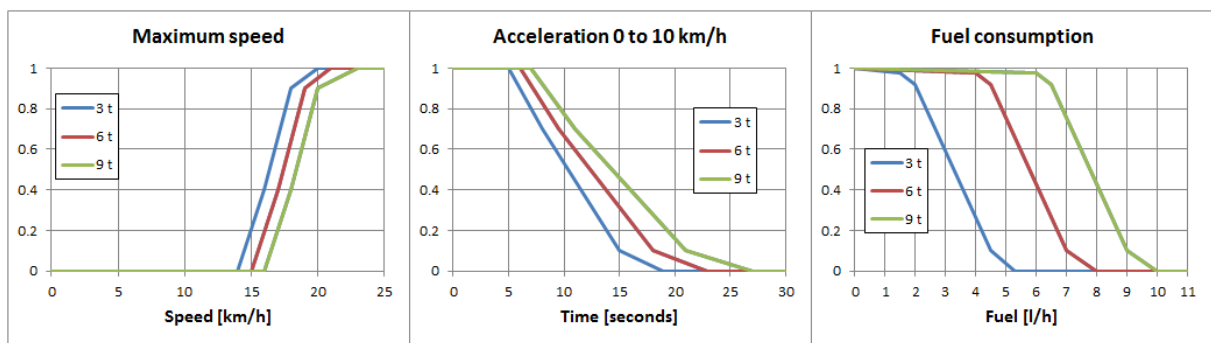

Figure 5. Fuzzy sets for the three attributes. Sets for the 3 vehicles plotted.

The meaning of the sets in Figure 5 for the 3 tons vehicle (blue lines) is:
- − Maximum speed: A maximum speed below 14 km/h is not acceptable. 20 km/h is optimal and anything in between is progressively better. A capacity for speeds in excess of 20 km/h does not add any value to the vehicle as those speeds are not realistic in the driving conditions.
- − Acceleration: 18 seconds is the minimum acceptable, and reducing it to 15 makes the attribute slightly better but still very poor. Less than 10 seconds is good, but less than 5 does not add any value as a truck would need to be artificially restricted for stability reasons.
- − Fuel consumption: 5.2 litres per hour is the maximum acceptable. The best possible, although unachievable, is zero. 2 litres per hour is a very good value and from there it gets progressively worse down to 4.3, which is the limit of what is acceptable.

Similar sets are defined for the other vehicles following the same approach, although the curves can be significantly different in both shape and limits. A model is required to weight the three attributes for each truck and another model to weight the values of the three vehicles, which is the overall value of the product family. These models need to consider the trade-offs between the different attributes of the different vehicles and the savings that result from using common parts. They also need to introduce all the necessary rules. These models are the biggest challenge of this method since they require good

approximations of the costs involved in development and production, as well as market uptake. A combination of technical knowledge, production knowledge and customer intelligence is required to define a meaningful value function. However, the optimization is intended to take place in the early stages of the design, so it is unrealistic to expect very accurate information. For this simplified case the value model carries out the two stage weighting; firstly a weight is applied to the three attributes for each vehicle and secondly a weight of the firstly calculated value of the three vehicles. In addition, the model rejects any combinations in which a single attribute of any vehicle is zero (unacceptable), and penalizes a combination in which the value of any two vehicles is very different. This last point reflects the desire to design a consistent product line.

4.2 Genetic algorithms for searching the design space

Once the optimization problem is defined and a design space is known, successive simulations can be run with potential vehicle configurations to obtain the best, when measured against the defined criterion. These simulations are implemented with a model of the vehicle dynamics that maps the design parameters to performance features. The model was composed in Matlab/Simulink and the searching algorithm written as a Matlab script. Even for this oversimplified example, a brute force analysis simulating all the possible configurations is not an option, since it will take a prohibitively long computing time to search the complete design space. Instead, a genetic algorithm (GA) was chosen for this example because, when compared to other search methods such as simulated annealing or multi-agent systems, it is recognised as being more effective for combinatorial problems such as this (Simpson and D'Souza, 2004). A similar approach has also been used for product line design under uncertainty and competition (Li and Azam, 2002).

In the GA, each possible product range is encoded as a nine component vector where groups of three components represent vehicle models with the three parameters under consideration, as illustrated in Figure 6. Following typical process for a GA, four different product families were simulated in each generation and assessed against the value function. The best performer was recorded and kept for the next generation. The other members in the next generation include combination of the elements of the previous as well new elements that arise from a stochastic selection of variables, i.e. mutations. The algorithm used was very basic and general, and was not specifically designed for the particularities of this problem, but does illustrate the potential of the approach for optimizing product-platforms.
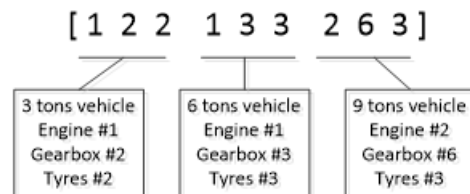

Figure 6. Encoding of product range for the searching algorithm

4.3 Results and observations

After 50 generations a product family was produced that satisfied the customer requirements to a reasonable degree. This is illustrated in Figure 7, which shows the evolution of the best performing products over the 50 generations.

In order to validate the search method, the value function was purposely constructed in a way that allows for the absolute maximum to be found with an alternative method, so that this can be used to compare the performance of the algorithm. In practice, this will not be the case, but for this example it is justified because the intention is to show the method and assess it. The algorithm was blind to the fast finding method and approached the absolute maximum treating the search as a combinatorial problem without any additional information. In that aspect the conclusion is that the method found a suitable value relatively quickly. Figure 7 shows the distribution of the value of all the possible families and where the best value found sits. The found value is not the absolute maximum, but it is in the 99.96 percentile. The number of simulations run represents less than 0.1% of the total possible combinations. The algorithm achieved a value of 99.67% of the absolute value 1166 times faster than the brute force analysis required to guarantee the finding of the absolute maximum. This was

calculated by dividing the number of simulations actually run by the number of possible combinations that can be formed with the defined design space.
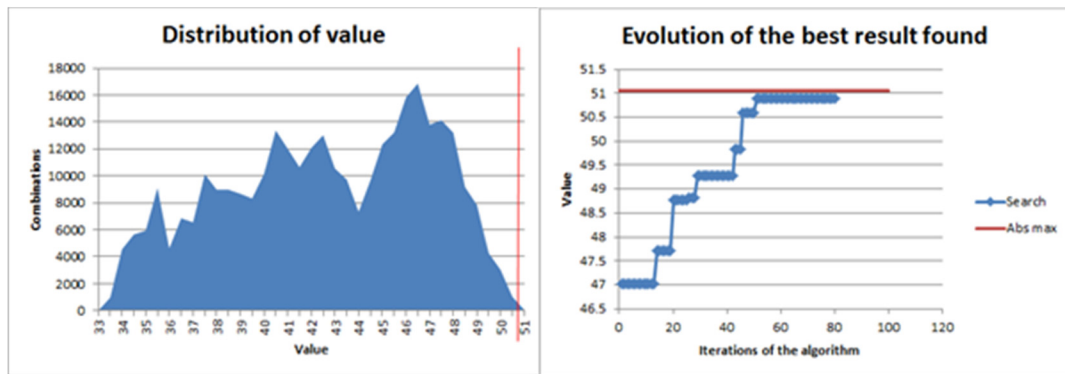

Figure 7.Left: Distribution of all the possible product families and the maximum found with the algorithm (red vertical line). Right: Evolution of the best performing over 80 generations. The red line shows the absolute maximum

An important observation from the experiment is that although the value found is close to the absolute maximum, the product family itself is not so similar, as shown in Table 2. For example the 3 tons vehicle uses the engine #2 in the absolute maximum family and engine #1 in the best found, which is a major difference. This reflects the fact that different options may be equally good, and that the solution for a product family in terms of what components should be made common is not necessarily unique. According to the found solution, the vehicle range could be designed with a common motor for the 6 and 9 tons vehicles and common tyres for the 3 and 6 tons, all the other components will be individual.

Table 2. Solution found with the algorithm vs optimal solution

	Found solution			Optimal solution		
	Engine	Gearbox	Tyres	Engine	Gearbox	Tyres
3 tons	1	4	2	2	1	3
6 tons	3	2	2	3	1	1
9 tons	3	7	3	3	8	3

5   SUMMARY AND CONCLUSIONS

The introduction of a platform design strategy is often justified in financial, development and logistic terms. But companies moving to a platform strategy face many challenges, among them are how many platforms to design, which components should be in the platforms and which should be product variant specific. The main constraints are that the products still need to meet an acceptable level of performance and the company needs to make decisions on the trade-offs between performance and cost. This makes it difficult to identify the best solution, and it is not possible to optimize the platforms without a clear definition of the criteria.

This paper proposed a method to select suitable platforms on which a product range can be designed as well as optimize the parameters of the platform and variant components in one step by assessing the value of the resulting product family. The method is being developed as part of a PhD and is not yet a finalized product. The example presented served to identify the areas that require further study, such as:

- − Fuzzification of customer needs and product clustering based on that.
- − Defining a value function as the criterion against which the product line can be optimized.
- − Modelling of the constraints that have an effect in that function.
- − Studying the performance of the search algorithms. The example presented in this paper is simple with a relatively low number of combinations and each simulation run in only 2 seconds. An industry realistic case can be several orders of magnitude more complicated. It is important to design a well suited algorithm and build the simulation models with the

appropriate degree of fidelity. Too low and the results are not reliable, too high and the computing time is not feasible.

− Interpretation of the results.

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