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ORIGINAL ARTICLE

Planning of manufacturing networks using an intelligent probabilistic approach for mass customised products

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Abstract Manufacturers around the globe are presented with the evident need to successfully capture and efficiently satisfy the increasing demand towards highly customised products. The trend for higher levels of customisation increases the operational costs, affects delivery times and worsens the environmental footprint of production. Moreover, the feasible alternative manufacturing network configurations increase together with the exploding product variety and the large pool of cooperating suppliers. The proposed research work describes an intelligent method that utilises three adjustable control parameters and can be used for the identification of efficient globalised manufacturing network configurations capable of carrying out the production of mass customised products. The decision support system presented allows the generation of alternative manufacturing network configurations and their evaluation, through a set of multiple conflicting user-defined criteria of cost, time, quality and environmental impact. The suggested approach, which is implemented into a web-based software tool, is investigated through a probabilistic analysis for guiding the decision-maker when selecting the values of the adjustable control parameters, in order to obtain high-quality manufacturing network designs. The applicability of the method is validated through a real-life pilot case, using data acquired from an automotive manufacturer.

Keywords Manufacturing network design · Mass customisation · Decision-making · Intelligent algorithm · Decentralised manufacturing

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1 Introduction

Original equipment manufacturers (OEMs) in the current highly competitive market landscape are presented with challenges, such as increased product and production complexity, the globalisation trend and environmental constraints among others (Fig. 1) [1]. In this landscape, OEMs must successfully capture and efficiently satisfy the increasing customer demand towards highly customised products [2]. The added value of products, created through customisation, must be accomplished through sustainable practices that are economically and technologically feasible.

In addition, these objectives must be achieved through reduced operational costs, satisfying at the same time performance measures of delivery times and quality. The strategic decision of designing the manufacturing network by allocating resources to satisfy production requirements, is very important for an enterprise, as it can support it operate more efficiently and face more effectively the intensive antagonism from its globalised competitors [3].

1.1 Motivation

Motivated by the current industrial needs of jointly achieving economies of scale and scope, the proposed research work focuses on developing a method for the identification of effective globalised manufacturing network configurations, capable of carrying out the production of customised products. A decision support system that incorporates an intelligent search algorithmic method that allows the generation of alternative manufacturing network configurations and their evaluation, through a set of multiple conflicting user-defined criteria of cost, time, quality and environmental footprint, is developed for that matter and is investigated though a probabilistic approach. The objective is to provide a decision-maker

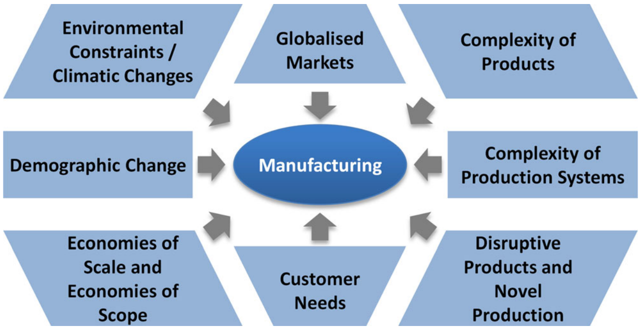


Fig. 1 Challenges that affect modern manufacturing

with a method for identifying efficient manufacturing network configurations in a timely manner.

2 State of the art

The manufacturing environment is nowadays more complex and dynamic due to the fact that globalisation and customer demand impose new requirements to industries [4, 5]. In this mass customisation environment, design for variety has attracted a significant attention in academia and industry. In order to achieve high product variety, numerous approaches have been developed including among other, postponement strategies, modularity in design, use and production [6]. The modularity concept in the automotive industry was extensively studied by Pandremenos et al. in [7]. Adding to that, postponement strategies, such as delaying the assembly of the products until after the customer orders arrive, or delaying the differentiation of the products until later stages of the supply chain activities, can be applied in order to efficiently achieve mass customisation. A study conducted in 2007 depicted that delayed differentiation techniques can be used to shorten lead times in batch process industries [8]. Another approach towards realising mass customisation is for a firm, having established a "flagship" product, to degrade it or in other ways alter it, in order to create a multitude of products with different attributes at a small "versioning" cost [9]. At present though, most researches are concerned with the strategic impact of mass customisation and do not address specific realisation issues [10].

The impact of product architecture and its coupling with product design, manufacturing processes and supply chain design were depicted in [11]. However, the industrial capability of realising more variants per model, and introducing new models of the same product faster, is in early stages of development [6]. A main limitation towards realising high product variety is the currently installed equipment for mass production operations, which is incapable of supporting product variability [12]. In addition, the propagation of complexity caused by high variety is another constraint that may trigger human errors and disturbances in the supply chain [13, 14].

Furthermore, a variety of issues, both established and emerging, related to the design of manufacturing networks, planning and control exist in this mass customisation landscape [1, 15]. Diverse approaches have been reported for the selection of initial manufacturing network setups. Mixed-integer mathematical methods that aim at optimising a set of performance indicators have been proposed [16]. Threatte and Graves addressed jointly issues of planning and transportation, in combination with inventory management [17]. A multi-criteria decision-making method to support the identification of business to business (B2B) collaboration schemes, especially for supplier selection, is proposed in [18]. A comprehensive literature review on the issue of partner selection in agile manufacturing chains is included in [19].

An additional problem that OEMs face is the identification of optimum configurations of their supply chains and subsequently their planning and operation. A method for modelling the dynamic behaviour of food supply chains and evaluating alternative designs of the supply chain by applying discrete-event simulation was proposed in [20]. Persson and Olhager proposed a simulation-based approach for the investigation of relations between key performance indicators of cost, time and quality during the design phase of a supply chain [21]. Different classes of distributed decision-making problems in supply chain management were identified in [22] and depicted the applicability of each one in different kinds of supply chain problems. A decision support system for strategic, tactical and operational level decisions was presented in [23], enabled by a generic modelling approach and simulation-based methods. A coloured Petri nets approach for providing modelling support to the supply chain configuration issue is proposed in [24]. The authors in [25] describe a dynamic optimization mathematical model for multi-objective decision-making for manufacturing networks that operate in a mass customisation environment. Fuzzy mathematical programming techniques have also been employed to address the planning problems in supply chains [26]. A literature review on mathematical programming for supply chain planning is documented in [27], and a report on coordination mechanisms for supply chains is found in [28].

2.1 Contribution of the proposed method

Existing approaches do not adequately consider the impact of customised product specifications to the initial design of the manufacturing networks in terms of satisfaction of multiple objectives related to cost, time, quality and environmental sustainability [29, 30]. In addition, most approaches consist of tailor-made solutions that require complex modelling in order to solve diverse problems [30–32].

The contribution of the proposed method is found in the following. The impact of product customisation to alternative manufacturing network configurations is examined, and decision support is provided during the selection of near optimum layouts that satisfy user-defined objectives of cost, time and environmental sustainability. In addition, a business near-shoring model is proposed, namely the decentralised manufacturing network topology, where the suppliers and dealers are capable of performing assembly tasks in proximity to the customer. Furthermore, the proposed approach enables the modelling of different levels of the wide range of manufacturing activities; the OEM (end user) can model the problem from a manufacturing network perspective down to a shop-floor level, even to problems of dedicated assembly lines. Moreover, an Intelligent Search Algorithm, developed by the authors [14, 33–35], is further extended and its robustness is investigated though a probabilistic approach. Concluding, the method is validated through its application to a real automotive manufacturing network configuration problem that involves the production and transportation of a customised product.

3 Manufacturing network models and customised product

The entry point of the presented method is the customisation of a product and the submission of an order by the customer. This process can be achieved through a supporting web platform [2]. The customer visits the web-platform, selects the basic version of the product and modifies it to his/her individual preferences. The web-based platform offers a 3D customisation tool and augmented reality visualisation to the customer. Afterwards, the OEM receives the order and is called to reconfigure an efficient manufacturing network structure. The decision-making engine processes the orders and returns the best or high quality manufacturing network configurations for the production and transportation of the customised product components. The decision-making component of the framework is analysed in the presented research work.

The approach is supported, on its lower level, by a generic data model that has been developed taking into consideration industrial requirements. Special focus was given towards the development of a domain data model that can accommodate the modelling of manufacturing entities regardless of the specificities of each industrial sector [2].

3.1 Manufacturing network modelling

The manufacturing networks in the present research work are modelled in two types of topologies, the centralised (CMN) and the decentralised manufacturing networks (DMN). A CMN is modelled including constraints so that only the OEM can perform assemblies and/or specialised customisation tasks. On the other hand, the business model introduced through the DMN topology includes a number of cooperating suppliers (S) and dealers (D) that are capable of performing assemblies and special customisation tasks in proximity to the customers, such as the application of a carbon wrapping on a hood or the installation of the lock support and hinges on the hood (red flow arrows) (Fig. 2). This model conditionally enables the efficient implementation of mass customisation [5].

3.2 Customised product—bill of materials and bill of processes

The customised product under investigation is a car hood that can be produced in several variants upon customer request. The variants considered here are L1, L2 (a and b) and L3. The non-customised hood assembly variant (L1) is comprised of the hinge support, the lock support, the external cover and the supporting frame component. These components comprise the bill of materials (BoM) of the hood (Fig. 3).

The other variants are extensions to the L1 and feature the addition of an ornament (L2a variant), addition of a cast carbon wrapping (L2b) and the L3 variant that includes both the ornament and the carbon wrapping.

These components can be produced and afterwards assembled by a set of suppliers, dealers and OEM plants, at different cost, time and quality. The final step in this value-adding chain is the delivery of the customised product to the customer that initially paced the customised product order.

4 The decision-making method

The decision-making process includes resource-task assignments, where a set of alternative resources can be assigned to a set of tasks (each resource can process only one task at a time). Resources are possessed by OEMs, suppliers and dealers on the manufacturing network. Moreover, the decision-making procedure considers multiple conflicting user-defined criteria simultaneously. The cardinal preference upon which the

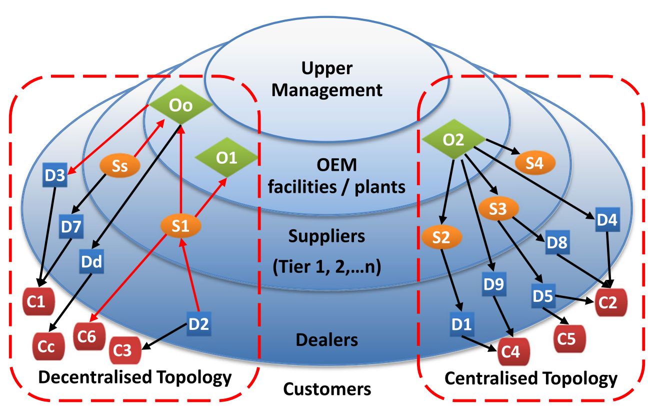


Fig. 2 The decentralised (*left-hand side*) and centralised (*right-hand side*) manufacturing network topologies

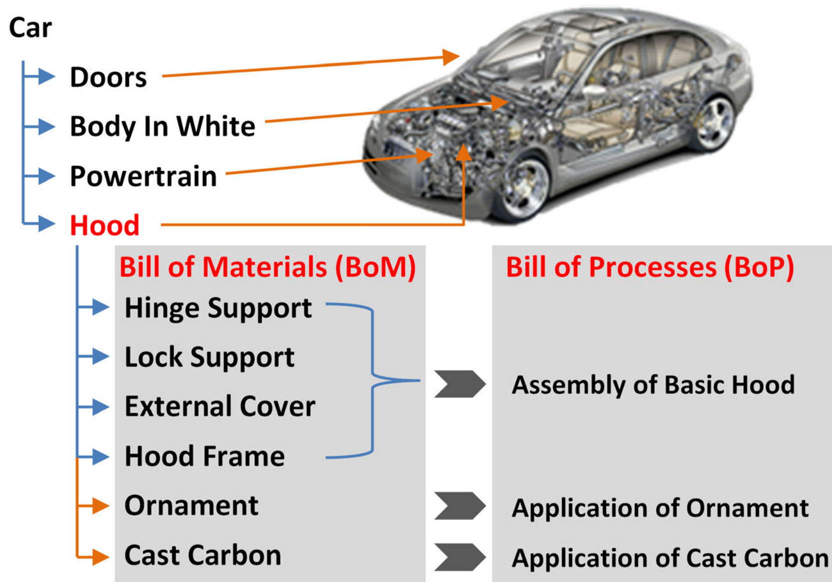


Fig. 3 BoM and BoP of the fully customised variant (L3)

performance of the alternative manufacturing network configurations is assessed is their utility value. The utility value is the weighted sum of the normalised values of the criteria and takes values in the range [0, 1]. The five-step workflow of the method is the following:

i. Generation of a number of *alternatives* (according to the values of the tuneable parameters of the search algorithm)
ii. Definition of decision-making *criteria* to satisfy a set of manufacturing objectives
iii. Definition of the *weight* of these criteria
iv. Calculation of the *utility value* of each alternative with respect to the selected criteria and
v. Identification of the *best* (*formed*) *alternative*

The decision-making process can be formalised as depicted in Fig. 4 through a decision matrix, the rows of which represent the alternatives (ALT_1, ALT_2,…, ALT_m) and the columns the decision criteria (CR_1, CR_2,…, CR_n). The cells of the matrix represent the normalised values of the criteria for a specific alternative. The column "Utility" represents the calculated utility value for each criterion (U_1, U_2,…, U_m). The alternative with the highest utility value is the preferred one [33]. Two decision-making algorithms are used for the generation of the alternative network configurations, as described below.

4.1 Exhaustive search

Using the exhaustive search (EXS) method, the entire solution space of the manufacturing network configuration alternatives is generated and evaluated. The output of this enumerative technique is the best alternative with respect to the selected criteria.

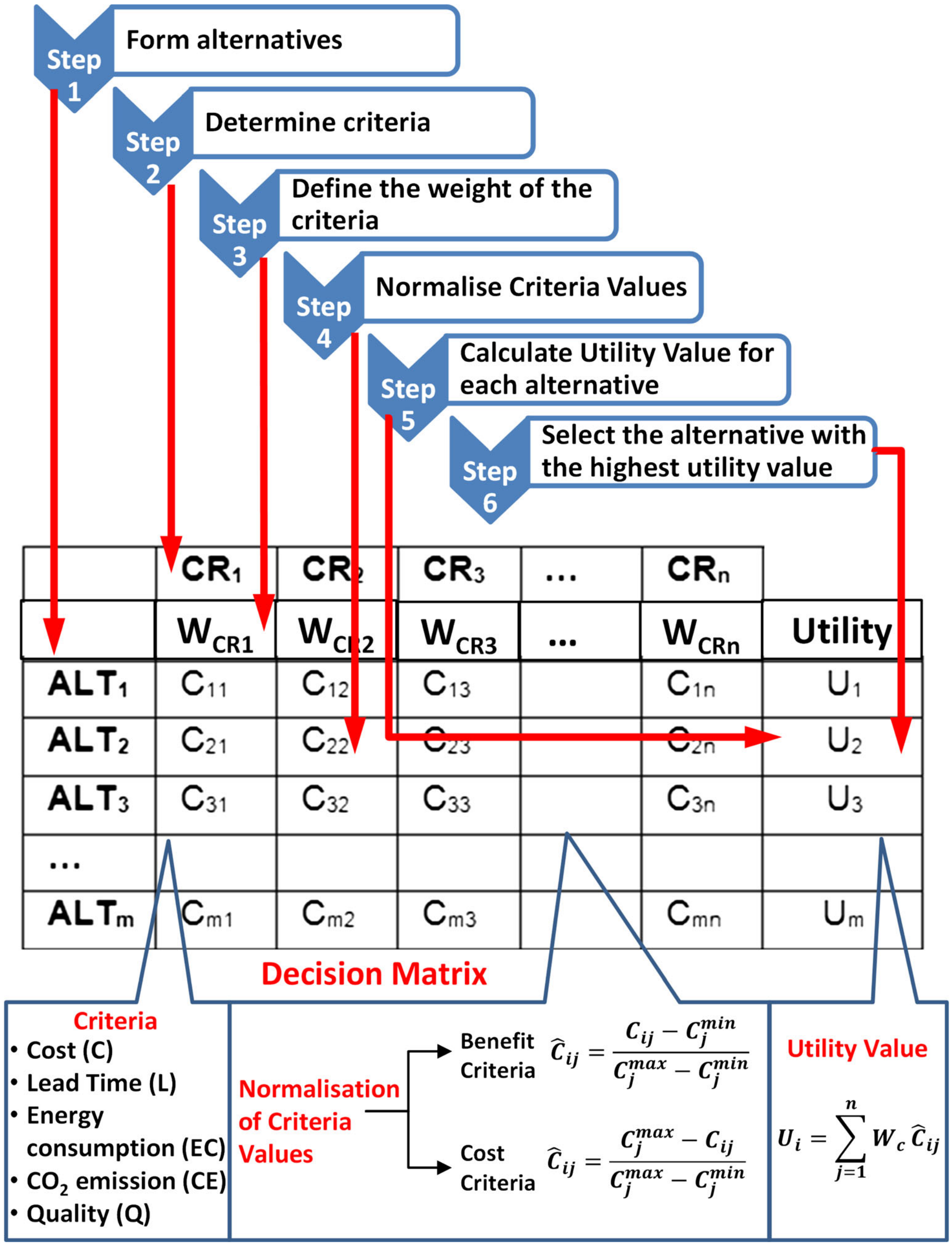
In realistic cases, however, the feasible alternative combinations may be in the order of billions of alternatives. Specifically, the simultaneous manufacturing of two fully customised hoods (L3) in a network that includes a pool of 24 partners (suppliers, OEMs and dealers) has 287×10^9 alternatives configurations. Therefore, significant computational resources and time may be required for an exhaustive search, constituting this method inefficient.

4.2 Intelligent search algorithm

In order to obtain a high quality solution (high utility value) to the manufacturing network planning problem in a timely manner, the intelligent search algorithm (ISA) has been developed [14, 33–35]. The ISA uses three adjustable control parameters, namely the selected number of alternatives (SNA), the decision horizon (DH) and the sampling rate (SR). SNA controls the breadth of the search (i.e. the number of alternative trees to be created), DH controls the depth of the search (i.e. the layers searched forward) and SR guides the search through the solution space for the identification of high quality paths (i.e. number of branches created for each alternative defined by the SNA). Each node in Fig. 5 represents a decision point, where a resource has to be assigned to a task. It should be mentioned here that all assignments made by the ISA are random.

The specific tree resulted by the following combination of factors: SNA=3, DH=3 and SR=2. Starting from the root, SNA dictates that three alternative paths will be searched and DH dictates the number of assignments that the algorithm will create before the SR defines the samples to be created. The node, e.g. supplier 4 and hinge support, is an ordered task-resource pair assignment, where the task hinge support of the job has been randomly assigned to the resource supplier 4.

Fig. 4 Steps of the decision method, the decision matrix, the decision criteria and the normalisation formulas



$$\hat{C}_{ij} = \frac{C_{ij} - C_j^{min}}{C_j^{max} - C_j^{min}}$$

$$\hat{C}_{ij} = \frac{C_j^{max} - C_{ij}}{C_j^{max} - C_j^{min}}$$

$$U_i = \sum_{j=1}^{n} W_c \hat{C}_{ij}$$

The red highlighted path represents an alternative manufacturing scheme. A first assessment of the performance quality of the ISA is included in [35].

For instance, Fig. 5 depicts a possible tree created by the algorithm for the values SNA=3, DH=3 and SR=2. The number of alternatives in the specific case is three, as defined by the SNA. The algorithms, for each alternative, look three layers forward, as defined by the DH. Finally, when all assignments have been randomly chosen for all layers and for all alternatives, the samples are created. For each branch, two samples are created as per the SR. The alternatives are assessed based on a multi-criteria decision-making procedure and the output is the alternative with the highest utility value.

The quality of the solutions provided by the ISA belong to the 10 % of the best alternatives identified by an exhaustive search for a specific problem, and the required completion time was reduced 65 times [33]. In Section 5, an investigation of the quality of the ISA is performed. Yet, the ISA can yield solutions of high quality after proper adjustment of the values of the three control parameters. Below, a probabilistic analysis is carried out for the tweaking of these control parameters.

4.3 Criteria

The set of decision-making criteria that must be satisfied in order to obtain a high-quality alternative is defined based on

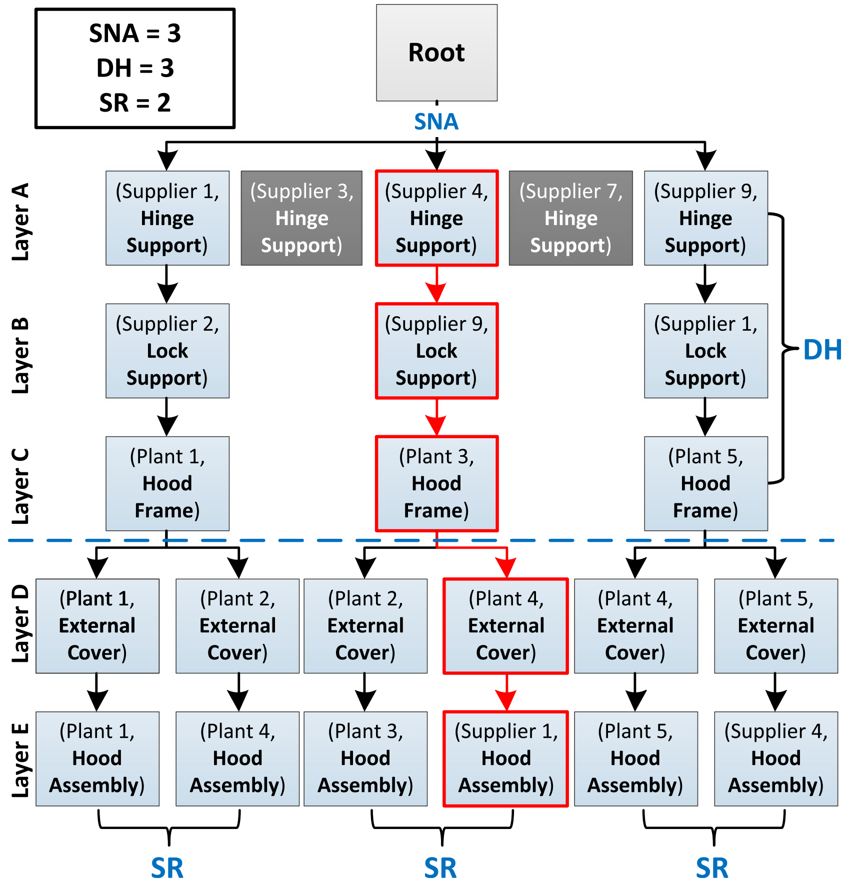


Fig. 5 An example graph developed by the ISA for SNA=3, DH=3 and SR=2

strategic level decisions. The criteria comprise the set of important manufacturing attributes that must be maximised/minimised. The relative importance (criteria weights) is defined by the decision-maker based on the design and planning objectives. The multi-criteria decision-making method takes into consideration conflicting criteria of cost, delivery time, quality and environmental indicators.

1. *Cost* (*C*) is the sum of production and transportation costs [33]:

$$C = \sum_{k=1}^{K} \mathrm{Pc}_k + \sum_{r=1}^{R} \mathrm{Tc}_r \quad (€) \tag{1}$$

   where Pc_k is the production cost for the task k (k=1, 2,… K) (€) and Tc_r is the transportation cost for the transportation route r (r=1, 2…R) (€)

2. *Lead time* (*L*) is the duration from the point a customer places an order to the point he receives the product [15, 25].

$$L = \sum_{k=1}^{K} \mathrm{Pt}_k + \sum_{r=1}^{R} \mathrm{Tt}_r + \sum_{k=1}^{K} \mathrm{St}_k \quad (\mathrm{h}) \tag{2}$$

   where Pt_k is the processing time for the task k, Tt_r is the transportation time for the route r and St_k is the setup time for the task k

3. *CO_2 emissions* (*CO*) are calculated by the distance travelled by the truck, the emissions of CO_2 per kilometre (km) and the number of products it carries [36, 37]:

$$\mathrm{CE} = \sum_{r=1}^{R} \frac{G * D_r}{N} \quad (\mathrm{kg\,of\,CO_2}) \tag{3}$$

   where G is the kilogrammes of CO_2 emissions per kilometre [37], D_r is the distance travelled for transportation route r and N is the number of products that one truck is carrying

4. *Energy consumption* (*EC*) considers the specifications of the machine (Watts), the processing time of tasks and the energy for transportation (fuels) [36]:

$$\mathrm{EC} = \sum_{r=1}^{R} D_r \times \mathrm{TC} + \sum_{k=1}^{K} \mathrm{Pt}_k \times \mathrm{RW}_k \quad (\mathrm{J}) \tag{4}$$

   where TC is the energy consumption per kilometre (J/km) [37] and RW_k is the Watts of the resource assigned to task k (J/s)

5. *Quality* (*QL*) is calculated as the average of the qualities of the supply chain partners that are selected in an alternative configuration [35]. The values for the qualities of the supply chain partners are obtained from the OEM of the case study based on empirical and historic data [14]:

$$QL = \frac{\sum_{k=1}^{K} QL_K}{K} \tag{5}$$

where QL_k is the quality of the supplier that performs task k.

5 Probabilistic investigation of the intelligent search algorithm

This section includes an assessment of the quality of the alternatives generation process in combination with the quality of the evaluation process through a probabilistic analysis. The research questions that lead to this probabilistic investigation are depicted in Fig. 6. The study includes a parametric investigation of the performance of the ISA, for various values of the SNA, and SR. It must be noted here that the DH parameter is not investigated due to the fact that it is constrained by the number of the decision points involved in specific scenarios. As an example, when 10 decision points exist in a specific case (i.e. 10 tasks to be performed), the DH parameter takes a maximum value of 10.

In the general case that a selected number of alternatives (SNA) are formed randomly from a population of total number of possible alternatives (TNA), then the probability P_o that the best alternative is formed is (6):

$$P_o = \frac{SNA}{TNA} \tag{6}$$

For realistic industrial cases, the number of alternatives may be in the order of billions. Examining the TNA for the customised product of the presented case study, for the L3 variant, it is TNA=535,392 and for a possible L4 variant (two ornaments and cast carbon wrapping), it is TNA=13,920,192. It is obvious that the P_o is unlikely to approach the optimum in such huge solution spaces. Thus, a search for a "good" alternative instead of the optimum is more efficient, taking into consideration the required computation burden. A "good" alternative is defined as one that its utility value is within a range Δ from the best alternative (u_{max}) [38].

5.1 Quality of the alternatives generation procedure

The quality of the alternatives generation procedure is defined as the probability $P_{(SNA,\ \Delta)}$, so that at least one from the generated SNA alternatives has a utility value equal to or less than Δ from the best alternative derived from the TNA solution space. A continuous density function f(x) is assumed that describes the distribution of the utility values from the exhaustive search. The probability that the utility value of a random alternative will be within Δ from the u_{max} is approximated by (7):

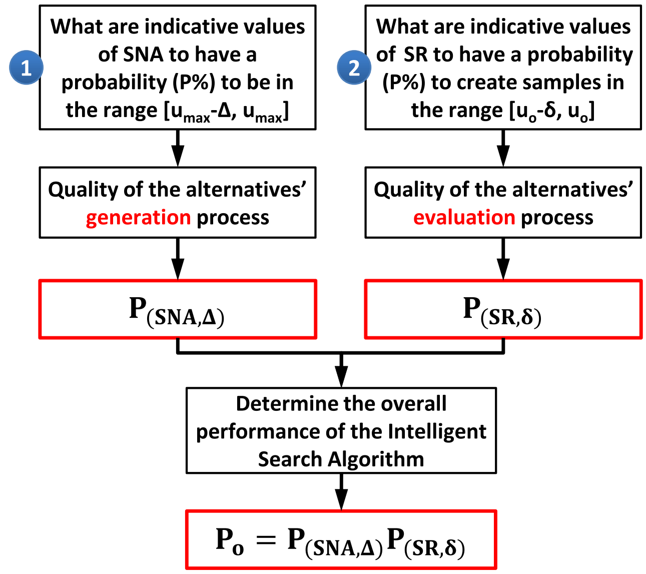


Fig. 6 Scenarios of the probabilistic investigation

$$P_\Delta = \int_{u_{max}-\Delta}^{\infty} f(x)dx \tag{7}$$

At each decision point, SNA alternatives are formed. The calculation of the probability $P_{(SNA,\ \Delta)}$ that at least one "good" alternative is performed as follows:

- P_Δ is the probability that one "good" alternative is formed when SNA=1, therefore, $(1-P_\Delta)$ is the probability that the alternative is not "good", i.e. the utility value of the alternative belongs to $[0, u_{max}-\Delta)$
- The probability that no alternative is "good" in SNA alternatives is formed is $(1-P_\Delta)^{SNA}$
- Thus, if P_Δ is known, the probability that at least one good alternative is formed in SNA alternatives is (8):

$$P_{(SNA,\Delta)} = 1-(1-P_\Delta)^{SNA} \tag{8}$$

Through a statistical analysis of the matrix of the utility values that derive from the exhaustive search (where TNA alternatives are formed and evaluated), the data fitting procedure approximated the distribution of these values with a normal distribution of mean μ=0.645 and variance σ= 0.126. Moreover, if f(x) is substituted in (7), the probability P_Δ is calculated by (9):

$$P_{\Delta} = \int_{u_{\max}-\Delta}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp\left[\frac{(x-\mu)^2}{2\sigma^2}\right] \mathrm{d}x \tag{9}$$

Based on the previous, the calculation of $P_{(\mathrm{SNA},\ \Delta)}$ is performed for the different values of SNA, Δ and σ.

5.2 Quality of the evaluation process

Further to that, the quality of the evaluation process is investigated. The $\overline{u}_{\mathrm{o}}$ value is defined as the mean value of the utilities of the samples (SR) of the alternative. Due to the fact that the possible samples may be many, the intelligent search algorithm evaluates the $\overline{u}_{\mathrm{o}}$ of an alternative with $\overline{u}_{\mathrm{SR}}$, assuming SR samples. The quality of the evaluation process of alternatives is defined as the probability $P_{(\mathrm{SR},\ \delta)}$ such that for a specific alternative, the $\overline{u}_{\mathrm{SR}}$ belongs to the $[u_{\mathrm{o}}-\delta,\ u_{\mathrm{o}}+\delta]$. Due to the fact that the dataset of the utility values follows a normal distribution, and by applying the central limit theorem, the probability $P_{(\mathrm{SR},\ \delta)}$ is (10):

$$P_{(\mathrm{SR},\delta)} = \int_{\overline{u}_{\mathrm{o}}-\delta}^{\overline{u}_{\mathrm{o}}+\delta} \frac{\sqrt{\mathrm{SR}}}{\sigma_o\sqrt{2\pi}} \exp\left[-\frac{\mathrm{SR}\left(x-\overline{u}_{\mathrm{o}}\right)^2}{2\sigma_{\mathrm{o}}^2}\right] \mathrm{d}x \tag{10}$$

Finally, the probability P_{o} is defined. P_{o} characterises the overall quality of the alternatives generation and evaluation mechanism of the intelligent search algorithm and is calculated from (11):

$$P_{\mathrm{o}} = P_{(\mathrm{SNA},\Delta)} P_{(\mathrm{SR},\delta)} \tag{11}$$

P_{o} represents the probability that among the SNA formed alternatives, at least one has a utility value within $[u_{\max}-\Delta,\ u_{\max}]$. Further to that, for each alternative that is evaluated, its $\overline{u}_{\mathrm{SR}}$ must deviate δ from the actual value $\overline{u}_o$. In Section 7 below, a case study is presented and this probabilistic investigation of the ISA is applied.

It should be noted here, that in this case study, the actual values for μ and σ are obtained due to the fact that an exhaustive search of the solution space was feasible. However, in cases were a solution cannot be searched exhaustively due to a large TNA (e.g. billions alternatives), a subset of the solutions can be examined in order to obtain approximated values of the entire population for μ and σ. In this probabilistic analysis, the distribution of the mean utility values would again be normal due to the following two reasons:

a. The central limit theorem. Let σ_{o} be the standard deviation of the distribution of the utilities (u_1, u_2,…) of all the samples (SR) of each alternative. If the SR is relatively large, then $\overline{u}_{\mathrm{SR}}$ is by approximation a random variable with a mean $\mu=\overline{u}_{\mathrm{o}}$ and $\sigma=\sigma_{\mathrm{o}}/(\mathrm{SR})^{1/2}$. Thus, in this case, the probability is calculated by a normal distribution.
b. The cumulative process followed for the calculation of the utility values from the samples taken for the alternatives tend to follow a normal distribution regardless if the criteria considered follow different distributions.

Therefore, in such cases, where the actual μ and σ are unknown, the max utility can be approximated by (12):

$$u_{\max} = \mu + 3\sigma \tag{12}$$

6 Software tool implementation

In order to test the functionality and performance of the decision support method, a web-based module using the JAVA™ programming framework has been developed. A Relational Database Management System (RDBMS) has been implemented using the Oracle 9i Database. The database is used for managing and storing the data of the conducted experiments. Moreover, an optimisation of the algorithm for reducing the memory consumption has been carried out. The software module is integrated in a web-based software platform and communicates through web services technology and XML files.

7 Application in an industrial case study—results and discussion

The presented case study comprises of 30 partners, with characteristics and capabilities coming from a real-life supply chain of a large European automotive manufacturer. Different actors are capable of different operations at varied cost, time, quality and environmental impact. The required processes (bill of processes (BoP)) of the hood variants are manufacturing of hinge support, lock support, external cover and frame, manufacturing of the additional customisation option, namely the cast carbon and the ornament, assembly of the components of the basic hood, application of the carbon to the basic hood, application of the ornament and finally delivery to the customer. This sequence of operation describes also the pre and post-conditions for the manufacturing and transportation of the hood. It must be noted here that the data of the customised product and the data of suppliers, dealers and OEM plants could not be mentioned for disclosure reasons.

An exhaustive search is conducted for obtaining the utility values of the optimum alternative manufacturing network configuration of the L3 variant. The L3 variant is selected because of the number of alternative configurations for this scenario that is calculated at 535.392 [15]. Based on the dataset of the exhaustive experiment, the density histogram diagram in Fig. 7 is created. This diagram includes the distribution of the utility values and the fitted normal distribution (red curve). The criteria values from the experiments on the L3 variant are included in Table 1.

At first, the probability $P_{(\mathrm{SNA},\ \Delta)}$ is calculated. The values of Δ are selected at 0.05, 0.1, 0.15 and 0.2. For these values, the derived probabilities are included in Table 2, and the diagram of Fig. 8 is created. The values of SNA factor are selected based on a statistical design of experiments (SDoE).

A preliminary observation derived by analysing the diagram of Fig. 8 is that the probability for ISA to yield a high quality solution for relatively small values of SNA is high. For instance, the probability of obtaining a solution that deviates from the maximum utility by Δ=0.15 is 0.912 or 91.2 % for SNA=20. This probability becomes 98.4 % in case the acceptance criterion becomes less stringent (Δ=0.2). Furthermore, the curves for Δ=0.15 and Δ=0.2 demonstrate a saturation point for SNA=20. Following on that, the probability $P_{(\mathrm{SR},\ \delta)}$ is calculated (Table 3) and the diagram of Fig. 9 is created.

Finally, using Eq. (11), the combined probability derives and is depicted in the diagram of Fig. 10. This diagram shows that the higher the values of SNA and SR, the higher the probability that at least one good alternative manufacturing network configuration will be formed. A general observation however, is that the probability of forming alternatives of high utility value rapidly increases at first, as the SNA and SR increase and level off for values of SNA=20 and SR=20. This leads to the conclusion that the alternatives generation and evaluation process yields high quality results for relatively small values of the adjustable parameters SNA and SR.

In general, the selection of optimum values for the ISA parameters greatly depends on the problem under investigation. The length of the alternative manufacturing network configuration (i.e. the number of ISA layers) is a restriction for the selection of the DH since the DH value should not exceed the length of the alternative. In case the DH equals the alternative's length, samples will not be created. Moreover, the definition of SNA is coupled, even loosely, with the magnitude of the search space, meaning that the selected number of alternatives to be generated

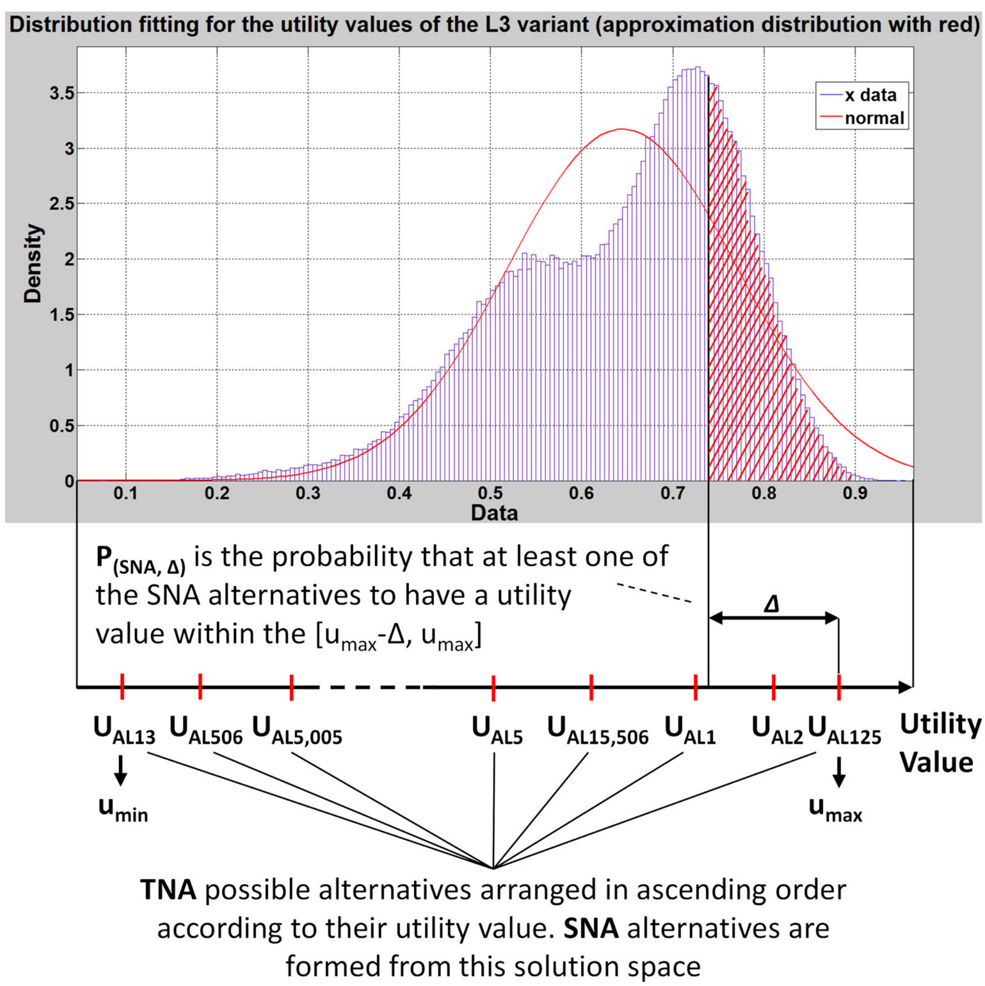


Fig. 7 Distribution fitting for the utility values of the L3 variant (approximation distribution with *red*)

Table 1 Criteria values of L3 variant (exhaustive search)

Production cost (€)	1,866.37
Lead time (h)	28.10
CO_2 emissions (kg of CO_2)	1,029.6
Energy consumption (MJ)	24,710
Quality	90

should be proportional to the search space. In the future work section, the intentions towards the generalisation and simplification of the method are reported.

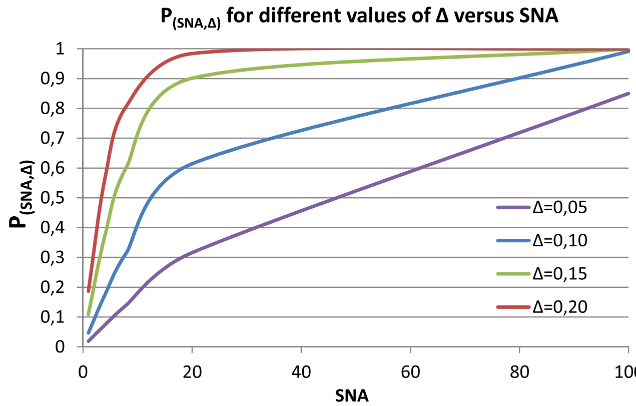


Fig. 8 $P_{(SNA,\ \Delta)}$ for different values of Δ and SNA

8 Conclusions and future work

This research work described a method for supporting the decision-making process of establishing high-performance manufacturing networks, which are capable to serve the needs of mass product customisation. The multiple conflicting criteria used in the decision-making method encapsulated important manufacturing objectives of today's demanding landscape. Apart from classical indicators of cost and time, environmental sustainability indicators and overall quality were considered in the design. Moreover, through the ISA, high-quality manufacturing network configurations were obtained by consuming significantly less computation resources and time, as opposed to an exhaustive search of the same solution space.

The ISA method can be utilised in cases where the feasible alternatives are in the order of millions or even billions of alternatives. Specifically in real-life problems, the design of manufacturing network configurations is a proven NP hard problem [39]. Exhaustive search techniques are not feasible in such cases due to the fact that they consume excessive computational resources and time. Therefore, by utilising the ISA, a small subset of the solution space can be examined. Based on this subset, the values μ and σ of the entire solution space can be approximated. Following that, the ISA can effectively provide a design that deviates by a small fraction (Δ) from the optimum solution, within a given confidence interval. As an example, the decision-maker can designate that an acceptable solution must be within the range $[u_{max}-\Delta, u_{max}]$, where $\Delta=0.2$. To achieve this quality in the solution with a probability $P_{(SNA,\ \Delta)}$=80.86 %, the SNA must be 8 for the specific case under investigation (Fig. 8).

The investigation of the quality of the alternatives generation and evaluation process depicted that with small values of the adjustable parameters of the ISA (SNA, SR), a saturation point is reached, over which the probability of obtaining a high quality solution is increased with a lower rate. Therefore, efficient manufacturing network configurations can be identified with relatively small values of SNA and SR. More specifically, from Eq. (8), it is observed that regardless of the distribution that characterises P_Δ, the value of $P_{(SNA,\ \Delta)}$ increases rapidly at first as SNA increases and levels off for larger values of SNA. Therefore, by forming a relatively small SNA subset, out of all possible TNA alternatives, just enough to reach the point at which $P_{(SNA,\ \Delta)}$ levels off, the probability of forming a good alternative can be made to approach the probability that would be obtained, in case a greater number of SNA was formed. Thus, a significant amount of computational burden is conserved. Additionally, as the σ decreases, the probability $P_{(SNA,\ \Delta)}$ increases (probability of forming a "good" alternative) due to the fact that the values are less dispersed and the distribution becomes narrower (the values of utility are more concentrated around μ). In addition, as the Δ increases, the $P_{(SNA,\ \Delta)}$ increases likewise because the criterion that classifies an alternative as "good" is loosened (less rigid).

The overall quality of the ISA, as it derived from the combined probability, showed that the increase of SNA yields

Table 2 $P_{(SNA,\ \Delta)}$ for different values of Δ and SNA

Δ	SNA				
	1	4	8	20	100
0.05	0.0188	0.0731	0.1409	0.3159	0.8501
0.10	0.0465	0.1734	0.3168	0.6141	0.9914
0.15	0.1093	0.3710	0.6039	0.9012	0.9999
0.20	0.1867	0.5623	0.8086	0.9840	0.9999

Table 3 $P_{(SR,\ \delta)}$ for different values of δ and SR

δ	SR				
	1	3	6	10	20
0.01	0.1145	0.2637	0.3814	0.4686	0.5125
0.02	0.2891	0.4322	0.5455	0.6231	0.7111
0.05	0.3966	0.6201	0.7902	0.8955	0.9705
0.10	0.6391	0.875	0.9671	0.9888	0.9999

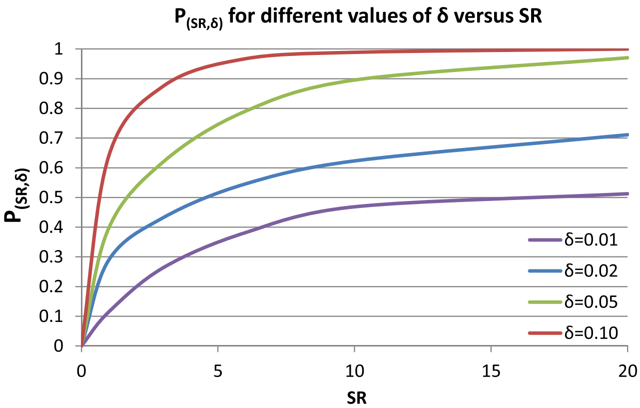


Fig. 9 $P_{(SR,\ \delta)}$ for different values of δ and SR

better results than an analogous increase of SR. This leads to the conclusion that an increase in SNA should be preferred over increasing the SR for obtaining results of higher utility value without increasing the computation burden. Moreover, this observation is in line with the results depicted in [35].

Future work will focus on the following directions. The implementation of additional criteria, such as reliability and customer service levels will be implemented. Moreover, further decision-making parameters will be introduced, as well as constraints that limit the solution space will be incorporated. Furthermore, the performance of the ISA method will be benchmarked against other approaches such as genetic algorithms and meta-heuristics. In addition, a rule-based software component will be developed in order to guide the definition of the SNA, DH and SR parameters in different pilot cases and specific problems. A smart mechanism will identify the characteristics of the problem under investigation and extract information regarding the magnitude of the search space, the number of stages, etc. Following on that, a set of rules will be executed in order to propose to the unfamiliar end user of the tool optimum combinations of the SNA, DH and SR factors for the specific problem. The end user of the software tool will be allowed to manually select the values for Δ and the parameters of the statistical distribution (μ, σ, etc.). Finally,

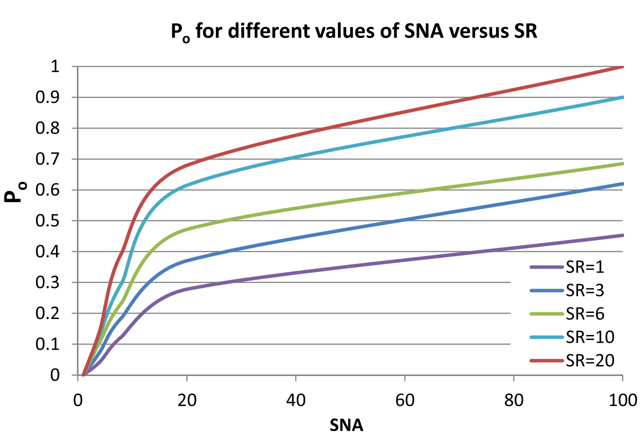


Fig. 10 P_o for different values of SR versus SNA

a long-term vision includes obtaining updated values of CO_2 emissions and energy consumption through smart sensors and grid-able infrastructures, under the concept of cyber-physical systems [40].

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