

# Design of Multi-Stage Manufacturing Networks for Personalized Products Using Metaheuristics

D. Mourtzis, M. Doukas, F. Psarommatis and N. Panopoulos

**Abstract** Manufacturers are nowadays highly affected by the ever-increasing number of product variants, under the product personalization trend. The large number of cooperating manufacturing network partners leads to enormous search spaces of alternative manufacturing network configurations. This obstructs effective decision-making towards configuring efficient network structures, a nonetheless crucial decision for a company. Exact methods guarantee that the identified solution is the optimum, with regards to the objectives set in the specified problem. However, in real life cases the magnitude of the solution space is such that these methods cannot be utilized due to computational constraints. For tackling such NP-hard problems, meta-heuristics can be utilized that provide a trade-off between the quality of solution and the computation time. This research work describes the modeling and solving of a manufacturing network design problem using the meta-heuristic methods of simulated annealing and tabu search. The quality of the results identified by these methods is compared with the results obtained from an intelligent search algorithm and an exhaustive enumerative method, which are implemented into a web-based platform for the design and planning of manufacturing networks. The approach is validated through its application to a real life case study with data acquired from the automotive industry.

**Keywords** Simulated annealing · Tabu search · Manufacturing network design · Decision-making · Metaheuristics

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## 1 Introduction

The introduced number of product variants under the trend of market's personalization needs constitutes the identification of effective and efficient manufacturing network structures an utterly challenging issue. In this personalization environment, manufacturers are called to materialise, customer unique requests [1]. The vast amount of alternative configurations especially for a newly introduced personalized variant requires immediate feedback from the production system and intelligent methods capable to suggest optimal ways of configuring the manufacturing resources [2]. Toward this end, this research work focuses to provide strategic level decision-support for the design of manufacturing networks in order to handle high product variety and demand volatility.

## 2 State of the Art

The increased complexity, the ever-existing competitiveness and the dynamic character in today's manufacturing landscape generates a series of difficulties in supply chain management [3]. Supply chain design, planning and continuous optimization is nevertheless a critical decision for modern enterprises and at the same time a flourishing research area. As most of the optimization problems and predominantly cases under uncertainty will be of large scale, the need for developing efficient and intelligent procedures is evident [4].

Optimization methods have been extensively utilized for the manufacturing network design. One of the most prominent family of techniques are metaheuristics, which use parallel and non-independent solution constructions [5]. Metaheuristics have been applied to the majority of manufacturing network design and planning problems, aiming at multi or single objective optimization [6]. Commonly used metaheuristics include the methods of simulated annealing [7], tabu search [8], cross-entropy [9] as well as nature-inspired methods like genetic algorithms [10], evolution strategies [11] and, more recently, ant colony optimization [12] and particle swarm optimization [13]. Other metaheuristics such as greedy randomized adaptive search procedures (Grasp) [14] and ant colony optimization (ACO) employ repeated probabilistic solution constructions. Moreover, approximate and non-deterministic tree search procedures (ANTS) [15] and probabilistic beam search derivative like Beam-ACO can be found [16].

Tabu Search is among the most effective approaches for solving hard combinatorial optimization problems, with high applicability in discrete search spaces [5]. Tabu search was preferred by Keskin and Ülster (2007) because it offered both high solution quality and computational time advantages [17]. A tabu search with path relinking was proposed in [18], and was used for the identification of the indicative number of parts to be produced. It also proposed the quantity of each

item to be delivered to the customers. Melo et al., proposed a tabu search method for the redesign of a multi-echelon supply network [19]. The study tackled a number of manufacturing network related issues, such as facility relocation scenarios and multi-period design horizons. Tabu search was utilized in a Markov chain bootstrapping procedure, in order to search through the exploding number of alternative scenarios [20].

Moreover, simulated annealing has been extensively applied for the design of manufacturing networks. A simulated annealing methodology that addressed the distribution network design and management problem was proposed in [21]. The study focused on the determination of the optimal set of warehouses and cross-docks to operate while minimizing the cost to operate such open warehouses and cross-docks, costs to transport multiple shipments of products from warehouses to cross-docks and costs to supply products based on customer demands. A simulated annealing approach was proposed to a bi-criteria sequencing problem in two-stage supply chain to coordinate required set-ups between the two successive stages [22]. Mansouri [6] also proposed a bi-criteria simulated annealing approach for a two-stage manufacturing network for the coordination required set-ups between two successive stages of a supply chain in a flow shop pattern. Furthermore, a recent study incorporated environmental objectives into the decision-making procedure for the design and planning of supply chains [23]. Finally, the authors in [24] focused on manufacturing network design for a single-product, single-period problem with constant demand and uncertainty in returns, incorporating also environmental impact factors. A comprehensive comparison among the methods of Tabu Search, Simulated Annealing and Genetic Algorithms is provided by Arostegui et al. [25].

The type of the problem tackled in this paper is a multi-objective decision-making problem that aims at the simultaneous optimization of multiple cost and benefit criteria. The problem is NP-hard [26] and the magnitude of the search space for the specific investigated model is in the order of millions of alternatives. The aim is the timely identification of high quality feasible alternative multi-stage manufacturing networks that support the production and transportation of heavily customized products.

This design of multi-stage manufacturing networks for personalized products problem is tackled using exhaustive, intelligent and metaheuristic techniques. The developed framework includes the following search methods: Exhaustive Search, Intelligent Search Algorithm, Simulated Annealing and Tabu Search. The performance of these methods is calculated in terms of solution quality and computational requirements. The solution quality takes into consideration classical indicators such as cost, lead time and quality, along with parameters of environmental impact and manufacturing network reliability. Finally, the approach is validated through a real life case study utilising data acquired from the automotive industry.

### **3 Manufacturing Network and Personalized Product Models**

The evolution of manufacturing resources and the establishment of Key Enabling Technologies (KETs) has allowed the realization of highly complex products cost-effectively. Moreover, innovative production concepts such as Flexible Manufacturing Systems grant capabilities for producing larger number of different parts using the same machines [27]. Apart from OEMs, who already implement such technologies, their cooperating pool of suppliers and dealers are forced to do the same. They are driven by the needs of maintaining their competitiveness, or they are imposed to reform their production system by the OEM they supply. Therefore, manufacturing tasks, such as assemblies and/or special personalization tasks can be outsourced to suppliers and dealers closer to the final customers [28]. This concept of decentralized manufacturing that has already been implemented in practice, is utilized in the presented research work for modeling the manufacturing networks.

The modeling of the personalized product structure includes a number of commonly shared parts by all variants and a series of customer-personalized components and accessories. The product personalization is carried out by the customer through a web-based three-dimensional configurator. The customer can select an accessory and modify its characteristics, ranging from simple colour and texture modifications up to more elaborate geometrical alteration. The system is checking in real-time the manufacturability of the customer preferences and in case the design is feasible, the order is forward to the production system, which is the starting point of the presented study.

### **4 Methods for the Design of Manufacturing Networks**

The decision-making methods used for the identification of manufacturing network alternatives and their evaluation is performed using the following four methods: Exhaustive Search, Intelligent Search Algorithm, and Simulated Annealing and Tabu Search.

#### ***4.1 Exhaustive Search***

The Exhaustive Search (EXS) is an exact enumerative method [27, 29]. During an EXS, the entire search space of the manufacturing network configuration alternatives is generated and evaluated. Therefore, EXS is capable of identifying the best alternative with respect to the selected criteria, as defined by the design and planning objectives. However, the EXS can be very time-consuming in realistic

cases, due to the enormous size of the search space. In real-life manufacturing cases, when the Total Number of Alternatives (TNA) is in the order of billions, EXS is non-executable in conventional workstations in real time, therefore, it is impractical for manufacturing needs.

## 4.2 Intelligent Search Algorithm

The ISA used for the digital experimentation is described in [29–32]. ISA is an artificial intelligence search method that utilizes three adjustable control parameters. The depth of the search is defined by the Decision Horizon (DH), the breadth of the search by the Selected Number of Alternatives (SNA) and the Sampling Rate (SR) guides the search towards paths of high quality. The algorithm's performance is investigated in [29, 32].

## 4.3 Simulated Annealing

In the Simulated Annealing (SA) method, an initial solution  $S$  is fed to the algorithm.  $S$  is randomly generated obeying the constraints of the manufacturing capabilities of the supply chain partners. This  $S$  is changed following a hill climbing notion. However, the difference with simple hill climbing is that when SA makes the decision on when to replace  $S$  with  $R$ , its newly tweaked offspring. More specifically, if  $R$  is better than  $S$ , SA will always replace  $S$  with  $R$ . But if  $R$  is worse than  $S$ , it may still replace  $S$  with a certain probability  $P(t, R, S)$ :

$$P(t, R, S) = e^{-\frac{UtilityValue(R) - UtilityValue(S)}{t}}, \text{ where } t \geq 0$$

Thus, the algorithm sometimes goes down hills. The fraction in the exponent is negative because  $R$  has a lower utility values than  $S$ . First, if  $R$  is much worse than  $S$ , the fraction is larger, and so the probability is close to 0. If  $R$  is very close to  $S$ , the probability is close to 1. Thus, if  $R$  isn't much worse than  $S$ , SA will still select  $R$  with a reasonable probability. Second, the tuneable parameter  $t$ , if close to 0, the fraction is again a large number, and so the probability is close to 0. If  $t$  is a large number, the probability is close to 1. Initially  $t$  is set to a high number, which causes the algorithm to move to explore new neighborhoods by adopting every newly-created solution regardless of how good it is. Afterwards,  $t$  decreases slowly, eventually becoming 0, at which point the algorithm is doing nothing more than plain hill-climbing. The rate at which  $t$  is decreased is called the algorithm's schedule. The longer  $t$  is stretched out the schedule, the longer the algorithm resembles a random walk and the more exploration it does. The pseudo-code of the SA implemented in this research work is as follows:

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1:  $t \leftarrow$  temperature (initially a high number)
2:  $S \leftarrow$  initially generated candidate solution
3:  $Best \leftarrow S$ 
4: repeat
5:  $R \leftarrow$  Tweak(Copy( $S$ ))
6: if Utility( $R$ ) > Utility( $S$ ) or if a random number chosen in  $[0,$ 
    $1] < e^{\frac{UtilityValue(R) - UtilityValue(S)}{t}}$  then
7:  $S \leftarrow R$ 
8: Decrease  $t$ 
9: if Utility( $S$ ) > Utility( $Best$ ) then
10:  $Best \leftarrow S$ 
11: until  $Best$  is the optimum solution or  $t = 0$  or another termination condition
    is met
12: return  $Best$ 

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#### 4.4 Tabu Search

TS employs a different approach to doing exploration, by exploiting a memory feature. TS stores a history of recently considered candidate solutions (known as the tabu list) and refuses to return to those solutions until they're sufficiently far in the past, i.e. removed from the list of taboos. Thus, if a hill climb is carried out, the algorithm will cause a back down walk on the other side because it is not permitted to stay at or return to the top of the hill. During TS, a tabu list  $L$ , of some maximum length  $l$ , of candidate solutions that have been searched so far is stored. Whenever a new candidate solution is adopted, it goes in the tabu list. If the number of rows of the tabu list exceed  $l$ , the oldest candidate solution is removed and it's no longer taboo to reconsider. The implemented TS algorithm is based on the following pseudo-code:

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1:  $l \leftarrow$  desired maximum tabu list length
2:  $n \leftarrow$  number of tweaks desired to sample the gradient
3:  $S \leftarrow$  initially generated candidate solution
4:  $Best \leftarrow S$ 
5:  $L \leftarrow \{\}$  a tabu list of maximum length  $l$ 
6: Enqueue  $S$  into  $L$ 
7: repeat
8: if Length( $L$ ) >  $l$  then
9: Remove oldest element from  $L$ 
10:  $R \leftarrow$  Tweak(Copy( $S$ ))
11: for  $n - 1$  times do
12:  $W \leftarrow$  Tweak(Copy( $S$ ))
13: if  $W \notin L$  and (UtilityValue( $W$ ) > UtilityValue( $R$ ) or  $R \in L$ ) then
14:  $R \leftarrow W$ 

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15: if  $R \notin L$  and  $\text{Quality}(R) > \text{Quality}(S)$  then
16:  $S \leftarrow R$ 
17: Enqueue  $R$  into  $L$ 
18: if  $\text{UtilityValue}(S) > \text{UtilityValue}(Best)$  then
19:  $Best \leftarrow S$ 
20: until  $Best$  is the optimum solution or another termination condition is met
21: return  $Best$ 

```

#### 4.5 Decision-Making Method

The underlying decision theory is based on five steps: (1) form a set of alternatives according to the selected method (EXS, ISA, SA and TS), (2) determine a set of decision-making criteria, (3) normalise the calculated criteria values, (4) calculate the utility value, and (5) select the best or a good alternative. The alternatives are selected according to their utility value, which is the weighted sum of the normalized criteria values multiplied by their corresponding weight factors. The weight factors are defined according to the specific design and planning objectives.

The normalization of the criteria values is necessary due to the fact that the considered criteria may be conflicting and have different units of measurement. Some of the criteria need to be maximized (quality and reliability) and others need to be minimized (e.g., production cost, lead time, CO<sub>2</sub> emissions, and energy consumption). The normalization of the benefit criteria is performed using Eq. (1) and for the cost criteria using Eq. (2) [29, 33]. The utility value is calculated using Eq. (3) [29, 30].

$$\hat{C}_{ij} = \frac{C_{ij} - C_j^{\min}}{C_j^{\max} - C_j^{\min}} \quad (1)$$

$$\hat{C}_{ij} = \frac{C_j^{\max} - C_{ij}}{C_j^{\max} - C_j^{\min}} \quad (2)$$

$$U_i = \sum_{j=1}^n W_c \hat{C}_{ij} \quad (3)$$

### 5 Mathematical Modeling of the Problem

The problem faced is expressed through the optimization of the following objectives (decision-making criteria). The weighted sum of these criteria is expressed through the utility values which must be maximized in the range [0, 1]:

**Production and Transportation Cost (PTC):** sum of production cost ( $PC$ ) for partner  $i$  to perform task  $k$  and of transportation cost ( $TC$ ) from partner  $i$  to  $j$ , where  $i, j, k \in \mathbb{N}$ ,  $i = 0, 1 \dots I$ ,  $j = 0, 1 \dots J$ ,  $k = 0, 1 \dots K$  [29, 34].

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$$\min PTC = \sum_i^I \sum_k^K PC_{ik} + \sum_i^I \sum_j^J TC_{ij} \quad (\text{€})$$


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**Lead Time (LT):** sum of processing and setup times ( $PT$ ) for partner  $i$  to perform task  $k$  and of transportation time ( $TT$ ) from partner  $i$  to partner  $j$  [34].

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$$\min LT = \sum_i^I \sum_k^K PT_{ik} + \sum_i^I \sum_j^J TT_{ij} \quad (\text{days})$$


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**Energy Consumption (EC):** sum of energy consumption ( $EP$ ) for partner  $i$  to perform task  $k$  and of the transportation energy ( $ET$ ) required from partner  $i$  to partner  $j$  [28, 35].

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$$\min EC = \sum_i^I \sum_k^K EP_{ik} + \sum_i^I \sum_j^J ET_{ij} \quad (\text{Joules})$$


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**CO<sub>2</sub> Emissions (CO):** the CO<sub>2</sub> tonnes for the transportation ( $CE$ ) of parts from partner  $i$  to partner  $j$  [28, 35].

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$$\min CO = \sum_i^I \sum_j^J CE_{ij} \quad (\text{tonnes CO}_2)$$


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**Quality (Q):** the mean quality of the partners of an alternative manufacturing network configuration [27].

$$\max Q = \frac{\sum_i^I QL_i}{I}$$

**Reliability (R):** total reliability, where  $s$  represents serial and  $p$  parallel resources,  $s, p \in \mathbb{N}$ ,  $s = 0, 1 \dots S$ ,  $p = 0, 1 \dots P$  [36].

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$\max R_{stot} = \prod_s^S R_s$	For serial resources
$\max R_{ptot} = 1 - \prod_r^R (1 - R_p)$	For parallel resources

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## 6 Software Tool Implementation

The digital experimentation was executed into a web-based software tool, where the ISA and EXS algorithms are coded using JAVA™, contained in the Apache Tomcat web-server and stored in a MySQL database. The SA and TS engines were



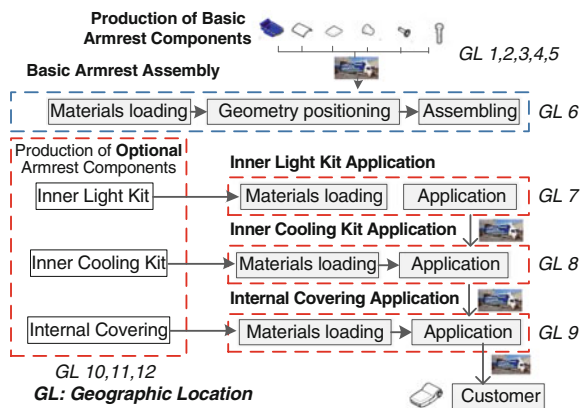
executed in the Matlab<sup>®</sup> environment. Graphical interfaces are shared among the four methods and are used for performing the required data entry (resources, tasks, materials etc.) and adjusting the parameters of the ISA, SA and TS methods. The user is capable to select the preferred decision-making method, execute the experiments and visualise the results, comparisons as well as the selected manufacturing network configurations within a web-browser.

## 7 Industrial Pilot Case

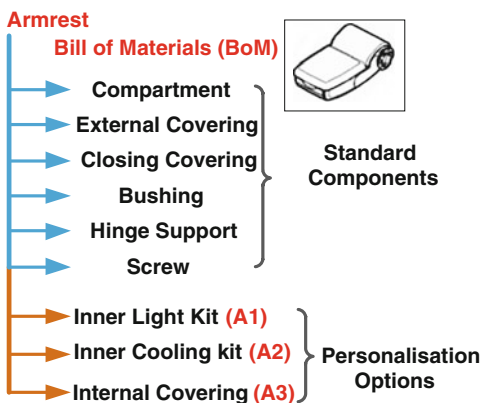
The dataset used in the experiments are obtained from an automotive manufacturer and includes the manufacturing resource characteristics (processing time, setup time, energy consumption, quality etc.), the armrest Bill of Materials (BoM) structure, the Bill of Processes (BoP), and the mapping between these three (Fig. 1).

Moreover, the locations of the production plants are entered to the system, in order for the integrated GoogleMaps<sup>™</sup> API to automatically calculate the distances between them, which are utilized for the accurate calculation of the transportation related impact. The distances are used for the calculation of transportation cost and time, CO<sub>2</sub> emissions and energy consumption. The armrest can be produced in 3 variants upon customer request. The basic non-customized armrest (A1 variant) is comprised by the compartment, the external covering, the closing covering, the bushing, the hinge support and the screw. The other variants are extensions to this A1 and feature the addition of an inner light kit and an inner cooling kit (A2 variant) an internal covering (A3 variant) (Fig. 2). These components can be produced and assembled by a set of suppliers, dealers and OEM plants, at different cost, time, and quality. The final stage of this value-adding chain is the delivery of the customized product to the customer.

**Fig. 1** BoP of the customized armrest



**Fig. 2** BoM of the customized armrest



## 8 Results and Discussion

The digital experiments conducted are: one execution of the EXS and ten executions for each of the ISA, SA, and TS, due to the inherent randomness of these methods. The adjustable parameters of the ISA method were obtained through a Statistical Design of Experiments, and were  $SNA = 1,000$ ,  $DH = 6$ , and  $SR = 20$  [37]. The cooling schedule ( $t$ ) for the SA was 0.99 and the initial temperature was 1. Moreover, the tabu list was a matrix with dimensions maintained at  $[150 \times l]$ , where  $l$  the number of stages in an alternative manufacturing network configuration. Other termination conditions jointly applied in these two algorithms were the maximum number of iterations ( $MI$ ), which was set at 65,000 and the maximum number of accepts ( $MA$ ) for a solution, which was set at 1,500. The  $MA$  for SA represents the number of occurrences for a tweaked solution to replace the parent solution. In the case of TS,  $MA$  counts the times when the newly created solution is not contained in the tabu list and therefore, replaces a current taboo solution. The obtained criteria values of the best alternatives as provided by each of the 4 methods are collectively depicted in Fig. 3.

The EXS values were superior when compared to the other three methods, as expected. More specifically, regarding the values of the cost criterion the alternative configuration obtained by the ISA is 24.05 % worse than the results of the EXS an 28.43 and 12.88 % better than the result of the SA and TS methods respectively. The value of the cost criterion obtained from the TS is 32.71 % higher than the value obtained from the EXS. Furthermore, the same trend is observed for the values of the CO<sub>2</sub> emissions quality and reliability. More specifically, the relative difference for the CO<sub>2</sub> Emission values between the EXS and the other three methods is 29.31 % from ISA, 54.82 % from SA and 46.92 % from TS. Additionally, the relative difference in the quality value of EXS is 0.12, 1.28 and 0.58 % higher than the ISA, SA and TS. Finally, the difference between the EXS and the other three methods for the Reliability criterion is 3.57 % for the ISA, 10.71 % for the SA and 1.19 % for the TS. The lead time as well as the energy

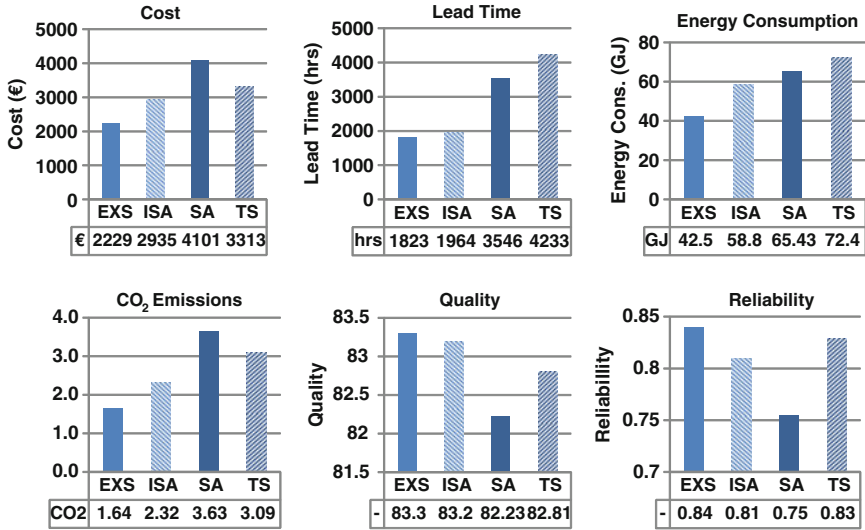


Fig. 3 Criteria values obtained from ESX, ISA, SA and TS methods

consumption values when comparing the SA and TS results however, are in favor of the first.

Moreover, Fig. 4 below includes a comparison of the utility value of the solutions of the four methods and graphically presents the performance of the methods. The figure on the right hand side includes normalized values for the criteria, utility and computation time indicators. Comparing the utility value with the computation time that each method required in order to solve the problem it becomes obvious that ISA, and TS are superior to the EXS and SA. The relative difference of the utility value obtained from the ISA and the EXS is  $-5.4\%$ , however, the computation time required from ISA was calculated at three orders of magnitude less than the respective time required from EXS (Table 1). Furthermore, the difference of the utility value of the EXS and the SA and TS is 20.46 and 14.52 % correspondingly. The difference in the computation times between the methods of ISA, SA and TS is relatively small. Thus, the trade-off between the

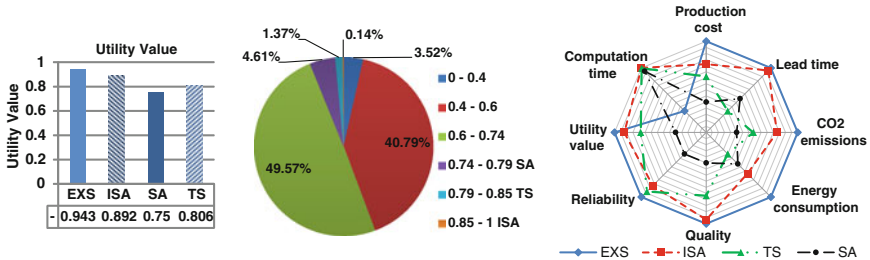


Fig. 4 Utility and criteria values as obtained from the four methods

**Table 1** Criteria values and required computation time for the four methods

Method	Production cost (€)	Lead time (hrs)	CO <sub>2</sub> emis. (tonnes CO <sub>2</sub> )	Energy cons. (GJ)	Quality	Reliability	Computation time (sec)	No. of alternatives
EXS	2229.7	1822.6	1.6396	42.5027	83.3	0.84	1,719	12,266,496
ISA	2935.5	1964.3	2.3168	58.7606	83.2	0.81	1.7	20,000
TS	3313.3	4233.3	3.0879	72.4214	82.8	0.82	12.6	1,626
SA	4101.8	3546.1	3.6308	65.4279	82.2	0.75	131.5	135,419

quality of the solution and the computation time is in favor of these methods as opposed to the EXS computationally intensive procedure. Moreover, the solutions identified by the ISA belonged to the top 0.14 % of the best alternatives of the solution space, the TS results to the 1.41 % and the SA to the top 6.12 %.

## 9 Conclusion and Future Work

The presented research work focused on the design of manufacturing networks that aim on the production of personalized products. The methods of Exhaustive Search, Intelligent Search Algorithm, and Simulated Annealing and Tabu Search were implemented in a software framework and compared based on the results they yielded. The comparison depicted that the solutions identified by the ISA are of high quality when compared to the results obtained by TS and SA, the latter yielding the lower performance of all examined methods. The deviation of the ISA, TS and SA solutions from the best solution acquired by the EXS is nevertheless acceptable taking into consideration the required computation time. Moreover, the exploding solution space of realistic manufacturing cases constitutes the use of EXS non-practical due to the computational resource constraints introduced by the magnitude of the solution space. In realistic manufacturing cases, the TNA may be calculated in the order of billions. Thus, a timely and efficient solution can only be then obtained through the utilization of the intelligent search techniques such as the ISA and other well-established metaheuristics, among which the SA and TS presented above. As a result, depending on the design and planning objectives, a trade-off between the time for obtaining the solution and its quality is necessary. Concluding, in case an objective function  $n = f(\text{utility value}, \text{computation time})$  was to be calculated, this trade-off will become apparent, as the EXS will yield results of lower  $n$  values as opposed to intelligent methods [38].

Future work will focus on enhancing the capabilities of the TS and SA methods. For TS, a novel memory feature will be introduced, supported by a knowledge-based repository. A set of rules will effectively aid the exclusion of already visited neighborhoods, enabling the exploration of larger search spaces. For SA, an

intelligent procedure will be devised for iteratively adjusting the cooling schedule, in order for the algorithm to decide when to focus on exploring the solution space and when to focus on the exploitation of discovered regions of high quality. Moreover, the developed TS and SA methods will be coded into a web-based design and planning software platform as components, under the Software as a service (SaaS) pattern. Finally, the wide applicability of the proposed framework will be depicted through its application in other industrial sectors, such as the CNC and robot building industries.

**Acknowledgments** The work reported in this paper has been partially supported by the EC-funded project “e-CUSTOM—A web-based collaboration system for mass customization” (260067).

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