MULTI-OBJECTIVE OPTIMIZATION IN THE CONSTRUCTION INDUSTRY

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ABSTRACT

Multi-objective-optimization-based positioning of houses in a residential neighborhood is described. The task is the placement of the buildings in a favorable configuration constrained by two objectives, which are *garden performance* and *visual privacy performance* requirements. The method used is evolutionary computation with the Pareto front based on a weighted function of the objectives. It is found that greedy non-dominated solution search is inferior to the relaxed counterpart. The analysis of the Pareto-front formation is described in detail and satisfactory operation of the algorithm is presented.

Keywords: Evolutionary algorithms, multi-objective optimization, Pareto optimal frontier, performance-based design

INTRODUCTION

Optimization is an important concept in science and engineering. The construction industry is one of the prominent areas benefiting from it for efficient and effective execution of projects, for instance. Optimization is applied in the design and scheduling of HVAC systems [1, 2], the design of structural systems and components [3-6], building layout [7-9], acoustic design[10], and the design of construction site layout [11]. With respect to HVAC systems optimization usually concerns the minimization of energy use. In structural design optimization usually concerns simultaneous minimization of material and construction cost and maximization of stability, stiffness and strength. With respect to building layout, optimization usually concerns maximization of accessibility and reachability as well as satisfaction of perceptual requirements, such as visual openness and privacy. Simultaneously compactness of the shape of a building's perimeter may be subject to maximization due to energy loss considerations. In acoustic design optimization usually concerns minimization of reverb time. In the layout of construction sites reachability is generally subject to maximization. Although optimization is a traditionally well-known concept, in many instances it is treated in single objective form, where the objective is known to be 'the cost function'. As an extension of this is the optimization where one or more constraints are simultaneously satisfied next to the minimization of the cost function. In the construction industry the essential concern is to reach optimality with a number of objective functions, in place of only minimizing a cost function. In the former case the functions involved are simultaneously minimized (or maximized) [12, 13]. The accomplishment of this task is due to the methodology known as multi-objective optimization (MO) [14]. The MO is gaining gravity especially in the last decade due to the increasing technological demand of optimization in many diverse areas. For instance in building design the building costs and the energy consumption of a building during its lifecycles are subject to minimization simultaneously [15]. With respect to the construction industry, there are many instances where multi-objectivity is an important computational aid for effective project executions. This is easily understood considering that in building design many criteria are conflicting and subject to optimal satisfaction, such as cost, functionality, aesthetic appeal, and sustainability.

The present research demonstrates the importance of multi-objective optimization in the construction industry. For this it briefly explains Pareto optimality, which is a well established concept but not commonly known in the building industry. It describes a new method carried out for the improvement of the Pareto based multi-objective optimality. As an emerging area of computation of the modern era, MO algorithms are being increasingly investigated for solving MO problems. The MO problem can be challenging due to the high dimensionality of the objectives. To deal with this complexity, evolutionary algorithms are outstandingly convenient [14, 16]. Some important features of the latest generation multi-objective evolutionary algorithms (MOEAs) address the selection of the potential solutions during the optimization process, and diversity-preserving strategies in objective space. MO problems of low dimensionality are successfully treated with traditional optimization methods. However, considering the complexity of the engineering and construction projects in the building industry, evolutionary optimization becomes important. In this respect MOEAs can play an important role in the higher-dimensional optimization tasks involving material, perception aspects, time, etc. The research aims to exemplify the utilization of the MOEA method taking an example from the design of a residential neighborhood and demonstrates the design alternatives within the Pareto concept where visual human perception [17] is central in the objectives and ensuing alternatives.

MULTI-OBJECTIVE OPTIMIZATION

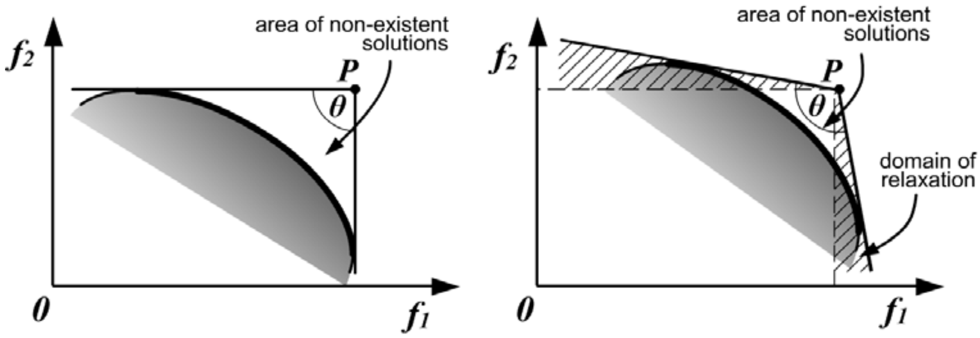
Multi-objective optimization deals with optimization where several objectives are involved. For a single objective case there are traditionally many algorithms in continuous search space, where gradient-based algorithms are most suitable in many instances. In discrete search spaces, in the last decade evolutionary algorithms are ubiquitously used for optimization, where genetic algorithms (GA) are predominantly applied. However, in many real engineering or design problems, more than two objectives need to be optimized simultaneously. To deal with multi-objectivity it is not difficult to realize that evolutionary algorithms are effective in defining the search direction. Basically, in a multi-objective case the search direction is not one but may be many, so that during the search a single preferred direction cannot be identified. In this case a population of candidate solutions can easily hint about the desired directions of the search and let the candidate solutions be more probable for the ultimate goal. Next to the principles of GA optimization, in MO algorithms, in many cases the use of Pareto ranking is a fundamental selection method. Its affectivity is clearly demonstrated for a moderate number of objectives, which are subject to optimization simultaneously [18]. Pareto ranking refers to a solution surface in a multidimensional solution space formed by multiple criteria representing the objectives. On this surface, the solutions are diverse but they are assumed to be equivalently valid in Pareto sense. Selection of one of the solutions among those many is based on some higher order preferences, which require more insight into the problem at hand. This is necessary in order to make more refined decisions before selecting any solution represented along the Pareto surface.

In this work, the formation of the Pareto front is based on a weighted function of the objectives which are of the form [19]

$$F_i(\boldsymbol{x}) = f_i(\boldsymbol{x}) + \sum_{j=1, j\neq i} a_{ij} f_j(\boldsymbol{x}), i = 1,2,..., N \ (objectives) \quad (1)$$

where a_{ij} is the amount of gain in the j-th objective function for a loss of one unit in the i-th objective function. The above set of equations require fixing the matrix $\boldsymbol{a}$, which has a one in its diagonal elements. For the Pareto front we assume that, a solution $\boldsymbol{x}_1$ dominates another solution $\boldsymbol{x}_2$ if $F(\boldsymbol{x}_1)\geq F(\boldsymbol{x}_2)$ for all objectives, and a contingent equality is not valid for at least one objective.

Figure 1 shows the contour lines corresponding to two linear functions for a two-objective MO case. In the case the contour lines are horizontal and vertical a_{ij} becomes zero and $F(\boldsymbol{x})=f(\boldsymbol{x})$. Please note that the modification of the contour lines departing from horizontal and vertical ones defines a modified solution space, which includes the domains of relaxation shown in the figure as hatched areas. For this modified solution space the area of non-existent solutions in the convex hull is diminished at the expense of deviating from the strict non-dominated solution condition as shown in figure 1.



(a) (b)

Figure 1 Contour lines defining the dominated region with respect to the point P: greedy dominance (a); relaxed dominance (b)

From the figure it should be noted that in case the strict non-domination condition is relaxed the area of non-existent solutions is smaller compared to the case of greedy search. However, this might be compensated during the Pareto front formation through the algorithm itself by moving the Pareto surface forward and making the front larger at the final stage of the search. This is demonstrated in the next section. Although the Pareto front concept is well defined, the formation of this front is dependent on the implementation of the MO algorithm and also the nature of application. Especially, for the greedy application of the MO algorithm, one uses the orthogonal contour lines as shown in figure 1a, so that many potential favourable solutions are prematurely excluded from the search process. To avoid this, a relaxed dominance concept should be implemented as shown in figure 1b where the angle θ can be considered as the *angle of tolerance*. The wider the angle beyond $\pi/2$ the more tolerant the search process is.

IMPLEMENTATION

Fuzzy neural tree as fitness function

In the following implementation being presented we aim to compare the sensitivity of the Pareto optimal front on a greedy vs. a relaxed Pareto ranking. For this purpose we implement genetic algorithm for the Pareto-optimal design of a housing neighbourhood. This is an existing lot for residences, which belongs to one of the largest areas in the Netherlands subject to development, named Leidsche Rijn. The design task is the identification of optimal locations of a number of housing units on their respective plots. Figure 2 shows 20 houses. 17 of them are subject to optimal positioning, since 3 of them, namely houses *E1*, *E2*, and *E*3, already exist on the site.

Figure 2 The buildings subject to optimal positioning; the buildings *E1*, *E2*, and *E3* are existing buildings that are not subject to positioning

The optimality is based only on the perceptual considerations pertinent to each individual house unit aiming to arrive at a compromise among various conflicting performance scores of all units. Namely, it concerns two main perceptual variables in objective space, namely the performance of the garden in south direction of each house and the *visual privacy* experienced for the south façade of a house. These aspects form the *design performance* in this design implementation. The relations among the design performance, its sub-aspects and their respective relevant design parameters are complex. Therefore it is formidably difficult to specify accurately the relative importance of individual requirements in an ad-hoc manner. To treat this issue we employ a special knowledge model in this work. The model is a *fuzzy neural tree* [20]. It is able to handle both the complexity of the relations among design aspects as well as imprecision involved in the assessment of requirement satisfaction. The essential methodologies that are responsible for these properties are neural tree structure and embedded fuzzy logic processing. The former treats the complexity of the relations, while the latter takes care of the imprecision of the information subject to processing. This combination yields a knowledge model that is able to evaluate different designs with rationale. The model employed in the present design implementation is shown in figure 3. The model output is labelled as node 6 and it represents the design performance. The inputs of the tree are shown as arrows pointing to square shaped nodes that are termed *leaf nodes* in the terminology of neural tree. In the leaf nodes the requirement satisfaction is computed concerning the *garden* and *visual privacy performance* for each house in the neighbourhood.

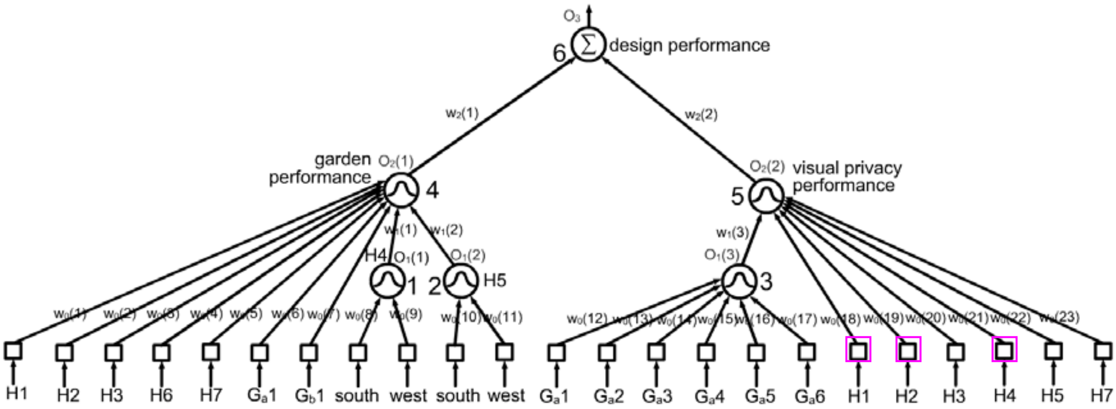


Figure 3 Neural tree structure for assessment of design performance

This means the relevant properties of a particular housing design, e.g. the size of the garden, is mapped to values between zero and one, reflecting satisfaction of an elemental design requirement. As the model used is entirely knowledge driven this mapping is accomplished by means of fuzzy membership functions provided by the designer, and it is referred to as *fuzzification* in the terminology of fuzzy logic. An example of the membership functions used is shown in figure 4. This function quantifies the satisfaction of the visual privacy requirements for the houses H1, H2, and H4 as marked in figure 3. In this example visual privacy is required to be value 6 or greater as an ideal situation. Then the leaf node output is unity. If the privacy is less than 6 the output of the respective leaf node is less than 1 as specified by the membership function.

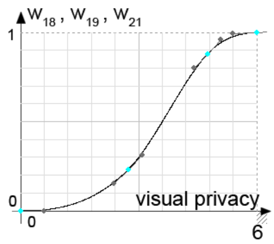
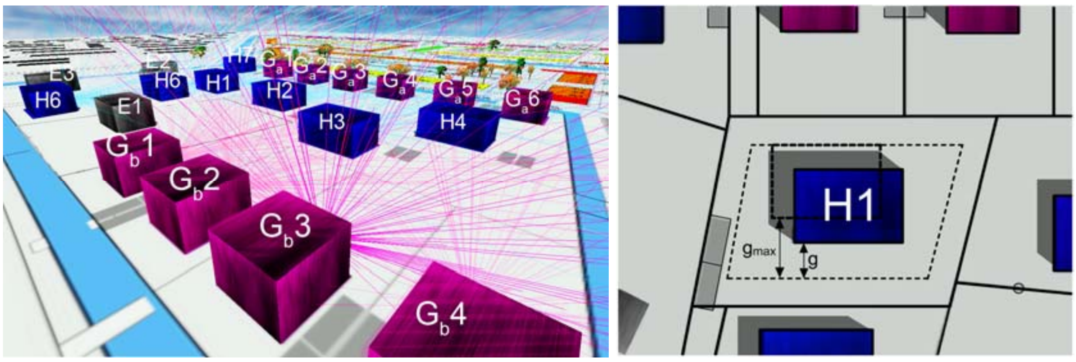


Figure 4 Membership functions at the terminal nodes.

The visual privacy is computed using a probabilistic perception model [17]. This is illustrated in figure 5. Visual privacy of a façade is considered the reciprocal of the sum of attention “impinging” on the facade. In other words it quantifies how low (or high) the degree of perception of a façade is. The garden performance belonging to a house is calculated by dividing the extent of a garden in south direction by the maximum extent the garden can have considering the boundary of the house’s plot. The garden extent is denoted g, and the maximum extent g_{max} in figure 5b. This is shown in figure 5b. The garden performance of a house is given by g/g_{max}.

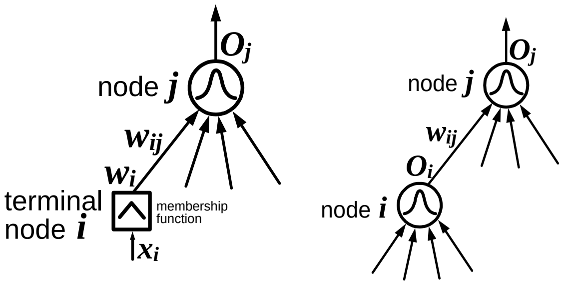
In the fuzzy neural tree the designer specifies the relative importance of aspects in the form of weights denoted by w_i in figure 3. During evaluation of a design alternative the tree is *stimulated* at its leaf nodes involving the fuzzification process described above. The resulting information is then processed by the nodes labelled 1, 2, 3, 4, and

5 in this figure. These nodes perform fuzzy logic AND operations using Gaussian membership functions, finally yielding the design performance at the output of the model. The detailed structure of node connections is shown in figure 6.



(a) (b)

Figure 5 Illustration of the computation of visual privacy based on a probabilistic model of human visual perception (a); Calculation of the garden performance g/g_{max} (b)



(a) (b)

Figure 6 The detailed structure of a neural tree with respect to different type of node connections: leaf node to inner node (a); inner node to inner node (b)

The fuzzy logic computations at node j shown in figure 6b is given by [21]

$$O_j = \exp\left(-\frac{1}{2}\sum_i^n \left[\frac{w_{ij}(O_i - 1)}{\sigma_j}\right]^2\right) \tag{2}$$

where O_i denotes the output of node i; w_{ij} is the connection weight between node i and node j; and σ_j Please note that the logic operators are tuned in a particular way, so that the model behaves consistently in logical reasoning sense. This tuning refers the adjustment of the widths of the Gaussians at the inner nodes. It is accomplished by a training algorithm [20]. After training the model provides conclusions about design performance with a rationale, consistent with the expert knowledge embedded in the model. Next to the evaluation of the design performance, due to the fuzzy logic operations at the inner nodes of the tree, the performance of any sub-aspect is obtained as well. This is a desirable feature in design, which is referred to as *transparency*. Having established the performance evaluation model it is used in an evolutionary search process aiming to identify designs with maximal design performance. In our case *garden performance* and *visual privacy performance* are to be maximized simultaneously, and we are interested in a variety of alternative solutions that are equal in Pareto sense. The design is therefore treated as a multi-objective optimization as opposed to a non-constrained optimization, where exclusively the design performance would be subject to maximization. In the multi-objective implementation the outputs of the nodes 4 and 5 of the neural tree are subject to maximization. Their values are used in the fitness determination procedure of the genetic algorithm. Employing the fuzzy neural tree in this way the genetic search is equipped with human-like reasoning capabilities during the search.

Analysis of the Pareto front

The results obtained from the optimality search based on Pareto-front are shown in figure 7, where the Pareto fronts are clearly seen.

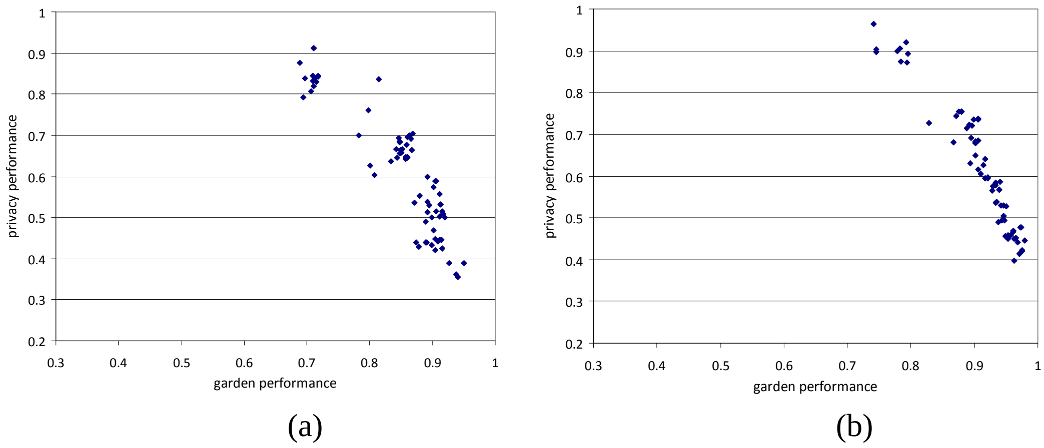


Figure 7 Garden and privacy performance of the solutions after 15 generations; angle of tolerance θ=90° (a); θ=150° (b)

In figure 7a the solutions are more scattered compared to those in figure 7b due to greedy dominance of the search process. Figures 7a and 7b are combined and shown in figure 8 for comparison.

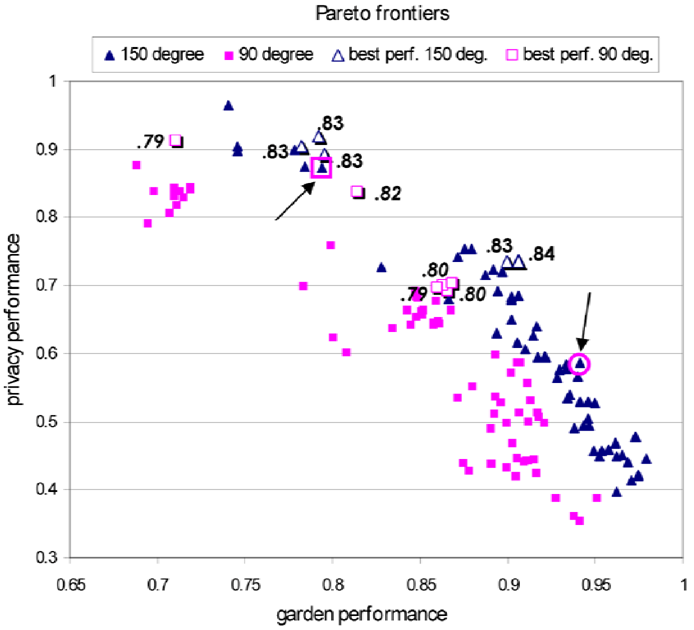
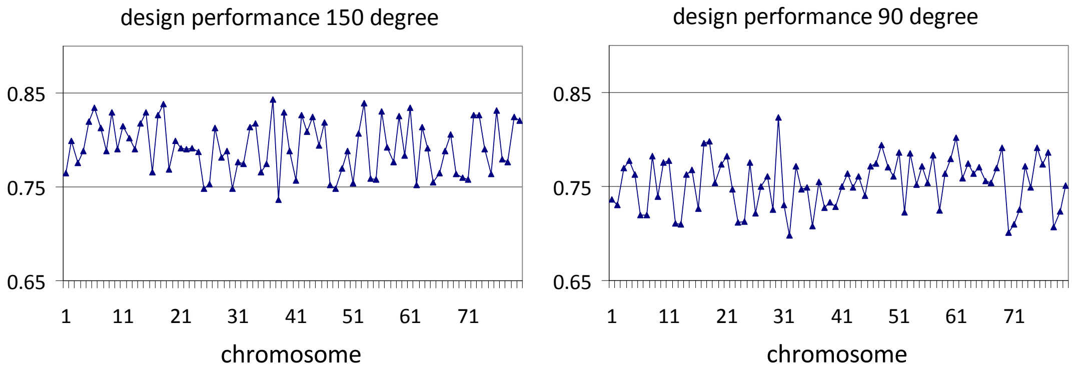


Figure 8 Comparison of the Pareto optimal frontiers for the angle of tolerance θ=90° vs. θ=150° after 15 generations.

From figure 8 we clearly see the different Pareto fronts for different values of θ. For the angle of tolerance $\theta=150^o$ the Pareto front is more at the front compared to $\theta=90^o$. In figure 8 some design performance scores belonging to respective design solutions are shown. Performance score is defined in this work as the weighted summation of the garden and privacy performance as shown in figure 3 and named as design performance. This means the score is the output value at the root node of the tree shown in figure 3. The scores of the total number of solutions are separately shown in figures 9a and 9b. It is observed that the scores fluctuate in a relatively narrow domain, so that the solutions along the Pareto surfaces are all approximately equally valid providing flexibility in the design.



(a) (b)

Figure 9 The design performance values of the different chromosomes for angle of tolerance θ=150° (a) vs. θ=90° (b)

Two resulting Pareto-optimal designs are shown in figure 10. The designs belong to different regions on the Pareto front. In figure 8 the solution indicated by a circle pointed at by an arrow corresponds to figure 10a and the one indicated by a square pointed at by an arrow belongs to figure 10b.

(a) (b)

Figure 10 Two Pareto-optimal designs found by the genetic algorithm; (a) corresponds to the solution marked by a circle in figure 8; (b) corresponds to the solution marked by a box in figure 8

Although, the design described above might be seen as reductionistic in nature, i.e. using two design parameters, namely *garden performance* and *visual privacy performance*. These are two major determinants of the design. Therefore the analysis of the design performance in terms of these parameters is highly significant. Moreover, in such an analysis there are a number of influential design issues in the lower level(s) and the input layer of the neural tree seen in figure 3. Identifying the final design in the light of influential design issues already has important merits, because of their due integration into the design process. Being commensurate with the complexity which might be afforded in the design, there can be more design determinants in the upper layer of the tree, whose weighted composition determines the design performance, such as accessibility. One should also note that the tree model of the performance is context depended, and therefore for each independent aspect of a design a new tree can be formed, so that complexity is distributed among several tree models. In the present demonstrative design exercise the context is restricted to the perception aspects, while the rationales in the design can be traced with careful observation of the results and some deliberation. It should be noted that in the design process exemplified above the design determinants are rather soft and they need special methods and techniques to be dealt with, in particular *soft computing* for that matter.

From the building construction viewpoint, the design method is highly significant for two major reasons. Firstly, design performance in a particular context is a major concern in construction since eventually the building is meant to have a high performance. The design performance should be analysed in different perspectives and eventually each perspective should give a contribution to the final outcome. Secondly, the neural tree approach applied to design can also be applied to various decision-making issues on constructions. Knowledge management can be one of such application examples. In this case the neural-tree concept remains the same and only the quantities involved at the inputs and the nodes take different aspects of concern. Therefore, fuzzy neural-tree should be seen as a generic concept with its *associated paradigm* which is, among others, *design performance* as described in this research.

CONCLUSION

Multi-objective-optimization-based positioning of houses in a residential neighborhood is described. The method used is evolutionary computation with the Pareto front based on a weighted function of the objectives. As result of this method the analysis revealed that greedy non-dominated solution search is inferior to the relaxed counterpart. This means the relaxation of the strict non-dominated domain search favours for the potential solutions, so that they are not prematurely excluded in the search process. Also the Pareto front is moved forward, i.e. more favourable position towards the non-dominated regions. The fitness function in the genetic search makes use of a neural tree for the computation of the objectives. The computations are based on fuzzy logical AND operations by means of Gaussians at the neural tree nodes providing rationale for the design. Combining multi-objective optimization with neural tree together with relaxed dominance makes the research a unique implementation with intelligent computational features yielding enhanced design.

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