Uncertainty based Evolutionary Optimisation

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ABSTRACT
This paper presents a robust evolutionary optimisation approach for real life design problems characterised by uncertainty. The proposed approach handles uncertainty in the design space, as well as in the objective functions and constrains, thanks to a new Pareto dominance criterion based on the neighbourhood around a solution. The approach is applied on a gearbox design optimisation problem as a case study. A comparison between two approaches, robust Pareto dominance criterion and a preference based penalty function, for deal with noisy environment is done for highlight the strength of the robust Pareto dominance criterion.

Categories and Subject Descriptors
G 1.6 [**Optimization**]: Constrained Optimization

General Terms
Algorithms, Design, Reliability, Experimentation

Keywords
Uncertainty, gearbox optimisation, applied multi-objective optimisation, robust optimisation, constraints handling.

1. INTRODUCTION
Real life optimisation of a complex assembly like a gearbox is always a challenge for designers due to presence of time consuming evaluation, expensive tests and uncertainty, that can be found either in objective functions, constraints and input variables. Genetic algorithm is an evolutionary computing method for solving multi objective problem, we may find in literature [1][2][3][4] some techniques for address the problem of uncertainty.

2. ROBUST DOMINANCE CRITERTION
This approach for the constraints handling in an uncertain environment is based upon the dominance criterion presented by Trautmann et al. [2], the and approach for dealing with uncertain constraints presented by Roy [1] and uses the information about the feasibility of an individual and the type of violation within the neighbourhood [1] for the ranking process of the individuals. The proposed sorting process can be schematised as follows in Figure 1 and Figure 2:

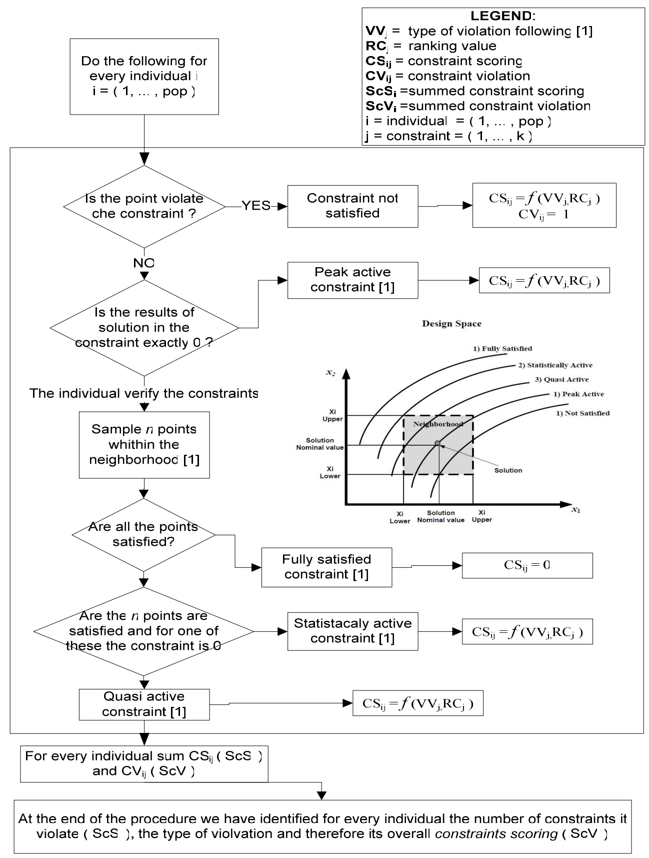

Figure 1 Evaluation of Constraint Scoring and Constraint Violation

2. RESULTS
Following the studies of [6][7][8] our aim is the optimisation of a speed reducer. In this section we present three different scenarios to highlight that, since uncertainty is introduced in the model, the results changes and the population converge towards a different Pareto front composed of more robust solutions [5]. If we implement the uncertainty just in the objective functions (Figure 3 crosses) the algorithm finds harder to converge close to the true Pareto front (squares), due to the spread of the possible results and because it hardly finds the non dominated set among the population. With the uncertainty in all the model and the new dominance criterion the results are better than before, with the proposed preference based dominance criterion the algorithm is able to converge towards a Pareto robust set of solution.

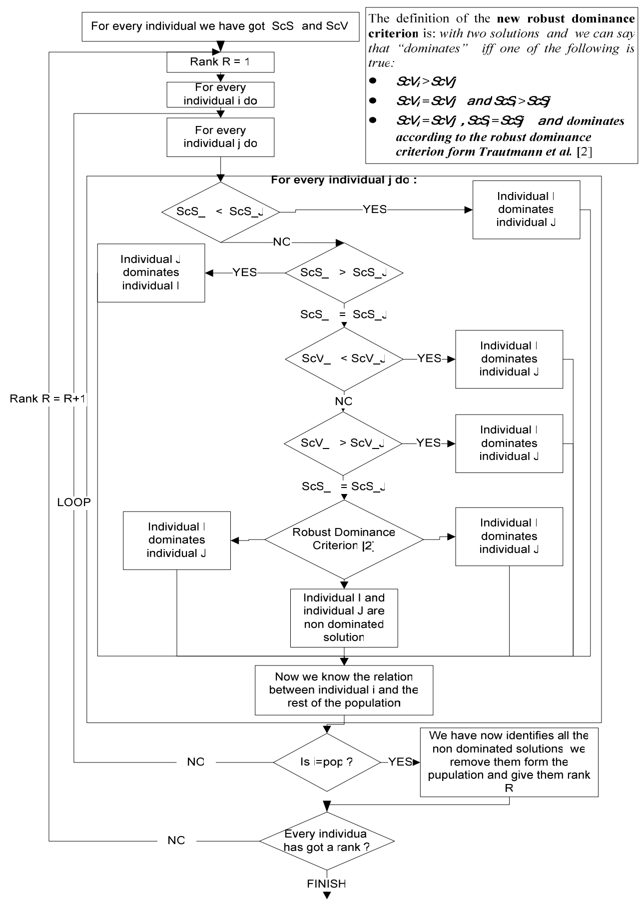

Figure 2 Robust dominance process

2.1 Different levels of uncertainty

In this section we have increased the uncertainty spread around every solution, both on the objective functions, constraints and design variables. As we can see from Figure 3 with the increase of the uncertainty the algorithm is still able to converge. However the solutions require a larger volume for the gearbox and a greater stress on the shaft, this is not because the algorithm did not find the previous non dominated set but because now the robust solutions lie on a different Pareto front due to the increased spread of their objective sensitivity region [5].

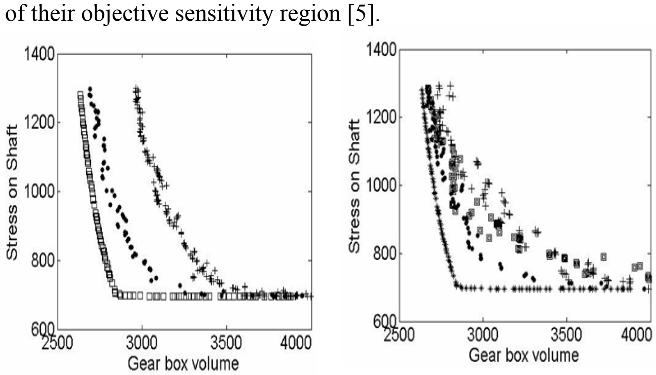

Figure 3: a) Different techniques: uncertainty in the entire model (dots) , no uncertainty (squares) and in just the objective space (crosses); b) Solution space with different level of uncertainty: dots σ = 5%, squares σ = 7.5%, crosses σ = 10%, stars NSGA II with σ = 0%

2.2 Dominance criterion and penalty function

In order to also consider different approaches to the problem, we have developed another algorithm that uses a penalty function instead of the proposed dominance criterion. Like the preference based dominance criterion also this penalty function allows the user to give the constraints a ranking value following his needs.

$$penalty_j = \alpha \times (1 + n\_con \times \beta) \times (gen)^{\gamma} \times violation$$

$$violation = \sum_{i=1}^{n} sample \times pen_j$$

Where α, β and γ are fixed parameters, gen is the number of the actual generation, sample is a value depending on the number of constraints violations hit by the sampled point around the neighbourhood. However as we see from Figure 4 the results that we get with dominance criterion are closer to the true Pareto Front in comparison with the preference based penalty function.

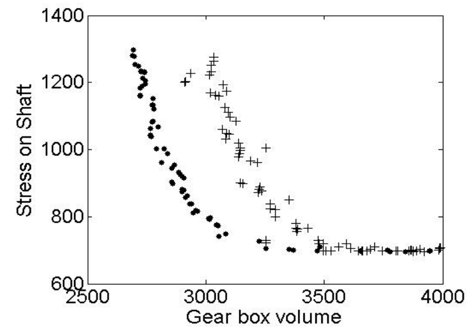

Figure 4 penalty function (crosses) and dominance approach (dots)

3. CONCLUSION

Design optimisation under uncertainty and noise represent one of the greatest challenges for engineers due to a lack of information, it is also one of the most common issues in a real life optimization. This paper presents an approach to represent the uncertainties within the design variables, objective functions and constraints. The evolutionary optimisation uses a novel dominance criterion to implement a concept of robust design solutions where the constraints violation is assessed within the neighbourhood of a design solution. It is observed that the dominance criterion based approach identified better design solutions in a gearbox case study than a penalty function based approach.

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