Multi-objective optimization of material model parameters of an adhesive layer by using SPEA2

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1. Abstract

The usage of multi material structures in industry, especially in the automotive industry are increasing. To overcome the difficulties in joining these structures, adhesives have several benefits over traditional joining methods. Therefore, accurate simulations of the entire process of fracture including the adhesive layer is crucial. In this paper, material parameters of a previously developed meso mechanical finite element (FE) model of a thin adhesive layer are optimized using the Strength Pareto Evolutionary Algorithm (SPEA2). Objective functions are defined as the error between experimental data and simulation data. The experimental data is provided by previously performed experiments where an adhesive layer was loaded in monotonically increasing peel and shear. Two objective functions are dependent on 9 model parameters (decision variables) in total and are evaluated by running two FE simulations, one is loading the adhesive layer in peel and the other in shear. The original study converted the two objective functions into one function that resulted in one optimal solution. In this study, however, a Pareto front is obtained by employing the SPEA2 algorithm. Thus, more insight into the material model, objective functions, optimal solutions and decision space is acquired using the Pareto front. We compare the results and show good agreement with the experimental data.

2. Keywords: Multi-objective optimization, parameter identification, micro mechanical model, adhesive, CZM

3. Introduction

Nowadays, adhesive joints are broadly used in industry due to providing galvanic insulation, vibration damping, and sealing capacity. In case adhesive joints are utilized to carry loads, finite element methods and constitutive laws are required to be developed in order to facilitate simulations in the product development process. The accuracy of the constitutive material model is highly dependent on the proper material parameters. Emphasis has to be put on accurately identifying these material parameters. Determination of material parameters have been done previously using inverse methods. Mahneken [1] introduces a unified strategy for identifying material parameters, by coupling a gradient based optimization algorithm with a FEM framework for inelastic material models. The constitutive model parameters of a thin walled tube in axial crushing were identified by Markiewicz [2]. Two identified parameters were optimized by using the BFGS algorithm. Traditionally only one objective, one load case, has been studied in literature. However, depending on the nature of the problem several load cases (ex. tensile and shear) might occur simultaneously. Optimizing parameters with consideration to only one load case, despite more cases being required, will result in an inaccurate numerical model. Accordingly, more than one objective is needed to be optimized, consequently it will require more experiments and simulations [3, 4]. Aguir et al. studied the behavior of an elasto-plastic material in a sheet metal forming process. They identified the material parameters of stainless steel based on shear and bulge experiments. The error between the experimental results and the FEM simulations were minimized by using surrogate base multi-objective optimization [4].

In optimization problems with more than one objective, one extreme solution would not satisfy both objective functions and the optimal solution of one objective will not necessarily be the best solution for the other objective(s). Thus, different solutions will produce a trade-off between different objectives and a set of solutions is required to represent the optimal solutions for all objectives. The characteristic of evolutionary methods which use a population of solutions that evolve in each generation is well suited for multi-objective optimization problems.

There are a number of significant studies comparing different MOEAs [5, 6, 7, 8, 9, 10, 11]. The most representative, discussed and compared evolutionary algorithms are Non-dominated Sorting GA (NSGA-II) [12], strength Pareto evolutionary algorithm (SPEA, SPEA2) [5, 13], Pareto archived evolution strategy (PAES)[14, 8], and Pareto enveloped based selection algorithm (PESA, PESA II) [15, 16]. Extensive comparison studies and numerical simulation on various test problems concludes to a better overall behavior of NSGA-II and SPEA2 compared to other algorithms.

Table 1: Parameter settings for the SPEA2 algorithm.

Init. pop.	Arch. pop.	Cross over prob.	Mutation prob.	SBX distr. index	Mutation distr. index
40	40	0.8	0.2	10	10

In this work, material parameters of an adhesive layer based on the previous work by Salomonsson and Andersson [17] are optimized by using SPEA2. The strength Pareto evolutionary algorithm has been applied on real world engineering applications previously [18]. The two objectives are defined as the error between the experiments and finite element simulations, to identify the optimal value of the material parameters. In the next section the material model and the original study are briefly introduced. The optimization process is outlined in section 5. Whereas section 6 presents the results and section 7 is devoted to the conclusions.

4. Problem definition

In adhesive material models, two deformation modes dominate; 1) peel deformation, and 2) shear deformation [19]. In research literature, a number of experimental methods have been developed to measure the stress elongation relations. An alternative approach is to develop a constitutive law for the adhesive layer, also referred as the cohesive zone model, that couples the peel and shear stresses in an integrated manner. Salomonsson and Andersson [17] developed a meso mechanical model in order to compare with experimental data [20, 21]. A representative volume element (RVE) of the adhesive layer was designed and the parameters for the interface elements in the FE-model were determined by calibrating the simulated peel and shear stress-elongation curves to the experimental curves.

The proposed model by Salomonsson and Andersson can to a sufficient extent simulate the stress-elongation relation in peel and shear. The study defined two objective functions as the fitness of the peel and shear simulations. They transformed the two objectives into one by using the product of the two. There is no prior knowledge about the objectives, whether they are conflicting or non-conflicting. In case of conflicting objectives, a set of Pareto optimal solutions would be needed while in non-conflicting objectives the optimization would result in one optimal solution. Therefore, their provided solution might have been one of the optimal solutions. The aim of this paper is to analyze the problem using a true multi-objective optimization method and generate a number of Pareto optimal points. Comparing the results of this paper and the previous research performed by Salomonsson and Andersson, either confirms global optimality of their solution or shows that there exist a set of trade-off solutions.

5. Procedure

The same mesomechanical model created by Salomonsson and Andersson [17] is used in this project. The model consists of a representative volume element (RVE) of an adhesive layer. The thickness of RVE is the same as the thickness of adhesive layer in the experiment which was 0.2 mm. Based on studies and preliminary simulations, the length of 0.8 mm for the RVE is chosen to be enough to capture the fracture process. A set of 9 parameters is chosen as the variables to be calibrated by the optimization study. The parameters with superscript I are related to the polymer blend and for the minerals the parameters are identified by superscript II. The set of nine variables are:

$$\kappa = [\sigma_Y^I, \lambda_2^I, \sigma_0^I, \delta_{nc}^I, \delta_{tc}^I, \lambda_2^{II}, \sigma_0^{II}, \delta_{nc}^{II}, \delta_{tc}^{II}] \quad (1)$$

See [17] for a detailed explanation.

The Young's modulus for the polymer blend is set to $E^I = 2\,\text{GPa}$ and the hardening modulus is $H^I = 200\,\text{MPa}$. Poisson's ratio for the polymer is set to $\nu^I = 0.35$. The Young's modulus and Poisson's ratio for mineral grains are set to $E^{II} = 70\,\text{GPa}$ and $\nu^{II} = 0.35$ and is considered elastic. The aforementioned parameters are fixed during all simulations. The two objective functions are defined by using FE simulations and the results from experiments. In this report, the case in pure peel load is denoted as MOD1 and the shear load is denoted as MOD2. The MOOP is defined by minimizing the two objectives.

The strength Pareto evolutionary algorithm (SPEA2) [13] is used to solve this optimization problem. Simulated binary crossover (SBX) and polynomial mutation are the operators employed in the SPEA2 algorithm. The parameter setting for the algorithm and the genetic operators are based on the recommendations in the literature and the author's experience which are presented in table 1.

The lower and upper limit for the all 9 variables are defined by Salomonsson, one of the authors of the original paper. The variables and their bounds are shown in table 2. The 40 initial sampling points known as design of experiment (DoE) are generated by using the Latin hypercube sampling method. The iterative Latin hypercube sampling method using maximin (maximize minimum distance between the point) with 20 iterations is the specific

Table 2: The upper and lower limits of the variables and the optimal solutions in the original study.

	σ_Y^I(MPa)	$\lambda_2^I(-)$	σ_0^I(MPa)	$\delta_{nc}^I(\mu\text{m})$	$\delta_{tc}^I(\mu\text{m})$	$\lambda_2^{II}(-)$	σ_0^{II}(MPa)	$\delta_{nc}^{II}(\mu\text{m})$	$\delta_{tc}^{II}(\mu\text{m})$
Range	[45, 55]	[0.1, 0.8]	[20, 25]	[45, 80]	[20, 60]	[0.1, 0.8]	[9, 11]	[10, 60]	[30, 100]
Optimal	50	0.31	23	53	38	0.39	10	21	49

method employed in this study. In order to reduce the convergence time and create better comparable results, one of the initial DoEs is replaced by the optimal solution obtained in the original study, listed in table 2.

The objective function for peel and shear are defined as the L_2-norm of the error between the experimental data and the simulation data.

$$f := \frac{1}{n}\gamma\|ED - SD\| \tag{2}$$

where ED and SD denote the experimental stress data and the simulated stress data and n denotes the number of simulation points. The objectives are penalized by γ in order to capture the crucial parts of the curves. This would also improve the accuracy of the comparison between the two curves.

In the simulation of the shear load case (MOD2) it is cumbersome to catch the descending part of the curve. The elements in the FE model become distorted and the analysis fails because of large deformation in some parts of the RVE when a large crack coalesce. Thus, in the simulation of the second objective only the stress values within the range of 0 to 70 μm of elongations are considered.

Each FE simulation of MOD1 varies between 30 min to approximately 2 hours, while MOD2 can take up to 8 hours. In every generation of the SPEA2 algorithm, 40 new fitness evaluations of both objectives are performed. Therefore, parallel computation across several work stations is beneficial.

In order to reduce the computation time of FE simulation one way could be to employ meta-modeling techniques. Employing meta-modeling methods to reduce the cost of FE simulations computational time is more or less mandatory. However, the “curse of dimensionality” is a known problem in surrogate modeling of high dimensional problems, that can affect the accuracy of the meta-models. Consequently the final non-dominated solutions can be affected. In this project, dealing with surrogate models generated from 9 variables for MOD1 and MOD2 can increase the error in computing the fitness functions. This approximation along with the definition of the objective functions, which are rough calculation of the errors between the two curves, will increase the error. This can lead the search direction of the MOO algorithm to an incorrect path. Thus, in this study it has been decided not to employ any surrogate modeling and compute the fitness functions by running the actual FE simulations. Despite that, the obtained results can be used to compare the accuracy of different meta-modeling methods.

Table 3: Original optimal parameters and optimal parameters of MOO

	σ_Y^I(MPa)	$\lambda_2^I(-)$	σ_0^I(MPa)	$\delta_{nc}^I(\mu\text{m})$	$\delta_{tc}^I(\mu\text{m})$	$\lambda_2^{II}(-)$	σ_0^{II}(MPa)	$\delta_{nc}^{II}(\mu\text{m})$	$\delta_{tc}^{II}(\mu\text{m})$
Orig. study	50	0.31	23	53	38	0.39	10	21	49
This study	49.67	0.29	22.88	52.6	38.51	0.36	10	20.39	52.39

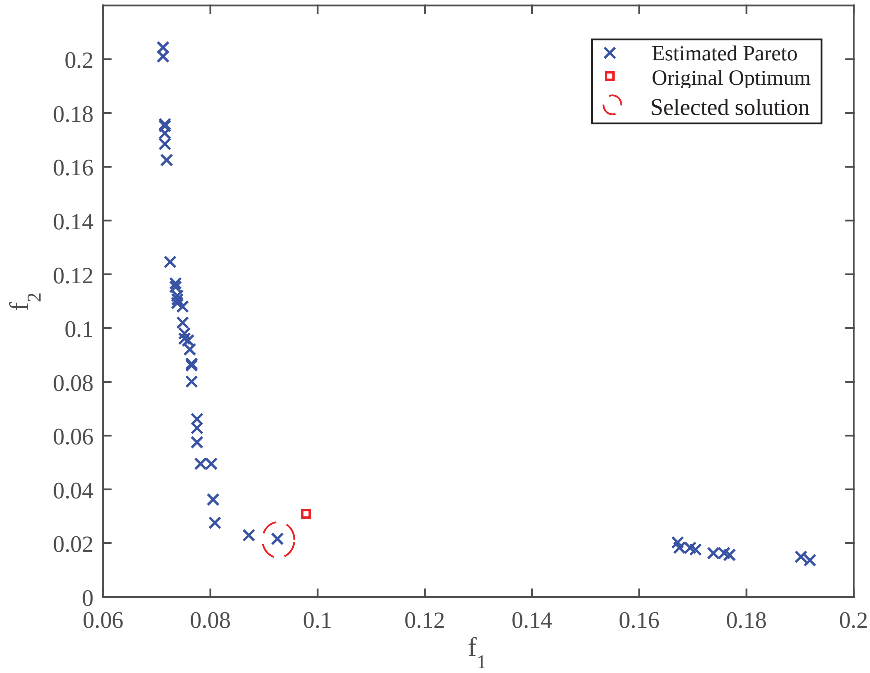
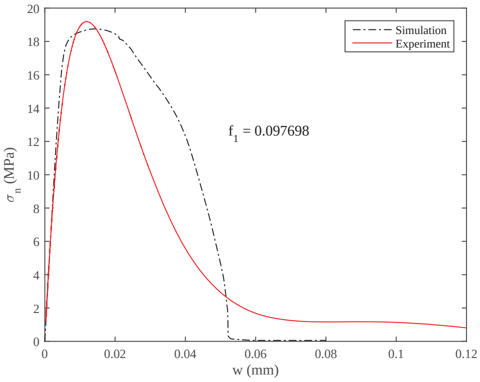


Figure 1: Pareto front (non-dominated solutions)

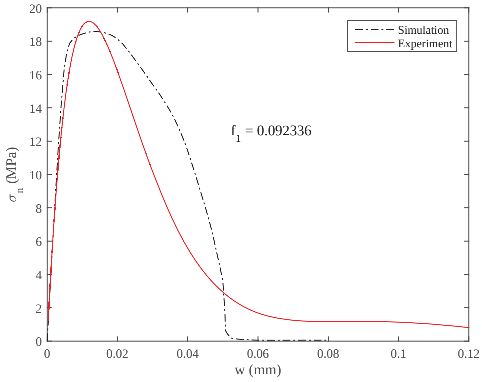
6. Results

The set of non-dominated solutions are illustrated in figure 1. It is clear that the objectives are conflicting and the original solution, indicated by the square, is not far off from the optimal set of solutions in the lower left corner. This can also be seen in both figures 2a and 2b, where the similarity between the curves is evident. On the other hand, a better fit to the experimental data is observed in figure 2d compared to figure 2c. The authors of the original study stated three reasons for not reaching a better fit to the peel curve: 1) A too narrow search space for the parameters, 2) the nature of conflicting objectives, 3) the inherit property of the cohesive model [17]. In this study the search space of the parameters is broadened. The conflicting nature of peel and shear can still be a reason for not reaching a better fit. The discrepancy between the MOD1 simulation curve and experimental curve is due to the nature of the cohesive zone model. As suggested by the original authors, using a different cohesive law with different fracture energies in peel and shear could improve the fitness.

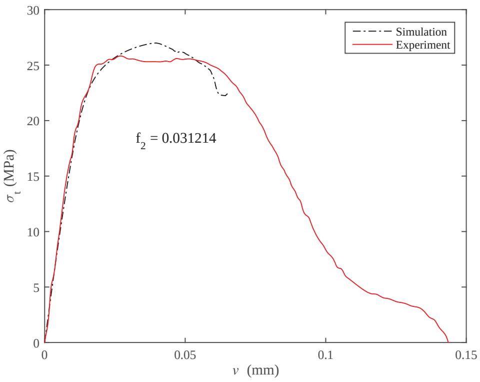
Table 3 shows the decision variables generating the selected optimal solution. The similarity in the values of the parameters indicate a need for a sensitivity analysis in order to further map the dependencies of variable changes to the objectives. However, by comparing the parameters σ_0^I and σ_0^{II} during the evolutions in the original study and the optimal selected solution in this study, it can be concluded that these parameters are almost constant.



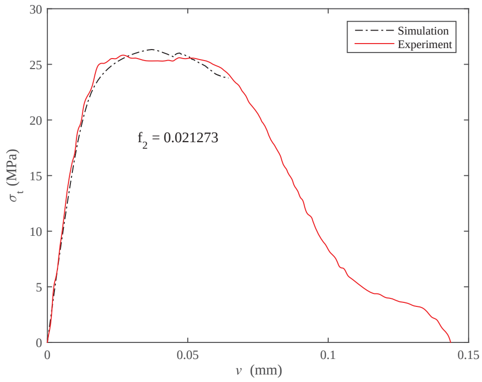
(a) MOD1, original study



(b) MOD1, MOO study



(c) MOD2, original study



(d) MOD2, MOO study

Figure 2: Stress-elongation curves.

7. Conclusion

In the future, the MOO of the adhesive layer can be further studied by performing sensitivity analysis in order to better understand the nature of the problem and provide a broad insight to the decision makers. Also, further studies on the parameter setting of the optimization algorithm for a faster convergence is useful. By obtaining the best set of non-dominated solutions, an interesting study can be carried out in employing or developing proper, accurate and fast meta models for these types of problems, including curve fitting and parameter identification. Another interesting study is to employ the guided evolutionary multi objective optimization method which focuses on finding more solutions in a user defined objective space.

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