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Combining genetic algorithms and the finite element method to improve steel industrial processes

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ABSTRACT

Most of the times the optimal control of steel industrial processes is a very complicated task because of the elevated number of parameters to adjust. For that reason, in steel plants, engineers must estimate the best values of the operational parameters of processes, and sometimes, it is also necessary to obtain the appropriate model for steel material behaviour. This article deals with three successful experiences gained from genetic algorithms and the finite element method in order to solve engineering optimisation problems. On one hand, a fully automated method for determining the best material behaviour laws is described, and on the other hand we present a common methodology to find the most appropriate settings for two cases of improvement in steel industrial processes. The study of the three reported cases allowed us to show the reliability and effectiveness of combining both techniques.

1. Introduction

In broad terms, evolutionary computation (EC), which comprises a fundamental component of soft computing (SC), involves using iterative process inspired by natural evolution in order to solve imprecise and complex problems [40]. These computational techniques are stochastic, and therefore suited to deal with real-world problems [12,3]. Together, genetic programming (GP) [22], evolutionary programming (EP) [35], evolution strategy (ES) [36], and genetic algorithms (GAs) form the backbone of EC approach. In particular, GAs have became well-known through the writing of John Holland and his colleagues at the University of Michigan [24]; we can now say that it is one of the most representative techniques of SC. GAs are defined as a large number of systematic methods used to solve optimisation problems applying the principles of biological evolution namely inheritance, selection, sexual reproduction (crossover) and mutation [28]. From this conception of GAs, it has been possible to find useful solutions to industrial optimisation problems which were impossible to tackle with the classical techniques previously. Generally if the search space is large, or not well understood, GAs will have a good possibility of finding better solutions than traditional methods [14,5].

Furthermore, the finite element method (FEM) [13] is a powerful tool based on numerical analysis for the design and mechanical study of products and industrial processes. Although FEM can be regarded as a standard tool for numerical computations in solid mechanics [51], nowadays it has entered other application areas such as biomechanical [48], aeronautical [47], and automotive industries [43]. The methodology in solid mechanics is usually divided in two phases: first, determining the behaviour laws of materials or operational parameters to be used from experimental data; second, complete the FE model incorporating those determined variables in the simulation. The FEM requires a lot of computation time similarly

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to other traditional methods of hard computing (HC). Advances in computer systems engineering have increased the microprocessor and storage capacity of computers, reducing the time required to converge a solution. In this article, we have reviewed three successful experiences performed applying SC techniques to improve the reduction of computation time.

By the combination of GAs and FEM, the article describes the results obtained in the optimising of two industrial processes and in the determination of the realistic material behaviour laws. Novelty hybrid techniques fusing SC and HC are a very promising field of development. The three real cases from the steel industry, in which the proposed methodology was applied, are the following: straightening process of long steel products, tension levelling process of steel profiles, and determining the optimum material model for ZSTE 800 high-strength steel (HSS).

Relevant related experiences are reported in Section 2. Section 3 shows a brief description of the methods employed to study the problems. Then, the description of the three experiences is presented along Section 4. Finally, conclusions and research works are reported in Section 5.

2. Background

The literature contains many references to methods for solving optimisation problems [42], adjusting industrial processes [15], and determining optimal setting parameters [38]. In all these problems, the traditional approach is based on mathematical relationships between the decision variables and the objective. How hard it is to solve the problem, it determines the method or algorithm that can be used. Actually the necessary equations to most of the industrial cases are too complex to be solved using a traditional approach [8]. In this context, GA has emerged as a promising technique to solve optimisation problems, being successfully applied to a wide range of industrial applications such as: continuous casting of steel [50,37], supply chain management [45], production scheduling of hot strip mill [16,10], allocating facilities in plant [23], process planning for multiple parts manufacturing [29], amongst others. Additionally, the FEM has also been used to analyse and optimise metal manufacturing [30] and forming processes [12], as well as other different research areas such as damage location in structures [17] or mechanics of earthquakes and seismicity [25].

In recent years, there have been several approaches proposed by various investigators to develop hybrid computing. A report by Ovaska et al. [31] includes several successful experiences fusing different SC and HC techniques. Examples are GAs formulated in an object-oriented framework, fuzzy rules coded in a Petri net and mathematical methods combined in an evolutionary architecture. In particular, the use of FEM and GAs combined as an optimisation tool has shown that, in many cases, it is a powerful method to optimise complex engineering problems [46]. This combination allows tackling important problems such as structural shape optimisation [3], electrical transformer design optimisation [21] and the determination of material parameters of advanced composites [20]. A good representative example is the work of Bernstein and Richter (2003) who developed using FEM a model of a structure and its parameters were identified by a procedure based on GAs [7]. In 2007, Petrescu et al. carried out another stochastic optimisation based on GA for optimum design of an electro-pneumatic device used to transmit small pressures and forces [33].

A review of the literature regarding problem solving in steel industry reported an increasing number of works based on combining FEM and GA in last decade [18,30]. Song and Zhang (2001) performed a systematic experimental investigation studying the effect of heat treatment on the mechanical properties for 7175 aluminium alloy [41]. Similarly, Mousavi Anijdan et al. (2006) developed a theoretical model based on artificial neural networks (ANNs) and GAs to optimise effective parameters on porosity formation in Al–Si casting alloys [2]. In 2004, Cheng and Yao reported a method using GAs for analysing laser forming processes of FE class of shapes [11]. In this case, the synthesis process was validated by experiments through several cases under diverse conditions. Gaitonde et al. (2008) investigated the application of GAs for burr size minimisation in drilling of AISI 316L stainless steel using HSS twist drills [19]. In 2009, another optimisation method based on GAs and linked with the FEM is presented by Abedrabbo et al. to determine forming parameters of tube hydroforming process for many advanced HSS materials [1]. Likewise, a physics-based process modelling using FEM for electric discharge machining was presented by Joshi and Pande in 2011. The FEM was integrated with ANNs and GAs to improve the accuracy of the prediction model with less dependency on the experimental data [26].

3. Methodology proposed

Many variables are involved in industrial processes and their interactions are usually very complex. In order to study these processes the engineers count on a powerful tool for providing a realistic simulation, the FEM. Once the engineers have obtained a reliable FE model it is possible a better understanding of the studied process. Nevertheless, it is mandatory a step forward and use this knowledge to optimise the process. However, there are many variables to tune and for this reason, automation of this optimisation process is always the right strategy. GAs can accomplish this task in an efficient way. Using a script it is possible to apply GAs for modifying the important variables in the FE model, guided by objective function results. In this way, improving the objective function from generation to generation, it is possible to obtain the optimum parameters of the process in the last generation. The methodology proposed can be seen in action in the next sections along the three cases exposed.

A brief overview is provided in this section explaining methods and models used to account for the mechanical response of the three studied problems. Since many details regarding these techniques can be found in the cited works, only the key aspects of them will be covered.

Table 1
Working principle of a genetic algorithm.

```
program GeneticAlgorithm ()
   const
    MAXGEN = cte.;
   var
    Gen: 0..MAXGEN;
    P[Gen]: void;
   begin
    Gen := 0;
    Initialization (P[Gen]);
    J := Evaluation (P[Gen]); Write(P[Gen],J);
    repeat
       Gen := Gen + 1;
       P[Gen] := Selection (P[Gen-1],J);
       P[Gen] := P[Gen] + Crossover (P[Gen]);
       P[Gen] := P[Gen] + Mutation (P[Gen]);
       J := Evaluation (P[Gen]); Write(P[Gen],J);
     until (end condition is not fullfilled OR Gen == MAXGEN)
end.
```

3.1. Genetic algorithms

Bäck et al. present a detailed introduction to EC in their writing [4]. The GA is a population-based optimisation and probabilistic search technique that works using the principles of genetics and natural selection [24]. A population composed of many individuals is created to evolve under determined selection rules to a new state that minimises an objective function. The working principle of the technique can be explained shortly as follows: first, the GA generates a random population of initial solutions and it determines the objective function value of each solution in the initial population. Depending on how we designed the evolutionary strategy, we will have to solve a minimisation or maximisation problem. In both cases the population of solutions is generated choosing the individuals with the best fitness value and also using different operators to modify the population. The purpose of the different operators used is explained next. The *reproduction operator* is able to choose the best solutions using their fitness values from a mating pool generated with the "good enough" solutions. There are several reproduction schemes, but two of the most well-known are roulette-wheel selection and tournament selection. The next operator is named *crossover*, and it is utilised to generate "children solutions" from the mating pairs randomly selected. Finally, mutation is another operator used to attain a local change around the actual solution, avoiding that the GA gets stuck in a local minimum. The GA is explained briefly in Table 1.

The most important advantages of this evolutionary technique are the following: it can be used with both continuous or discrete variables, it is ideally suited to parallel computing, and it solves problems in which the variables have extremely complex cost surfaces.

3.2. The finite element method

The FEM is considered the best choice to achieve a solution for partial differential equations as well as integral equations over complex domains, specially when the domain changes, the desired precision varies over entire domain, or the solution lacks smoothness [51]. The drawback to FEM is that solution is only an approximation, whereas an algebraic method always gives the exact solution. For finding the approximate solution, the FEM normally eliminates the partial differential equations completely or renders them into an approximating system of ordinary differential equations. The FEM uses numerical integration for finding the solution. For structural mechanics, FEM is, in most cases, the technique of choice (i.e. solving for deformation and stresses in solids). Its practical application is often known as finite element analysis (FEA). There are different types of finite element methods such as generalised finite element method (GFEM), extended finite element method (XFEM), meshfree method and finite volume method (FVM). The last one is the easiest way for analysing problems that involve fluid flows, usually known as computational fluid dynamics (CFD).

3.3. Material behaviour models

The model chosen to represent the material behaviour was the *multiple component nonlinear kinematic hardening model of Chaboche* [9,49] with only one component. This material behaviour model includes a nonlinear kinematic hardening rule to represent the change of the yield surface centre (evolution of the back-stress tensor, α) according to plastic strain, and an isotropic hardening equation to take into account the change of the yield surface radius. The isotropic hardening behaviour of the model that defines the evolution of the yield surface size, σ^0, as a function of the equivalent plastic strain, $\bar{\varepsilon}^{pl}$, is represented by:

$$\sigma^0 = \sigma_0 + Q_\infty\left(1 - e^{-b\cdot\bar{\varepsilon}^{pl}}\right) \tag{1}$$

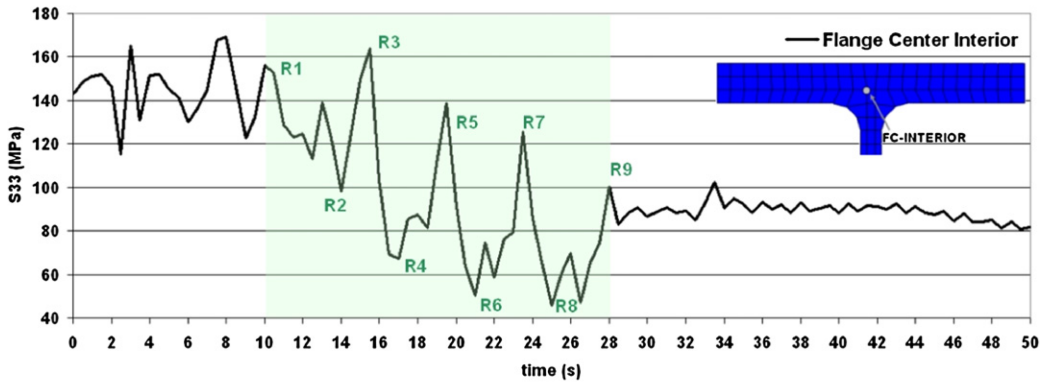

Fig. 1. Flange-centre lengthwise tension (S33) of an HEM500 beam during the straightening process. It is possible to observe the reduction of the residual stresses after the process.

where σ^0 is the yield stress at zero plastic strain, Q_∞ defines the maximum change in the size of the yield surface and b defines the rate at which the size of the yield surface changes.

The nonlinear kinematic hardening component is represented by:

$$\alpha = \frac{C}{\gamma}\left(1 - e^{-\gamma \cdot \varepsilon^{pl}}\right) \tag{2}$$

where γ is the back-stress tensor that defines the initial kinematic hardening modulus and the rate at which the kinematic hardening modulus decreases with increasing plastic deformation. b, Q_∞, C and γ are material parameters that must be obtained from cyclic test data.

4. Experiences and results

The methodology explained in the previous section is described below as a novelty solution of three real problems from the steel industry: tuning straightening process of long steel products, setting parameters of complex material models and optimising tension levelling process. Even though the name and the description of the phases are somewhat different in each case, the general conception is shared by all those works. Two constitutive models, an FE model and a GA were employed in the body of the three works.

4.1. Tuning straightening process of steel sections

Steel beams and rails are both mainly known as long steel products. In the first, we reviewed study, we analysed the broadly use in the straightening process of these steel products [32]. The straightener machine usually receives profiles from a cooling process at a certain temperature and curvature. Nine rollers are its major components. Cyclically, the machine bends the profile upwards and downwards to achieve the plastic behaviour of steel for straightening the beam and reducing residual stresses. Fig. 1 shows the simulation results of a straightening process simulation on an HEM500 beam through an FE model. The initial value of the residual stress at the flange centre was of 145 MPa at the beginning of the process. At the end of the process this value was reduced to 85 MPa, which means a reduction of 43%. It is also important to keep the residual stresses under a tolerance as they could cause a reduction on the carrying capacity of steel beams or lead the propagation of cracks in rails [44]. To attain the desired result (minimal residual stresses and curvature), it is necessary to adjust correctly the position of the rollers, which is a difficult and very time-consuming task, and also dependent on the operators expertise.

Advances in simulation software combined with experimental results have permitted the study of residual stresses during cooling and straightening processes in different steel sections [6,32,39]. The FE model of the process can help to find the suitable rollers position, but to achieve the optimal position of the rollers using only FE models is a too hard task. For this reason, the optimisation method using GA was implemented for tuning the process in an automatic way.

Before explaining the process in detail, we define the objective function (J) as the mean of the absolute values of residual stresses for the web and flange of various beam cross-sections; to this end, J is described by the following equation:

$$J = \frac{1}{n} \cdot \sum_{k=1}^{n} \left(\frac{1}{m} \cdot \sum_{h=1}^{m} |S_{web.kh}| + \frac{1}{p} \cdot \sum_{u=1}^{p} |S_{flange.ku}| \right) \tag{3}$$

where the number of cross-sections in the beam is given by n, the number of parts into which the web's cross-section is divided is given by m, the number of parts into the flange's cross-section is divided is given by p, S_{web} is the residual stress of each web's partition, and finally, S_{flange} is the residual stress of each flange's partition.

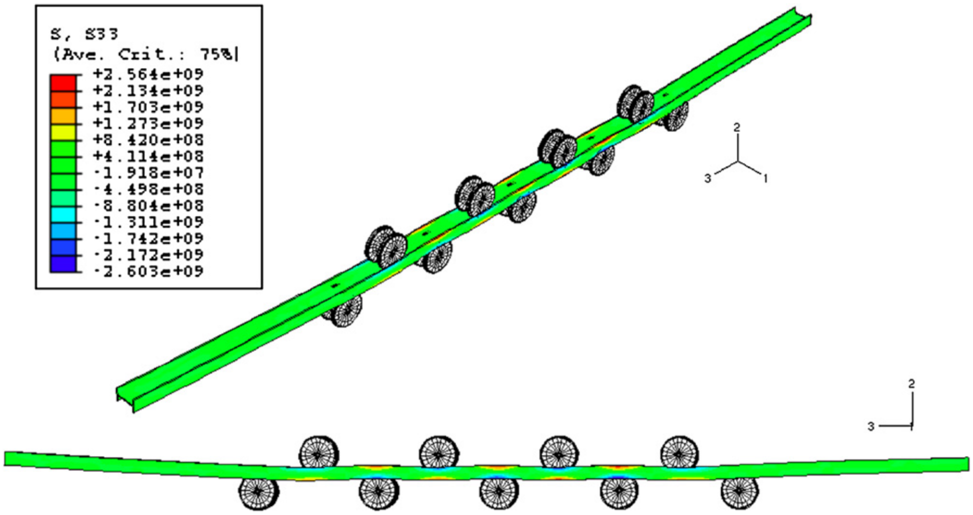

Fig. 2. Straightener FE model for the IPE100 beam in ABAQUS.

Fig. 3. Straightener pilot plant used to validate the methodology (photo courtesy of Betriebsforschungsinstitut, BFI).

We present the procedure and options on the following paragraphs.

First, a realistic FE model of the process was developed in ABAQUS, a well-known FEM software, in order to reproduce the behaviour of the IPE100 sections during the straightening process. Temperatures and residual stresses generated in the previous manufacturing process (cooling process) were considered by this FE model (Fig. 2). The model was calibrated and validated with data recorded from both the real industrial process and the pilot plant (Fig. 3). Once the realistic FE model was created, thereupon the proposed methodology combining FE and GA was applied as follows:

With a total of 20 individuals, the initial generation was randomly created. Each individual in the population is a code that represents different positions for rollers 3, 5, 7 and 9 from a set of possible search solutions (Fig. 4). Once the random positions for the 20 individuals were set, ABAQUS generated 20 realistic FE models using these positions, and after that, the objective function of each case was calculated with the simulation of these first 20 FE models.

When all objective functions were calculated, the five best individuals (the five with less J) were chosen as parents to create the next generation. The 20 individuals in this next generation were generated in the following way:

- Twenty-five per cent of the generation was made up of the five best individuals in the previous generation.
- Sixty per cent was made up of the crossover of the five parents. The crossover process was executed by changing several digits in the chromosomes (roller positions) between two parents (Fig. 5).
- The remaining 15% was obtained by random mutation creating new roller positions.

This procedure is repeated until convergence.

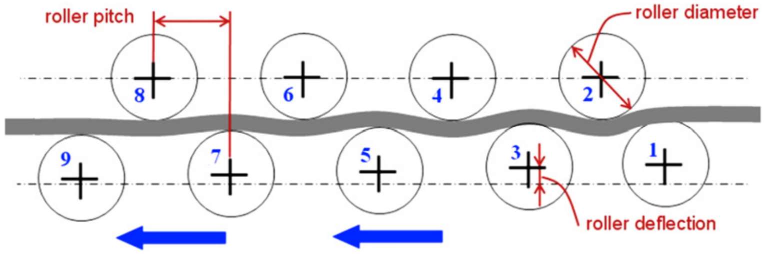

Fig. 4. Scheme with positions for rollers 3, 5, 7 and 9.

Pos 2 ↓ Pos 4 ↓ Pos 1 ↓

Parent 1 : (0 **6 0 0** , 0 4 7 **0** , 0 2 8 0 , **0 1** 3 0)

L = 3 L = 1 L = 2

Parent 2 : (0 **5 3 2** , 0 3 6 **5** , 0 3 6 2 , **0 0** 1 5)

Son : (0 **5 3 2** , 0 4 7 **5** , 0 2 8 0 , **0 0** 3 0)

Fig. 5. Crossover example: Search for the best positions of the rollers numbered 3, 5, 7 and 9 in the straightening processing, changing three digits from position 2, one digit from position 4, and two digits from position 1 respectively.

Table 2
Values obtained by the GA-FEM methodology for the position of rollers 3, 5, 7 and 9.

File name	R_POSY3	R_POSY5	R_POSY7	R_POSY9	T_VALUE	Time (min)
GEN_6_1.inp	**6.55**	**4.44**	**2.48**	**0.48**	**10.749**	**43 235**
GEN_6_2.inp	7.28	3.84	0.89	−2.23	12.534	43 232
GEN_6_3.inp	8.45	4.74	1.98	−1.76	12.818	43 245
GEN_6_4.inp	7.28	4.44	1.91	2.21	12.844	43 233
GEN_6_5.inp	8.45	4.74	2.56	−3.06	12.968	43 230
GEN_6_6.inp	7.8	4.45	−0.41	−7.23	19.211	43 231

Table 2 lists the values proposed by the methodology for rollers 3, 5, 7 and 9 (under 'R_POSY3', 'R_POSY5', R_POSY7', and 'R_POSY9' labels). The objective function value is also showed (under 'T_VALUE' label) as well as the time required to achieve the solution. The best solution obtained through this methodology produced on average 44% less residual stresses than the original (10.75 MPa against 19.20 MPa). The roller configuration given by the best solution was verified with acceptable results in the pilot plant (Fig. 3 left side) built by Betriebsforschungsinstitut for the European project no. RFS-CR-03012 (TESTRA). Implementing for IP100 beams, the new roller configuration demonstrated a good correlation between real and simulated final residual stresses.

4.2. Optimising tension levelling process

The second work reported [34] is a step forward in the adjustment of a tension leveller formed by seven rolls (Fig. 6). Tension levelling process involves a set of rolls placed one after the other, through which pretensioned steel is passed and subjected to alternate bends by applying cyclic loads. Using this steel process, both flatness shape defects and residual stresses can be reduced. In our experiments, tension levelling process consisted of seven (7) rollers with a radius 101 mm, processing a high-strength steel strip (ZSTE-800) of 1.2 mm thick and 350 mm wide. The configuration variables of the process were the lengthwise tension of the strip (σ_t), the plate federate (V), and the roll penetration (d). Combining FEM and GA (see flow chart in Fig. 7) within the range of parameters shown in Table 3, the process was successfully optimised.

This was achieved in two steps: first, the material behaviour model was obtained with realistic parameters to develop the most accurate FE model of tension levelling. The details of this first phase are explained in the next section (Section 4.3). The objective of the second phase was to automatically adjust the parameters of the tension levelling process. The methodology for finding the optimum roller positions was similar to that of Section 4.1. Tension in rolling direction (S_{11}) was obtained at both surface of the strip through the FE model of Fig. 6. Once each model (individual) was simulated, the objective function (J), representing the residual stresses, was calculated as follows:

$$J = \frac{1}{2 \cdot m \cdot n} \cdot \sum_{x=1}^{m} \sum_{y=1}^{n} \left(|S_{11,top_{xy}}| + |S_{11,bottom_{xy}}| \right) \tag{4}$$

where $S_{11,top}$ is the final stress in the top surface, $S_{11,bottom}$ is the final stress in the bottom surface and the number of nodes considered for calculating is given by $m \times n$. The best solutions were those with the lowest objective functions

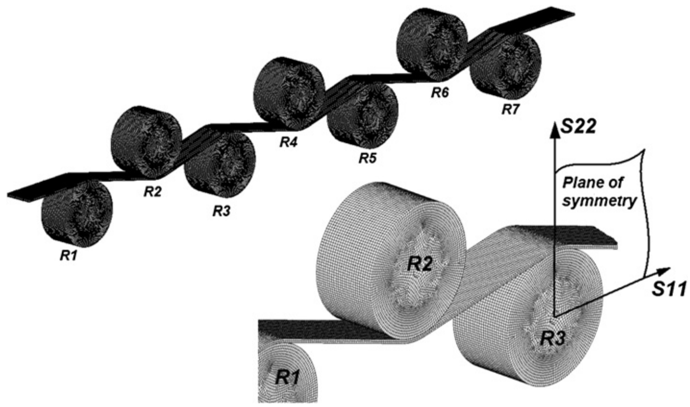

Fig. 6. FE model of tension levelling process in ABAQUS.

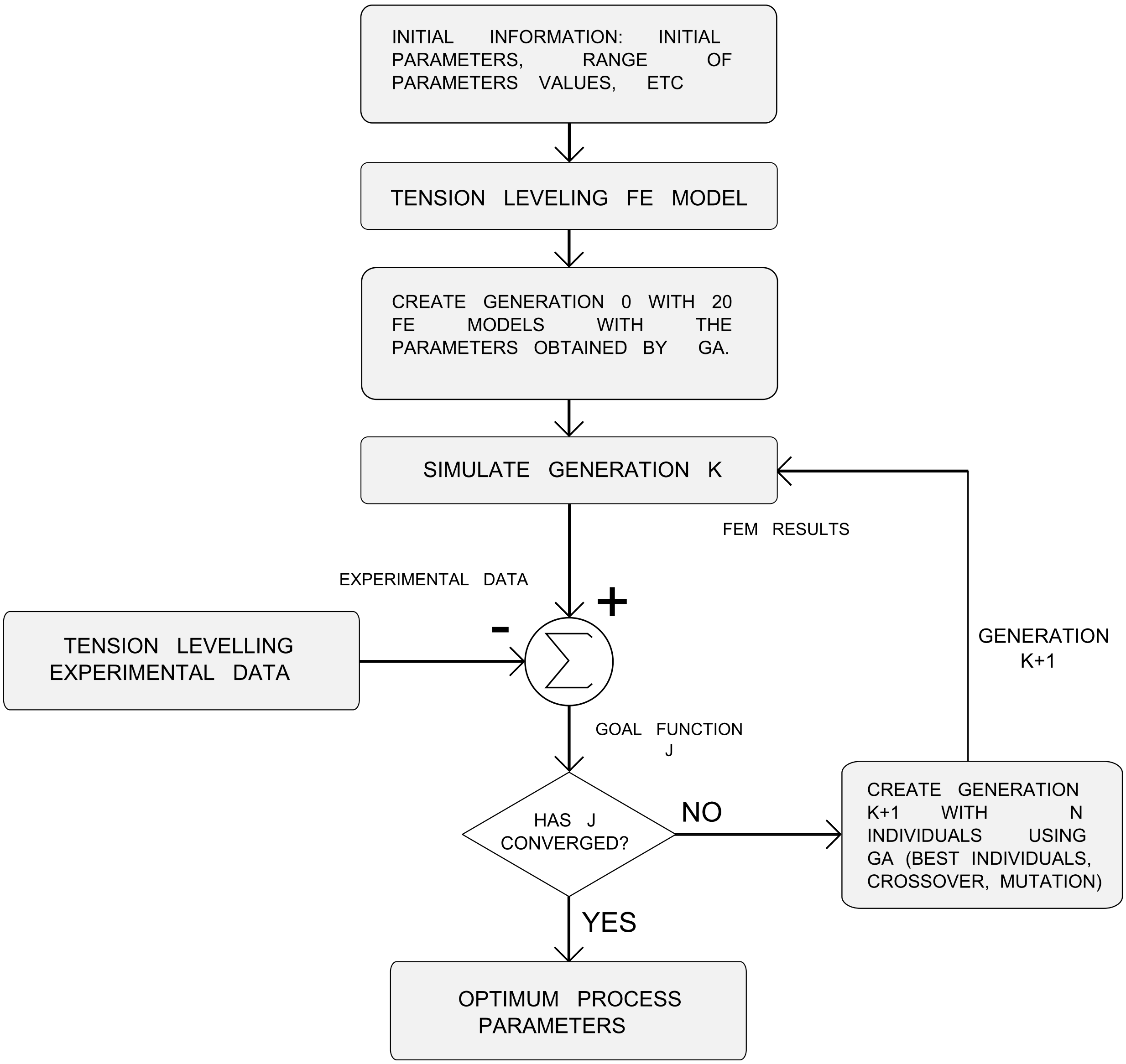

Fig. 7. Methodology proposed using GA for tension levelling optimisation.

Table 3
Range of configuration parameters (σ_t, V, d) for tension levelling process.

	Min.	Max.
σ_t	43	73
V	100	200
d	60	80

Table 4
Values of the five best individuals from the 10th generation.

Pos. no.	σ_t	V	d	J	Time (min)
1	64.5	129.3	63.2	42.34	4535
2	68.4	132.1	62.3	42.42	4568
3	69.8	121.4	63.9	43.35	4529
4	62.3	123.2	64	43.48	4796
5	67.2	118.3	63.5	45.34	4498

(residual stresses), always in compliance with the next constraint: tensions are equally distributed on both surfaces, to avoid further shape defects. Therefore, the mean absolute value of the difference between residual stresses in the top and bottom surfaces was limited to be lower than a predefined threshold γ:

$$\frac{1}{m \cdot n} \cdot \sum_{x=1}^{m} \sum_{y=1}^{n} |S_{11,top_{xy}} - S_{11,bottom_{xy}}| \leqslant \gamma \tag{5}$$

Next generations were created using the same scheme as in Section 4.1 and the best solution was obtained in the 12th generation. Table 4 shows as an example the values of the five (5) best individuals from the 10th generation. The second individual is the one selected, because although error is a little greater than the first individual, the processing velocity is higher.

4.3. Optimising material behaviour model in finite element models

As described in the previous section (Section 4.2), to ensure realistic results with FE model of tension levelling, it is mandatory to work with a realistic material behaviour model that incorporates all the complex phenomena observed during cyclic load tests [27]. It is a common practice to estimate parameters of material models from tables or theoretical calculations. However, in doing so, it opens the possibility of that small differences between the actual material and its behaviour model will be greatly amplified in the presence of Bauschinger effect, ratcheting, and other effects.

The study sets out a fully automated method for determining the material behaviour model to use in numerical simulation programs and the optimum constitutive parameters that define that material. These parameters were based on experimental data and the combined use of GA and FEM. Two types of model were compared: a linear kinematic hardening model and Chaboche model (a nonlinear isotropic/kinematic hardening model).

The main idea involves of simulating several controlled cyclic strain tests through FE models of standard steel test-piece with different cyclic material behaviour models. Then, a GA is used to adjust the parameters of the model until the behaviour of the material model matches the results obtained from actual experiments as closely as possible (see flow chart in Fig. 8).

The developed system can automatically adjust the material model to be used in FE models so that their behaviour approximates that of the actual material. First, experimental data from a low-cycle fatigue test (ASTM E606) was obtained. From this, equivalent stress–accumulated strain curves were generated in order to facilitate checking the differences between test curves and those obtained from each simulation. Then the material behaviour models were obtained by GA following these steps:

1. The FE models (n individuals of the initial generation) were created from a standard test-piece. The same values (strain and number of cycles) were imposed on the FE model during experimental tests using the testing machine.
2. Different material models and their parameters from the initial generation were simulated.
3. Stress distribution for each simulation was obtained and the mean absolute error (MAE) for each individual is evaluated as the objective function:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_{FEM}(i) - y_{exp}(i) \right| \tag{6}$$

where $y_{FEM}(i)$ are the stresses obtained in the FE model simulation process, $y_{exp}(i)$ are the stresses obtained from experimental data, and n is the number of points i on a total accumulated stress curve.

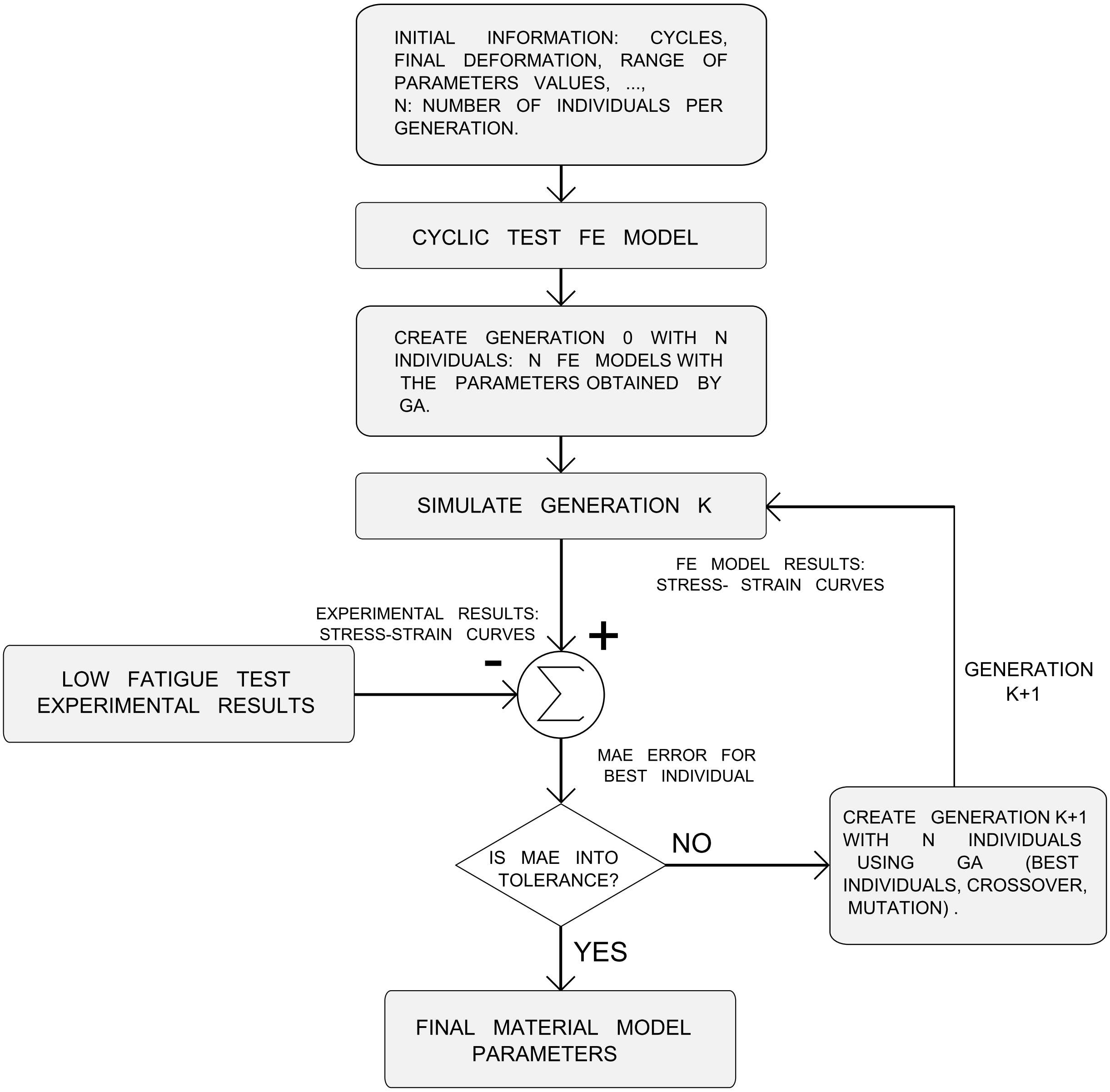

Fig. 8. Methodology proposed for obtaining material model parameters based on FEM and GA.

4. The best individuals (lowest MAE) were selected for the next generation.
5. In an iterative process, the next generation was made up via reproduction mechanism with certain probabilities as described in Section 4.1. In Fig. 9 we show the MAE of the best individual in each generation.

In this way, a fully automated method combining GAs and FEM was developed. Once successfully validated, the method is able to determine the parameters that define material behaviour models used in FE model simulations. Moreover, the process was developed in such a way that it can be used to obtain any material model from any cyclic load test with any strain degree and number of cycles.

5. Conclusions and future work

In general terms, it may be concluded that the FEM combined with GAs methodology can help to optimise steel industry problems. On one hand, techniques based on FEM are used to improve design and optimise control processes; on the other hand, GA is one of the major components of SC which has demonstrated efficiency in applications where traditional optimisation algorithms are not able to provide solutions. We have presented three cases where both techniques have been

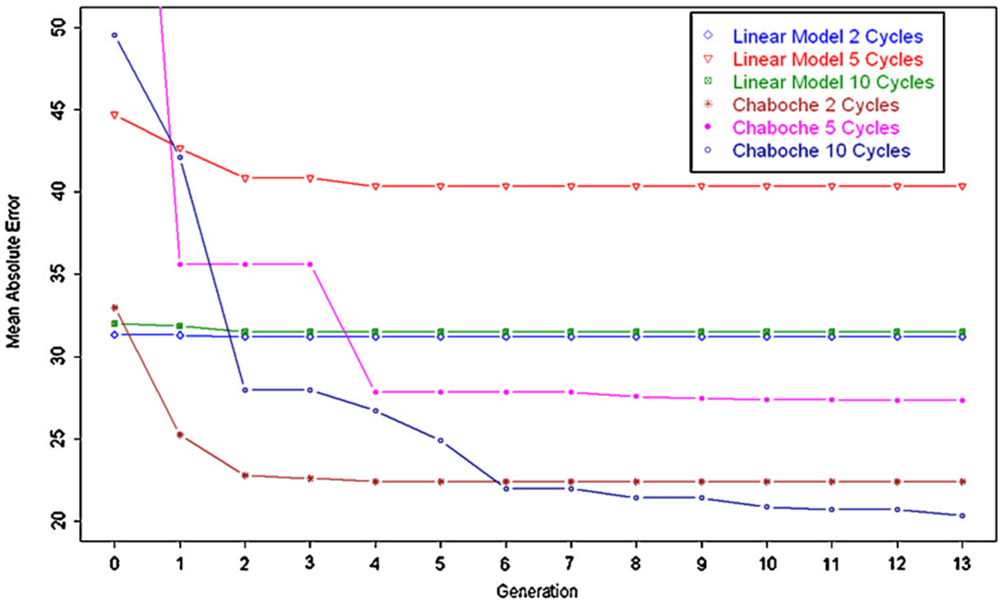

Fig. 9. Changes in MAE of the best individual in each generation.

combined to simulate complex problems, leading to several generations of individuals and enabling the optimal solution. The feasibility and efficiency of this methodology was validated through these real cases from the steel industry. We emphasise the importance of discussing results with experts from the industries involved because they are able to adapt the methodology for their particular requirements.

Future work will concentrate on improving the optimisation procedure including into the methodology new bioinspired techniques. In order to reduce the computation time of FE models we will also implement grid computing. Given the fact that this method offers several key advantages over other strategies previously applied, our aim is to extend it for solving other industrial problems.

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References

[1] N. Abedrabbo, M. Worswick, R. Mayer, I. van Riemsdijk, Optimization methods for the tube hydroforming process applied to advanced high-strength steels with experimental verification, Journal of Materials Processing Technology 209 (2009) 110–123.
[2] S.M. Anijdan, A. Bahrami, H.M. Hosseini, A. Shafyei, Using genetic algorithm and artificial neural network analyses to design an Al–Si casting alloy of minimum porosity, Materials & Design 27 (2006) 605–609.
[3] W. Annicchiarico, M. Cerrolaza, Structural shape optimization 3D nite-element models based on genetic algorithms and geometric modeling, Finite Elements in Analysis and Design 37 (2001) 403–415.
[4] T. Bäck, D. Fogel, Z. Michalewicz, Evolutionary Computation 1 – Basic Algorithms and Operators, Institute of Physics Publishing, Bristol, United Kingdom, 2000;
T. Bäck, D. Fogel, Z. Michalewicz, Evolutionary Computation 2 – Advanced Algorithms and Operators, Institute of Physics Publishing, Bristol, United Kingdom, 2000.
[5] T.P. Banerjee, S. Das, J. Roychoudhury, A. Abraham, Implementation of a new hybrid methodology for fault signal classification using short-time Fourier transform and support vector machines, in: Soft Computing Models in Industrial and Environmental Applications, 5th International Workshop (SOCO 2010), in: Advances in Intelligent and Soft Computing, vol. 73, 2010, pp. 219–225.
[6] J. Basu, S. Srimani, D. Gupta, Rail behaviour during cooling after hot rolling, The Journal of Strain Analysis for Engineering Design 39 (2004) 15–24.
[7] S. Bernstein, M. Richter, The use of genetic algorithms in finite element model identification, in: Australian Mathematical Society General Meeting, 2001.
[8] A. Bustillo, J. Sedano, L. Curiel, J. Villar, E. Corchado, A soft computing system for modelling the manufacture of steel components, in: M. Kurzynski, M. Wozniak (Eds.), Computer Recognition Systems 3, in: Advances in Intelligent and Soft Computing, vol. 57, Springer, Berlin, Heidelberg, 2009, pp. 601–609.
[9] J.L. Chaboche, Time-independent constitutive theories for cyclic plasticity, International Journal of Plasticity 2 (1986) 149–188.
[10] Y.W. Chen, Y.Z. Lu, M. Ge, G.K. Yang, C.C. Pan, Development of hybrid evolutionary algorithms for production scheduling of hot strip mill, Computers and Operations Research 39 (2012) 339–349.
[11] J.G. Cheng, Y.L. Yao, Process synthesis of laser forming by genetic algorithm, International Journal of Machine Tools and Manufacture 44 (2004) 1619–1628.

[12] J.S. Chung, S.M. Byon, H.J. Kim, S.M. Hwang, Process optimal design in metal forming by double-objective genetic algorithm, Transactions on NAMRI/SME XXVII (2000) 51–56.
[13] R.W. Clough (Ed.), The Finite Element Method in Plane Stress Analysis, Proceedings of the Second ASCE Conference on Electronic Computation, Pittsburgh, PA, 1960.
[14] E. Corchado, A. Herrero, Neural visualization of network traffic data for intrusion detection, Applied Soft Computing 11 (2010) 2042–2056.
[15] X.Z. Du, Q. Yang, C. Lu, A.L. Wang, T.A. Kiet, Optimization of short stroke control preset for automatic width control of hot rolling mill, Journal of Iron and Steel Research, International 17 (2010) 16–20.
[16] H.L. Fang, C.H. Tsai, Genetic algorithm approach to hot strip mill rolling scheduling problems, in: Proceedings of the Tenth IEEE International Conference on Tools with Artificial Intelligence, 1998, pp. 264–271.
[17] M.I. Friswell, J.E.T. Pennyb, S.D. Garvey, A combined genetic and eigensensitivity algorithm for the location of damage in structures, Computers and Structures 69 (1998) 547–556.
[18] Z. Fu, J. Mo, L. Chen, W. Chen, Using genetic algorithm-back propagation neural network prediction and finite-element model simulation to optimize the process of multiple-step incremental air-bending forming of sheet metal, Materials & Design 31 (2010) 267–277.
[19] V. Gaitonde, S. Karnik, B. Achyutha, B. Siddeswarappa, Genetic algorithm-based burr size minimization in drilling of AISI 316L stainless steel, Journal of Materials Processing Technology 197 (2008) 225–236.
[20] N. Garshasbinia, J.E. Jam, Identification of mechanical properties in laminated composite plates using genetic algorithm, Iranian Polymer Journal 14 (2005) 39–46.
[21] P. Georgilakis, Recursive genetic algorithm-finite element method technique for the solution of transformer manufacturing cost minimisation problem, IET Electric Power Applications 3 (6) (2009) 514–519.
[22] D.J. Hand, Evolutionary computation, 1994. Review of Koza's Genetic Programming.
[23] L. Hernandez, L. Morera, A. Azofra, An interactive genetic algorithm for the unequal area facility layout problem, in: Soft Computing Models in Industrial and Environmental Applications, 6th International Conference SOCO 2011, in: Advances in Intelligent and Soft Computing, vol. 87, Springer, Berlin, Heidelberg, 2011, pp. 253–262.
[24] J.H. Holland, Adaptation in Natural and Artificial Systems, MIT Press, Cambridge, MA, USA, 1992.
[25] R. Jankowski, Non-linear FEM analysis of earthquake-induced pounding between the main building and the stairway tower of the olive view hospital, Engineering Structures 31 (2009) 1851–1864.
[26] S. Joshi, S. Pande, Intelligent process modeling and optimization of die-sinking electric discharge machining, Applied Soft Computing 11 (2011) 2743–2755.
[27] R. Lostado, F.J.M. de Pison, R. Fernandez, J. Fernandez, Using genetic algorithms to optimize the material behaviour model in finite element models of processes with cyclic loads, The Journal of Strain Analysis for Engineering Design 46 (2011) 143–159.
[28] M. Mitchell, An Introduction to Genetic Algorithms, The MIT Press, Cambridge, 1998.
[29] F. Musharavati, A.S.M. Hamouda, Modified genetic algorithms for manufacturing process planning in multiple parts manufacturing lines, Expert Systems with Applications 38 (2011) 10770–10779.
[30] V. Oduguwa, A. Tiwari, R. Roy, Evolutionary computing in manufacturing industry: an overview of recent applications, Applied Soft Computing 5 (2005) 281–299.
[31] S. Ovaska, A. Kamiya, Y. Chen, Fusion of soft computing and hard computing: computational structures and characteristic features, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews 36 (2006) 439–448.
[32] A.V. Pernia, F.J.M. de Pison, J. Ordieres, F. Alba, J. Blanco, Fine tuning straightening process using genetic algorithms and finite element methods, Ironmaking & Steelmaking 37 (2011) 119–125.
[33] C. Petrescu, L. Ferariu, R. Olaru, Genetic algorithm combined with finite element method for optimum design of ferrofluid actuator, in: P. Thuraisingham (Ed.), 15th IMEKO TC4 Symposium on Novelties in Electrical Measurements and Instrumentation, 2007.
[34] F.J.M. de Pison, R. Lostado, A.V. Pernia, R. Fernandez, Optimising tension levelling process by means of genetic algorithms and finite element method, Ironmaking & Steelmaking 38 (2011) 45–52.
[35] M.L. Raymer, Book review: Evolutionary computation in bioinformatics, Genetic Programming and Evolvable Machines 6 (2005) 229–230.
[36] I. Rechenberg, Evolution Strategy: Optimization of Technical Systems by Means of Biological Evolution, Fromman-Holzboog, Stuttgart, 1973.
[37] C.A. Santos, J.A. Spim, A. Garcia, Mathematical modeling and optimization strategies (genetic algorithm and knowledge base) applied to the continuous casting of steel, Engineering Applications of Artificial Intelligence 16 (2003) 511–527.
[38] C.A. Santos, J.A. Spim, M.C.F. Ierardi, A. Garcia, The use of artificial intelligence technique for the optimisation of process parameters used in the continuous casting of steel, Applied Mathematical Modelling 26 (2002) 1077–1092.
[39] G. Schleinzer, F.D. Fischer, Residual stress formation during the roller straightening of railway rails, International Journal of Mechanical Sciences 43 (2001) 2281–2295.
[40] J. Sedano, L. Curiel, E. Corchado, E. de la Cal, J.R. Villar, A soft computing method for detecting lifetime building thermal insulation failures, Integrated Computer-Aided Engineering 17 (2) (2010) 103–115.
[41] R.G. Song, Q.Z. Zhang, Heat treatment optimization for 7175 aluminum alloy by genetic algorithm, Materials Science and Engineering: C 17 (2001) 133–137.
[42] G. Stumberger, D. Dolinar, U. Palmer, K. Hameyer, Optimization of radial active magnetic bearings using the finite element technique and the differential evolution algorithm, IEEE Transactions on Magnetics 36 (2000) 1009–1013.
[43] S. Subbiah, O. Singh, S.K. Mohan, A.P. Jeyaraj, Effect of muffler mounting bracket designs on durability, Engineering Failure Analysis 18 (2011) 1094–1107.
[44] J. Szalai, Overall sensitivity analysis of hot-rolled beam-columns, in: K. Jámai, J. Farkas (Eds.), Metal Structures: Design, Fabrication, Economy, Proceedings of the International Conference on Metal Structures – ICMS-03, Millpress, Miskolc, Hungary, 2003.
[45] C.X.H. Tang, H.C.W. Lau, A fuzzy-GA decision support system for enhancing postponement strategies in supply chain management, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 5361, Springer, Berlin, Heidelberg, 2008, pp. 141–150.
[46] A. Tiwari, V. Oduguwa, R. Roy, Rolling system design using evolutionary sequential process optimization, IEEE Transactions on Evolutionary Computation 12 (2) (2008) 196–202.
[47] X. Xiang, Y. Li, T. Suo, B. Hou, Shock enhancement of aluminum foam under impact loading using FEM simulations, Advanced Materials Research 160–162 (2011) 1077–1082.
[48] M. Yeoman, B. Reddy, H. Bowles, P. Zilla, D. Bezuidenhout, T. Franz, The use of finite element methods and genetic algorithms in search of an optimal fabric reinforced porous graft system, Annals of Biomedical Engineering 37 (2009) 2266–2287.
[49] F. Yoshida, M. Urabe, Computer-aided process design for the tension levelling of metallic strips, Journal of Materials Processing Technology 89–90 (1999) 218–223.
[50] P. Zheng, J. Guo, X.J. Hao, Hybrid strategies for optimizing continuous casting process of steel, in: Proceedings of the IEEE International Conference on Industrial Technology, vol. 3, 2004, pp. 1156–1161.
[51] O.C. Zienkiewicz, R.L. Taylor, Finite Element Method, Vol. 1 – The Basis, 5th edition, Elsevier, 2000.