Chapter 4
On Efficiency Increase of Evolutionary Algorithms for Large Non-linear Constrained Optimization Problems with Applications to Mechanics

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Abstract Advances in development of highly efficient dedicated Evolutionary Algorithms (EA) for a wide class of large non-linear constrained optimization problems are considered in this paper. The first objective of this general research is development and application of the improved EA to residual stress analysis in railroad rails and vehicle wheels. However, the standard EA are not sufficiently efficient for solving such large optimization problems. Therefore, our current research is mostly focused on development of various new very efficient acceleration techniques proposed, including smoothing and balancing, adaptive step-by-step mesh refinement, as well as a'posteriori error analysis and related techniques. This paper presents an efficiency analysis of chosen speed-up techniques using several simple but demanding benchmark problems, including residual stress analysis in elastic-plastic bodies under cyclic loadings. Preliminary results obtained for numerical tests are encouraging and show a clear possibility of practical application of the improved EA to large optimization problems.

Keywords Evolutionary algorithms · Large non-linear constrained optimization · Computation efficiency increase

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4.1 Introduction

A lot of scientific and engineering problems, including many important problems of mechanics, may be formulated in terms of constrained optimization. Complexity of such problems results mostly from their non-linearity, as well as from a large number of decision variables and constraints. Thus, this paper considers development of an efficient optimization approach based on the Evolutionary Algorithms (EA) for a wide class of large non-linear constrained optimization problems.

In contrast to most deterministic methods, the EA may be successfully applied with similar efficiency to both the convex and non-convex problems [4, 10]. However, general efficiency of the standard EA is rather low. Therefore, significant acceleration of the convergence process is needed. Moreover, the improved EA should provide possibility of solving such optimization problems, when the standard EA fail. Improvement of the standard EA may be obtained in several ways. We have already proposed several new acceleration techniques [5, 15, 16, 18]. These techniques have been preliminarily tested using several demanding benchmark problems. Numerical results of these tests indicate significant acceleration of the large optimization processes involved.

The engineering objective of our research includes residual stress analysis in railroad rails and vehicle wheels [7, 12, 13], as well as a wide class of problems resulting from the Physically Based Approximation (PBA) of experimental and/or numerical data [8]. Tensile residual stresses are of great importance in reliable prediction of rail and wheel life service resulting from its fatigue failure. Both the theoretical and experimental investigations of residual stress may be expressed in terms of constrained optimization problems. Theoretical model of residual stress analysis in bodies under cyclic loadings is based on the shakedown theory and may be found in [12–14]. Several discrete methods (Finite Element Method, Boundary Element Method, Meshless Finite Difference Method) and the deterministic solution approach were already used to solve such problems [13, 14]; neural networks were also investigated. The experimental model is based on the PBA approach [8, 13]. In general, the PBA may be applied for smoothing of any experimentally measured data. It allows for simultaneous use of the whole experimental, theoretical, and heuristic knowledge of analyzed problems in a way dependent on the reliability of such information [8]. The PBA may be also applied for smoothing of discrete data obtained from any rough numerical solution of any boundary value problem. So far mostly the deterministic methods have been used for solving the PBA problems [8, 13]. However, preliminary attempts of application of the EA to such problems have been also recently made in [17].

Due to the size and complexity of the considered optimization problems, our research is focused, first of all, on the efficiency increase of the algorithms applied. We are presenting here the state of the art of our research, including overview of the proposed acceleration techniques, advances in their development, and chosen numerical results carried out for various benchmarks problems. The present work is a continuation of the previous papers [5, 15–18].

4.2 General Problem Formulation

Considered is a wide class of large non-linear constrained optimization problems. Usually such problems are formulated as optimization of functionals, where a function $u(\mathbf{x})$, $\mathbf{x} \in R^N$ is sought, usually in the discrete form of the vector $\mathbf{u} = \{u_i\}$ consisting of nodal values u_i, $i = 1, 2, \ldots, n$. These nodal values are defined on a mesh formed by arbitrarily distributed nodes. Here, N is the dimension of the physical space (1D, 2D or 3D), and n is a number of decision variables. In general, considered optimization problems may be posed as follows:

find a function $u = u(\mathbf{x})$, that yields the stationary point of a functional $\Phi(u)$, satisfying the equality

$$\mathbf{A}(u) = 0 \tag{4.1}$$

and inequality constraints

$$\mathbf{B}(u) \leq 0 \tag{4.2}$$

In particular case of the PBA approach [8], the functional

$$\Phi = \lambda\, \Phi^E + (1 - \lambda)\, \Phi^T, \quad \lambda \in [0, 1] \tag{4.3}$$

consists of the experimental $\Phi^E(\sigma)$ and theoretical $\Phi^T(\sigma)$ parts, scaled to be dimensionless quantities. Here, σ is the required solution, and λ is a scalar weighting factor. In the PBA, the equality constraints are usually of theoretical nature, while the inequality ones are mostly of experimental nature.

The experimental part of the functional is defined as the weighted averaged error resulting from discrepancies between the measured data and its approximation [8]:

$$\Phi^E(\sigma) = \frac{1}{m} \sum_{i=1}^{m} F\left(\frac{f(\sigma(r_i)) - f_i^{\exp}}{e_i} \right) \tag{4.4}$$

where σ represents the required unknown field, f is a measured function of σ, $f_i^{\exp}$ is its experimental value at the point r_i, e_i is an admissible experimental error, m is a number of measurements, $F(x) = p(\bar{x}) - p(x - \bar{x})$ is a data scattering function defined by the probability density function $p(x - \bar{x})$, and $\bar{x}$ is the expected value.

The enhanced field $\sigma(r)$ cannot differ too much from experimental data. Thus, the inequality constraints are defined as local requirements:

$$\left| f(\sigma(r_i)) - f_i^{\exp} \right| \leq e_i, \quad i = 1, 2, 3, ..., m \tag{4.5}$$

It is useful to impose also an averaged global constraint:

$$\sqrt{\Phi^E} \leq e_E \tag{4.6}$$

Admissible experimental errors e_E and e_i, $i = 1, 2, 3, \ldots, m$ should be evaluated taking into account the true statistics of measurements.

The theoretical part of the functional (4.3) is based on a known theory, and/or on heuristic principles [8]. In mechanics it may be represented by an energy

functional that has to be minimized, e.g., the total complementary energy of statically admissible stresses. On the other hand, as a heuristic principle, e.g., requirement of smoothness may be also introduced. In such case, the minimal average curvature κ in the whole domain Ω can be used, hence

$$\Phi^T = \frac{1}{\Omega} \int_{\Omega} \kappa^2 d\Omega \tag{4.7}$$

where

$$\kappa^2 = \frac{1}{2\pi} \int_0^{2\pi} \left(\frac{\partial^2 f}{\partial \nu^2} \right)^2 d\varphi \tag{4.8}$$

In the 2D Cartesian coordinate system the above definition may be replaced by the following one:

$$\kappa^2(f) = \tfrac{1}{4}(f_{xx} + f_{yy})^2 + \tfrac{1}{8}(f_{xx} - f_{yy})^2 + \tfrac{1}{2} f_{xy}^2 \tag{4.9}$$

and transformed to the polar coordinate system if necessary.

One of the main difficulties in the general formulation is the problem of how to establish the weighting factor λ, i.e., how to determine a reasonable balance between experiment and theory involved. Specific formulations addressing this problem may be found in [8].

4.3 Evolutionary Algorithms and Acceleration Techniques

Nowadays, the EA form a wide group of biologically inspired methods based on theory of evolution and genetics. This group includes such methods like genetic algorithms, genetic programming, evolutionary strategies, evolutionary programming, and others [4, 10]. In this paper, the EA are precisely understood as genetic algorithms with decimal (floating-point) chromosomes. The standard algorithm consists of three operators: selection, crossover and mutation [4]. Significant acceleration of the EA-based solution approach may be achieved in various ways, including appropriate hardware, software, and algorithm improvements.

Hardware acceleration techniques include distribution and parallelization of calculations on various parallel architectures, e.g., general-purpose Graphics Processing Units (GPUs), Field-Programmable Gate Array (FPGA) devices, or standard computer clusters. Efficient software implementations dedicated for particular hardware architectures are crucial as well. Many various parallel EA have been already developed and tested [9, 11]. Algorithmic acceleration of an optimization process may be obtained by, e.g., development of hybrid algorithms

[2, 6] combining the EA with deterministic methods (such as feasible direction method), and introduction of new, problem-oriented operators.

Our approach includes three ways for the EA speed-up. At first, a choice of the most efficient combination of particular selection, crossover, and mutation operators was sought, out of a variety of available ones. Three types of classification rules were proposed and applied for this purpose. Evaluation of the best values of EA parameters (like population size, probability of mutation and crossover) was done as well. Later on, we have proposed and preliminarily investigated several new acceleration techniques based on simple concepts. These techniques include smoothing and balancing [15, 16], a'posteriori error analysis and related techniques (like solution averaging and cloning, creating population of representatives) [18], as well as adaptive step-by-step mesh refinement [5, 16], and possible combinations of the above. Proposed techniques are well supported by non-standard use of parallel and distributed calculations. Some of them are problem- (or class of problems) oriented, other are of more general nature. Some of these techniques are addressed to optimization of functionals, where a large set of nodal values of a function is searched. Appropriate constraint handling [3] is also very important, especially in the case of optimization problems involving large number of inequality constraints. Therefore, we have paid particular attention to investigation of various penalty functions for constraint handling and their impact on the convergence rate of the optimization process. Finally, we consider application and further development of chosen well-known acceleration techniques, such as standard distribution and parallelization of computations, hybrid approach, and use of other evolutionary operators (e.g. gradient mutation).

4.3.1 Smoothing and Balancing

In the case of optimization processes involving large number of decision variables, raw results obtained from the EA approach usually present a collection of locally scattered data. If information about solution smoothness (at least in subdomains) is available, it may be used for acceleration of the solution process. This may be done in various ways [5, 15]. First of all, an extra procedure based on the Moving Weighted Least Squares (MWLS) technique [19, 20], or any other equivalent approximation method, is applied in order to smooth the raw results obtained from the standard EA procedure.

In the MWLS technique, the weighted error functional

$$B = \sum_{i=1}^{n} (u_i - \bar{u}_i)^2 w_i^2 \tag{4.10}$$

is minimized at each point $\bar{x}$ with the respect to the set of local derivatives of function u. Here u_i is a nodal function value supplied by the EA, while $\bar{u}_i$ presents

its approximation by means of expansion into the p-th order truncated Taylor series, and w_i is a weighting factor. In the case of 1D, a local p-th order approximation is obtained as follows:

$$\bar{u}_i = \bar{u}(x_i) = \bar{u} + h_i \bar{u}' + \frac{1}{2} h_i^2 \bar{u}'' + \cdots + \frac{1}{p!} h_i^p \bar{u}^{(p)} + R \tag{4.11}$$

where $h_i = x_i - \bar{x}$, and R is a residuum of the Taylor series. Weighting function may be introduced as in [8]:

$$w_i^2 = \left(h_i^2 + \frac{g^4}{h_i^2 + g^2} \right)^{-p-1} \tag{4.12}$$

where g is a smoothing parameter, allowing us to control the intensity of smoothing. Minimization conditions:

$$\frac{\partial B}{\partial \bar{u}} = 0, \quad \frac{\partial B}{\partial \bar{u}'} = 0, \quad \frac{\partial B}{\partial \bar{u}''} = 0, \quad \ldots, \quad \frac{\partial B}{\partial \bar{u}^{(p)}} = 0 \tag{4.13}$$

provide a set of linear equations to be solved for the unknown function $\bar{u}$ and its derivatives up to the order p at each point $\bar{x}$.

The above formulation may be easily transformed into a 2D one. It may be found in [19, 20].

Appropriate choice of a value of the smoothing parameter $g \geq 0$ is of significant importance. For $g = 0$ the weighting function is singular and provides interpolation. Otherwise, we deal with the best approximation problem. The higher the value of the parameter is, the smoother is the approximation obtained.

In problems of mechanics each smoothing may result in the global equilibrium loss of a considered body. The equilibrium may be restored by the standard EA approach in a series of iterations. However, it may be also faster restored by means of an artificial balancing of body forces performed directly after the smoothing [16].

Information about smoothness may be also used in a selection of chromosomes process [5, 15]. A new criterion based on a mean solution curvature may be introduced into any selection operator. Mean local solution curvature κ may be calculated, e.g., using the definition based on the directional derivative, the same as in the case of the PBA formulation (4.8 and 4.9). The mean curvature of the solution in the whole domain may be calculated using the formula (4.7).

4.3.2 A'posteriori Error Analysis and Related Techniques

Due to stochastic nature of evolutionary computations, solutions obtained from independent populations may differ from each other. The weighted average of the best solutions taken from such populations is expected to be more precise than majority of these solutions. Such averaged and additionally smoothed afterwards solution may be used as a reference one for a'posteriori error estimation [1, 18].

Later on, the knowledge about the magnitude and the distribution of solution errors is used in order to intensify calculations in zones of large errors. We have proposed improved mutation and crossover operators taking into account information about local solution errors [18]. Information about estimated global error may be used by the modified selection operator.

A'posteriori error analysis may be well supported by parallel and distributed calculations in addition to other standard advantages provided by clusters. Moreover, representation of the best chromosomes, collected at the same time from all populations involved, may be also very useful, and significantly improve the solution process. All independent populations, as well as a population of representatives, are calculated simultaneously in a parallel way. Calculations carried out in each population may be partitioned among processing units as well.

More detailed information and wider numerical analysis of mentioned techniques using chosen benchmark problems may be found in [18].

4.3.3 Adaptive Step by Step Mesh Refinement

Solution time needed for optimization of functional is in many problems strictly dependent on the number of decision variables used, i.e. on the mesh density in the domain. The denser is a mesh in the domain the more time-consuming the solution process is. Therefore, the analysis can start from a coarse mesh and a fast, though not precise enough solution may be obtained at first. Starting from such solution, the mesh may be refined by inserting new nodes. Initial function values at these new nodes are found by means of an approximation built upon the nodal values of the coarse mesh. A general approach for most optimization problems may be obtained by using the MWLS approximation [19, 20] approach. However, any other approximation or interpolation method might be applied as well. Such approach may be repeated several times, until a sufficiently dense mesh is obtained.

Furthermore, the step-by-step mesh refinement may be also combined with the a'posteriori error analysis. Such strategy, using all techniques mentioned above, may be found in [5, 16].

4.4 Selected Benchmark Problems

The EA efficiency was examined using several benchmark problems, including residual stress analysis in chosen elastic perfectly-plastic bodies under various cyclic loadings. In particular, we have analyzed the residual stress in a cyclically bent bar, and in a thick-walled cylinder subject to cyclic loadings, like internal pressure, torsion and tension, including combined loadings [5, 15, 16, 18]. These problems may be analyzed as either 1D (taking into account existing symmetries)

or as 2D ones as well. Another advantage of the considered benchmark problems is possibility of testing almost any number of decision variables involved.

We have also investigated several benchmark problems using simulated pseudo-experimental data and the PBA approach, including smoothing of beam deflections, and reconstruction of residual stresses in a thick-walled elastic-perfectly plastic cylinder subject to cyclic internal pressure [17]. For smoothing of beam deflections we also used real experimental data obtained by vision measurement system.

Three chosen benchmark problems are described in a more detailed way below.

4.4.1 Residual Stress Analysis in Bending Bar

Considered is the residual stress analysis in an elastic-perfectly plastic bar of the rectangular cross-section subject to cyclic bending by the moment exceeding its elastic capacity. In the simplest 1D case the solution of the following optimization problem was searched:

Find self-equilibrated normal stress $\sigma = \sigma(z)$ minimizing complementary energy of the bar

$$\min_{\sigma} \int_0^H \sigma^2 dz \tag{4.14}$$

and satisfying the global self-equilibrium bending moment equation

$$M = \int_0^H \sigma \, z dz = 0 \tag{4.15}$$

as well as the inequality conditions resulting from the yield criterion

$$\left| \sigma + \sigma^e \right| \leq \sigma_Y \tag{4.16}$$

where σ_Y is the yield stress (plastic limit), and σ^e is the purely elastic solution of the problem considered. After discretization, where the sought normal stress $\sigma = \sigma(z)$ is replaced by the piecewise linear function spanned over the nodal values σ_i, the following formulation is obtained:

Find stresses $\sigma_1, \sigma_2, \ldots, \sigma_n$ satisfying

$$\min_{\sigma_1, \sigma_2, \ldots, \sigma_{n-1}} \left(\sum_{i=1}^{n-1} \sigma_i^2 + \frac{1}{2}\sigma_n^2 \right), \quad \sigma_n = -\frac{2}{z_n} \sum_{i=1}^{n-1} \sigma_i z_i \tag{4.17}$$

and inequality constraints

$$-\sigma_Y \leq \sigma_i + \sigma_i^e \leq \sigma_Y, \quad i = 1, 2, 3, \ldots, n \tag{4.18}$$

Numerical integration is used providing the exact results for piece-wise linear functions.

The target 3D non-linear constrained optimization problem resulting from residual stress analysis in railroad rails, and vehicle wheels is of similar, though much more complex nature. The exact formulation of this problem is given in [12, 13].

4.4.2 *Residual Stress Analysis in Pressurized Thick Walled Cylinder*

Considered is an elastic-perfectly plastic thick-walled cylinder under cyclic internal pressure. The following optimization problem given in the polar coordinates for residual stress is analyzed:

find the minimum of the total complementary energy

$$\min_{\sigma_r^r, \sigma_t^r, \sigma_z^r} \frac{1}{2E} 2\pi L \int_a^b \left((\sigma_r^r - \sigma_t^r)^2 + (\sigma_t^r - \sigma_z^r)^2 + (\sigma_z^r - \sigma_r^r)^2 \right) r \, dr \tag{4.19}$$

subject to the equilibrium equation

$$\frac{\partial \sigma_r^r}{\partial r} + \frac{\sigma_r^r - \sigma_t^r}{r} = 0 \tag{4.20}$$

the yield condition

$$\varphi(\sigma_r^r, \sigma_t^r, \sigma_z^r, \sigma^e) \leq \sigma_Y \tag{4.21}$$

the incompressibility equation

$$\sigma_z^r = \nu \, (\sigma_r^r + \sigma_t^r) \tag{4.22}$$

and boundary conditions

$$\sigma_{r|a}^r = 0, \quad \sigma_{r|b}^r = 0 \tag{4.23}$$

where σ_r^r, σ_t^r, σ_z^r are respectively the radial, circumferential and longitudinal residual stresses, $\sigma^e = \{\sigma_r^e, \sigma_t^e, \sigma_z^e\}$ is the purely elastic solution of the same problem, σ_Y is the yield stress, a, b are respectively the internal and external cylinder radii, L is its length, and E is the Young modulus.

4.4.3 Reconstruction of Residual Stresses Using the PBA Approach

Given are strains $\varepsilon_i^{\exp}$, $i = 1, 2, 3, \ldots, n$, experimentally measured in the 2D cross-section of the thick-walled cylinder under cyclic internal pressure. Find the residual stresses in its 2D cross-section. The following formulation in the polar coordinate system is used:

find the stationary point of the functional

$$\Phi(\sigma) = \lambda\, \overline{\Phi}^E(\sigma) + (1-\lambda)\, \overline{\Phi}^T(\sigma)\ , \quad \lambda \in [0,1] \tag{4.24}$$

where

$$\Phi^E(\sigma) = \left(\frac{1}{n} \sum_{i=1}^{n} (\varepsilon_i^{\exp} - \varepsilon_i^{app}(\sigma))^2 \right)^{\frac{1}{2}} \tag{4.25}$$

$$\Phi^T(\sigma) = \frac{1}{\Omega} \int_{\Omega} \kappa^2(\sigma) d\Omega \tag{4.26}$$

satisfying equality constraints (4.20, 4.22 and 4.23), and inequality constraints for admissible local and global errors

$$\left| \varepsilon_i^{\exp} - \varepsilon_i^{app}(\sigma) \right| \le e_i\ , \quad i = 1, 2, 3, \ldots, n \tag{4.27}$$

$$\sqrt{\Phi^E(\sigma)} \le e_E \tag{4.28}$$

The mean solution curvature is calculated using the formula (4.9).

4.5 Numerical Results

The main objective of numerous executed tests was to evaluate correctness, efficiency, and ability of the proposed acceleration techniques to deal with large, and very large optimization problems. At first a choice of the most efficient combination of the standard EA operators was sought. Searching the best combination of operators, as well as adjusting their parameters, the acceleration up to several times may be reached. From numerous variants of operators we preliminarily chose several popular ones: rank and tournament selection, arithmetic and heuristic crossover, uniform, non-uniform and border mutation. Using the best

combination found, namely rank selection, heuristic crossover, and non-uniform mutation, particular already mentioned acceleration techniques were analyzed. Some other results of our efficiency analysis were also described in [16, 18], and very briefly in [5, 15].

Acceleration of calculations was measured using four speed-up factors proposed, and defined in [18]. These factors take into account convergence of mean solution error as a function of time, or number of iterations. Convergence of fitness function is also measured.

All presented results were averaged over 10 independent solution processes.

4.5.1 Smoothing and Balancing

In the considered tests, the MWLS technique was used for additional smoothing of raw EA results. When using this technique it is necessary to establish values for two extra parameters: order of local approximation p, and smoothing parameter g. Various values of these parameters may have significant influence on the convergence of the solution process. Number of standard iterations between subsequent smoothing and balancing operations has to be considered as well. In Figs. 4.1 and 4.2 one may see results obtained in the bending bar analysis (benchmark 4.4.1).

In the case of this benchmark test, the best results were obtained for the linear local approximation $p = 1$ (see Fig. 4.1). There is also no significant difference between results obtained for $p = 2$ and $p = 3$. However, the best results obtained in case of $p = 1$ may result from the specific features of the sought solution of the problem, which is piece-wise linear. For more complex solutions higher local approximation orders will be needed. In general, the order of local approximation should depend on the order of differential operators used.

In Fig. 4.1 you may also see additional time needed for each smoothing and balancing operation. These operations were repeated after each 300 iterations. All optimization processes shown in Fig. 4.1 were carried out for 3000 iterations, so you may find the whole additional time needed for all extra smoothing operations. This extra time is not significant when compared to obtained gains. The results were obtained for smoothing parameter $g = 5$. Other executed tests, not presented here, showed that choice of the value of g parameter was not significant, excluding small ones. For $g \in [3, 20]$ obtained results were very similar.

Application of our smoothing technique based on the MWLS, and balancing procedure based on the linear correction terms allowed to achieve up to about 4 times efficiency increase (see Fig. 4.2). Smoothing technique was also tested using benchmark 4.4.2 and gave encouraging results as well.

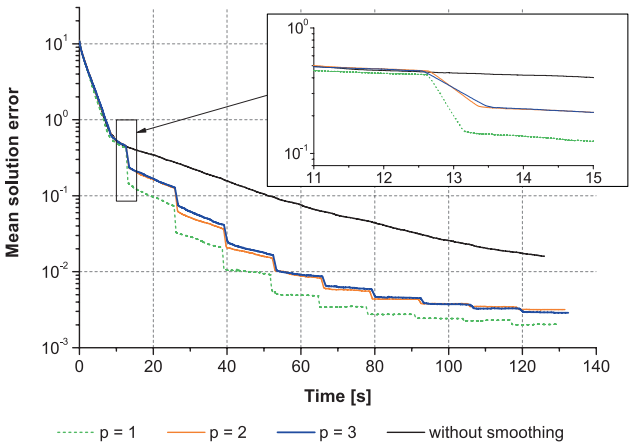

Fig. 4.1 Results of smoothing and balancing for various orders of local approximation in the MWLS technique

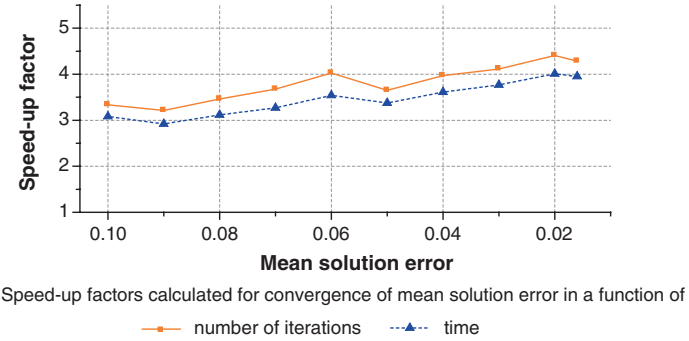

Fig. 4.2 Speed-up factors for smoothing and balancing

4.5.2 Constraint Handling—Penalty Functions

A type of penalty function, as well as its parameters may have a significant impact on the convergence rate of the optimization process. In our research, the following function was used for constraint handling:

$$F = f + \sum_{i=1}^{n} \alpha \, d_i^{\beta} \tag{4.29}$$

where F is the new (expanded) objective function, f is the standard fitness function, d_i is the distance of i-th decision variable to constraint boundaries, n is the number of decision variables, α and β are parameters.

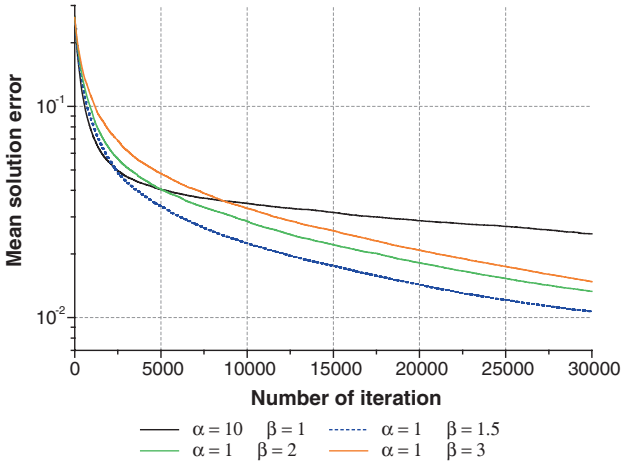

Fig. 4.3 Comparison of convergence of mean solution error for various penalty functions

In Fig. 4.3 one may see results obtained for various values of parameters α and β in cyclically pressurized cylinder analysis (benchmark 4.4.2). In this example, the best results were obtained for $\alpha = 1$ and $\beta = 1.5$. When comparing the best and the worst cases shown in Fig. 4.3, the speed-up about 3 times was reached.

4.5.3 Step by Step Mesh Refinement

Results shown in Fig. 4.4 were obtained in reconstruction of residual stresses in the thick walled cylinder under cyclic internal pressure using pseudo-measurements of strains and the PBA approach (benchmark 4.4.3). Numerical data used in this experiment were randomly generated using the true (analytical) solution as a base curve. A strain gauge technique was simulated. Assumed were delta type rosettes, giving three components of strains. All calculations were carried out in the 2D domain. The random data generator used Gaussian distribution. More detailed description of methodology of such tests, as well as solutions obtained, may be found in [17]. In this paper only a brief analysis of calculation efficiency is presented.

Comparison of the convergence of mean solution error for standard and improved algorithms is shown in Fig. 4.4. In this case, the improved EA used a series of denser and denser meshes, combined with smoothing technique. The process started with 16 nodes, and was continued until the number of 1248 nodes was reached. The mesh was refined 4 times. Each nodal value corresponded to one decision variable (gene in a chromosome). In comparison to the standard EA, the acceleration factor of the optimization process up to about 140 times was reached.

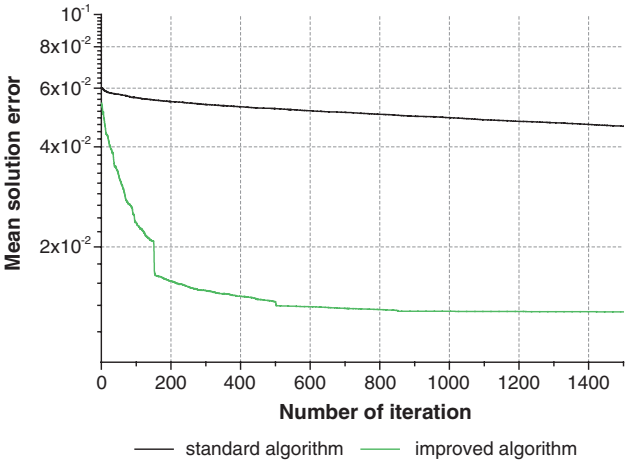

Fig. 4.4 Comparison of convergence of mean solution error for standard and improved algorithm

4.6 Conclusions

The general objective of this research is development of highly efficient, dedicated EA for solving large non-linear constrained optimization problems. Preliminary results of many executed tests clearly show a possibility of significant efficiency increase when using all proposed acceleration techniques. The speed-up about 140 times was reached. It is also worth noticing, that the improved EA allowed obtaining solutions in cases when the standard EA failed to solve problems due to too large number of decision variables. Results obtained indicate also a clear possibility of practical application of the improved EA to the PBA of experimental and/or numerical data for large optimization problems. Application of the accelerated EA to the PBA is still at the initial stage of research development, however preliminary results are very encouraging.

Future research includes continuation of various efforts oriented towards efficiency increase of the EA-based optimization approach, analysis of further, demanding benchmark problems, and application of such developed method to residual stress analysis in railroad rails, and vehicle wheels [8, 12, 13]. The PBA approach for smoothing of experimental data is also expected.

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