Comparison of Differential Evolution, Particle Swarm Optimization and Genetic Algorithms for the identification of Bouc-Wen hysteretic systems

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Abstract

In this paper, several variants of Differential Evolution, Particle Swarm Optimization and Genetic Algorithms are employed for the identification of a Bouc-Wen hysteretic system that represents a full-scale bolted-welded steel connection. The purpose of this work is to assess their comparative performance in a highly non-linear identification problem. Interesting results are produced that reveal the strengths and weaknesses of each algorithm.

Keywords: differential evolution, particle swarm optimization, genetic algorithms, identification, Bouc-Wen.

1   Introduction

In this study, the problem of identifying an unknown hysteretic system is addressed. The system represents a full-scale bolted-welded steel connection and identification is based on actual experimental data. The model structure is assumed known; in particular, the Bouc-Wen model [1], [2] is used which is assumed to be able to capture all the major system characteristics. Thus, system identification reduces to estimation of the unknown Bouc-Wen model parameters. Nevertheless, the problem remains highly non-linear; parameter estimation even of single-degree-of-freedom systems is not trivial, as will be demonstrated.

Recent research by the Authors [3] has shown that Evolutionary Algorithms (EAs) are better suited for the task at hand. Apart from the algorithms examined in [3], i.e. Standard Genetic Algorithm (SGA), micro-GA (μGA), a hybrid method originally presented in [4] and two variants of Particle Swarm Optimization (PSO), three variants of another candidate algorithm, namely the Differential Evolution (DE), are examined herein. Comparative analysis of all results reveals interesting conclusions.

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2   The Bouc-Wen model

2.1   General

The Bouc-Wen model is a smooth endochronic model that is often used to describe hysteretic phenomena. It was introduced by Bouc [1] and extended by Wen [2]. The versatility of the Bouc-Wen model has been demonstrated in numerous cases. It has been used extensively for the modeling of magnetorheological (MR) dampers [5], wood joints [6], welded steel joints [7] and isolation devices [8], [9], to name a few. An extensive survey on the implementation of the Bouc-Wen hysteretic model can be found in the work of Ismail et al [10].

2.2   Model formulation

The equation of motion of a single-degree-of-freedom system without viscous damping is expressed as:

$$m\,\ddot{u}(t) + F(t) = f(t) \tag{1}$$

where, m is the mass, $u(t)$ is the displacement, $F(t)$ the restoring force, $f(t)$ the excitation force and overdot denotes the derivative with respect to time. According to the Bouc-Wen model, the restoring force is expressed as:

$$F(t) = a\frac{F_y}{u_y}u(t) + (1-a)F_y\,z(t) \tag{2}$$

where, F_y the yield force, u_y the yield displacement, a the ratio of post-yield to pre-yield (elastic) stiffness and $z(t)$ a dimensionless hysteretic parameter that obeys the following non-linear differential equation:

$$\dot{z}(t) = \frac{1}{u_y}\Big[A - \big|z(t)\big|^n\,(\beta + \mathrm{sgn}(\dot{u}(t)\,z(t))\,\gamma)\Big]\dot{u}(t) \tag{3}$$

where, A, β, γ, n are dimensionless quantities controlling the behavior of the model and $\mathrm{sgn}(\cdot)$ is the signum function. For small values of the positive exponential parameter n the transition from elastic to post-elastic branch is smooth, whereas for large values the transition becomes abrupt, approaching that of a bilinear model. Parameters β and γ control the size and shape of the hysteretic loop. Parameter A was introduced in the original formulation of the model, but it became evident that it is redundant [11].

From Eq. (2) it follows that the restoring force $F(t)$ can be analyzed into an elastic and a hysteretic part as follows:

$$F_e(t) = a \, \frac{F_y}{u_y} \, u(t) \tag{4}$$

$$F_h(t) = (1-a) \, F_y \, z(t) \tag{5}$$

Thus, the model can be visualized as two springs connected in parallel (Figure 1) where, $k_e = F_y/u_y$ and $k_p = a \, k_e$ are the initial and post-yielding stiffness of the system. Further analysis regarding the response of the Bouc-Wen model can be found in [12].
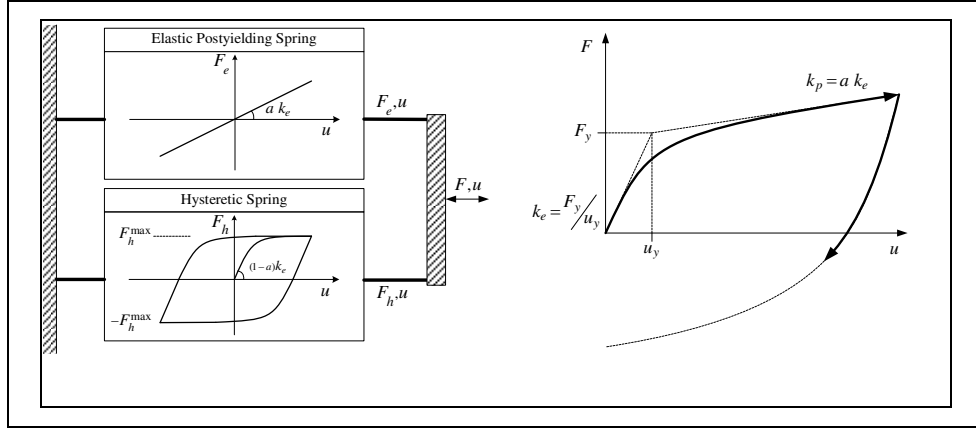

Figure 1: The Bouc-Wen model

2.3 Parameter constraints

It has been proven [11] that the parameters of Bouc-Wen model are functionally redundant, i.e. there exist multiple parameter vectors that produce an identical response for a given excitation. This redundancy is best removed by fixing parameter A to unity, [5], [9], [11].

Parameters β and γ control the shape of hysteretic loops [2]. These parameters do not have clear physical meaning and affect the entire behavior in an indirect way. Constantinou and Adnane [13] impose a certain constraint, viz. $A/(\beta+\gamma)=1$, to reduce the model to a formulation with well-defined properties.

Adopting the aforementioned constraints, the total number of unknown parameters is reduced to five, i.e. γ, n, a, F_y and u_y. Moreover, following the recommendations of Constantinou and Adnane [13], parameter γ is bounded in the range of [0,1]. It is noted that additional parameters are required in cases when additional phenomena are taken into account, such as degradation effects e.g. [14], or hysteretic loops with inflexion points, e.g. [15].

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2.4 Identification

Due to its highly non-linear nature, the identification of Bouc-Wen hysteretic systems constitutes a challenging problem even for the simplest single-degree-of-freedom case. Consequently, it has been tackled by a variety of methods, such as Gauss-Newton [16], modified Gauss-Newton [17], Least squares [18], Simplex [19], Levenberg-Marquardt [19], [20], extended Kalman filters [19], [21], reduced gradient methods [19], Genetic Algorithms (GAs) [22], real-coded GAs [23], Differential Evolution [24], [25], adaptive laws [26], etc.

Various techniques have been used to alleviate performance problems. In some methods [17], [21], [24], the exponential parameter of the model is fixed *a priori* to a specific value. In other cases [16], [25], a two-stage scheme is employed which reduces the complexity of the problem. Approximate initial ranges for the parameter values are determined prior to identification on the basis of phenomenological reasoning [22]. In some cases, other system parameters, most commonly stiffness and viscous damping, are generally considered known.

3 Identification scheme

3.1 Objective function and identification problem

Herein, the normalized Mean Square Error (MSE) of the predicted time history $\tilde{y}(t|\mathbf{p})$ as compared to the reference time history $y(t)$ is used as the objective function. When cast in discrete form, it can be expressed as:

$$OF(\mathbf{p}) = \frac{\sum_{i=1}^{N}(y(t_i) - \tilde{y}(t_i \mid \mathbf{p}))^2}{N \ \sigma_y^2} \tag{6}$$

where, $\mathbf{p}$ is the parameter vector, σ_y^2 the variance of the reference time history and N the number of points used. The time history of the displacement and external force is used for force- and displacement-controlled experiments, respectively.

Formally, the optimization problem can be stated as the minimization of the objective function $OF(\mathbf{p})$ when the parameter vector is subjected to the following side constraints:

$$\mathbf{x}_{LB} \leq \mathbf{p} \leq \mathbf{x}_{UB} \tag{7}$$

where, $\mathbf{x}_{LB}$ and $\mathbf{x}_{UB}$ are vectors defining the lower and upper values of model parameters, respectively, and vector inequalities apply element-wise. For PSO and DE algorithms, a linear penalty function is implemented to constrain the particles within the prescribed Design Space (DS). In case an invalid parameter value occurs (e.g. negative n), the error handler is invoked and the particle is assigned a prescribed large objective function value.

3.2 Investigated problem

The algorithms are used to identify a hysteretic system representing a full-scale steel cantilever beam. The experiment, namely experiment No. 5, was conducted by Popov and Stephen [27] at Berkeley in 1970 and refers to a WF 24×76 beam (A36 Grade) that was connected to a rigid column. The flanges were welded to the column, while the web was bolted using seven 7/8" bolts (Figure 2a). The free end of the beam was subjected to a cyclic displacement pattern of increasing amplitude [27]. The response exhibited shows a clear non-degrading hysteretic behavior (Figure 2b).
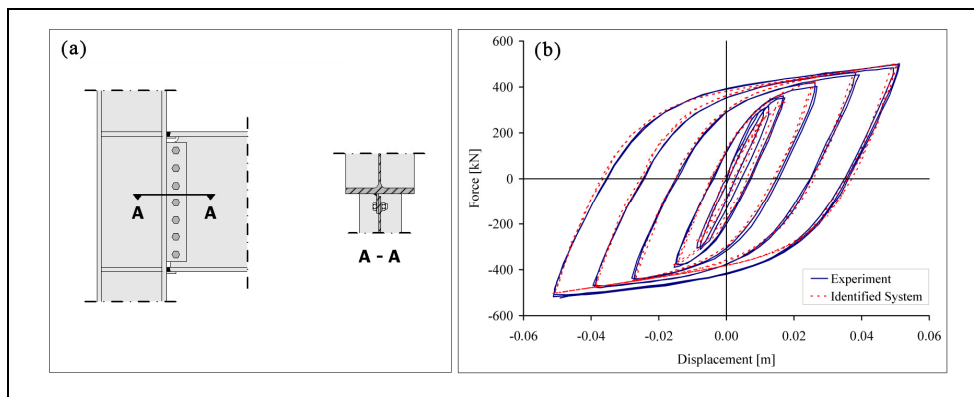

Figure 2: (a) Bolted-welded connection (b) force-displacement graph

4 Algorithms

4.1 SGA

Genetic algorithms (GAs) are population-based evolutionary algorithms that originated from the work of Baricelli [28] and Fraser [29], evolved in their present form by Holland [30] and De-Jong [31], and later employed in a plethora of applications. Standard GA (SGA) is implemented and tested herein, which can be described by the following pseudo-code:

1. Initialize the population of individuals (chromosomes).
2. Calculate the fitness of each individual in the population.
3. Select individuals to form a new population according to each one's fitness.
4. Perform crossover and mutation.
5. Repeat steps (2) to (4) until some condition is satisfied.

Implementation is based on [32]. The parameters of SGA are taken as follows: gene length L_g=10 bits; population size P=25 and P=50; single crossover with probability 0.7; jump mutation probability $1/P$; creep mutation probability $L_c/N_p/P$

(N_p=5=number of variables); biased roulette wheel selection and elitism with one individual.

4.2 μGA

Micro-GA (μGA), proposed by Goldberg [33] and first implemented by Krishnakumar [34], is also implemented herein. The properties of μGA are (a) P=5, (b) L_g=10 bits and (c) single crossover.

4.3 Hybrid algorithm

A hybrid algorithm, presented in [4], is also employed. The hybrid method consists of SawTooth-GA [35], a local optimizer, namely the Greedy Ascend Hill Climber [1], and a bounding method that gradually decreases the size of the DS. The H2 configuration of the hybrid method is employed [4].

4.4 Simple PSO

Particle Swarm Optimization (PSO) is a stochastic algorithm suitable for global optimization with no need for direct evaluation of gradients. The method, introduced by Kennedy and Eberhart [36], mimics the social behavior of flocks of birds and swarms of insects. A simple PSO variant is employed herein, which is based on [3]. Assume that the population consists of p individuals. Within the DS, each individual is characterized by its position and velocity, determined at time instant k by the corresponding vectors $\mathbf{x}_k$ and $\mathbf{v}_k$. Initially, the particles are distributed randomly in the box-constrained search space, as follows:

$$\mathbf{x}_{LB} \leq \mathbf{x}_0^d \leq \mathbf{x}_{UB} \ \ \forall d \in \{1, 2, ..., p\} \tag{8}$$

The position vector of individual d at the next time instant $k+1$ is given as:

$$\mathbf{x}_{k+1}^d = \mathbf{x}_k^d + \mathbf{v}_{k+1}^d \tag{9}$$

where the time step Δt between the distinct time instants is assumed to be equal to unity. The velocity vector $\mathbf{v}^d_{k+1}$ is given as:

$$\mathbf{v}_{k+1}^d = w_k \ \mathbf{v}_k^d + c_1 \ \mathbf{r}_1 \circ (\mathbf{p}_k^d - \mathbf{x}_k^d) + c_2 \ \mathbf{r}_2 \circ (\mathbf{p}_g - \mathbf{x}_k^d) \tag{10}$$

where, w_k is the inertia factor at time instant k; c_1, c_2 are the cognitive and social parameters of the algorithm, respectively; $\mathbf{p}^d_k$ is the best ever position vector of individual d at time instant k; $\mathbf{p}_g$ is the best ever position vector amongst all individuals at time instant k; $\mathbf{r}_1$, $\mathbf{r}_2$ are vectors of random variables with uniform distribution in the interval [0,1] and the ($\circ$) operator indicates element-by-element multiplication. This formulation is compatible with the diverse "classical" version of

PSO [37]. The Simple PSO algorithm imposes no limitations with regard to the maximum velocity of the particles.

In this study, the Simple PSO algorithm features the following properties: (a) population size $p=20$, (b) cognitive parameter $c_1=2$, (c) social parameter $c_2=2$, (d) constant inertia factor $w=0.8$.

4.5 Enhanced PSO

The enhanced PSO variant is based on the work of Fourie and Groenwold [38], as follows:

- The initial maximum velocity of the individuals is evaluated so that in one time step an individual may travel up to a certain fraction of the search space:

$$\mathbf{v}_0^{max} = \gamma(\mathbf{x}_{UB} - \mathbf{x}_{LB})$$ (11)

- If the best solution found in the whole swarm is not improved over a period of h consecutive steps, then it is assumed that the velocities are large and the algorithm cannot locate better solutions due to overshooting. For this reason, both the inertia factor and the maximum velocity are decreased as follows:

$$\text{If } OF(\mathbf{p}_g)\big|_k = OF(\mathbf{p}_g)\big|_{k-h} \Rightarrow w_{k+1} = a\ w_k,\ \mathbf{v}_{k+1}^{max} = \beta\ \mathbf{v}_k^{max}$$ (12)

- The craziness operator assigns a random velocity vector to an individual resulting in its moving away from the swarm and thus exploring other regions of the search space. The operator is activated with a probability P_{cr} as follows:

$$\text{If } r < P_{cr} \Rightarrow \text{randomly assign } \mathbf{v}_{k+1} \text{ with } \mathbf{0} < \mathbf{v}_{k+1} \leq \mathbf{v}_{k+1}^{max}\ \forall \text{ particle } d$$ (13)

where r is a random variable with uniform distribution in the interval [0,1].
- The algorithm employs both an elite particle and an elite velocity. The individual with the worst performance is moved to the best ever position of the swarm which implies a gradual shift towards the region where good solutions reside:

$$\mathbf{x}^{pe} = \mathbf{p}_g$$ (14)

In addition, if the velocity vector $\mathbf{v}^d_k$ resulted in an improvement of $\mathbf{p}_g$, then:

$$\mathbf{x}_{k+1}^d = \mathbf{p}_g + c_3\ \mathbf{r}_3 \circ \mathbf{v}^{pe}$$ (15)

where, $\mathbf{v}^{pe}=\mathbf{v}^d_k$, c_3 is a parameter of the algorithm and $\mathbf{r}_3$ is a vector of random variables with uniform distribution in the interval [0,1]. Note the difference with respect to [38], where a single random variable r_3 is used to multiply the whole vector $\mathbf{v}^{pe}$.

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In this study, the Enhanced PSO algorithm features the following properties: (a) population size $p=20$ (b), cognitive parameter $c_1=0.5$, (c) social parameter $c_2=1.6$ (d) maximum velocity coefficient $\gamma=0.4$, (e) initial inertia factor $w_0=1.40$, (f) maximum steps without improvement $h=3$, (g) fraction for the decrease of the inertia factor $a=0.99$, (h) fraction for the decrease of maximum velocity $\beta=0.95$, (i) craziness factor $P_{cr}=0.22$, (j) elite velocity factor $c_3=1.30$.

4.6   DE

Differential Evolution (DE) is a relative new stochastic method which has attracted the attention of the scientific community. It was introduced by Storn and Price [39] and has approximately the same age as PSO. However, it bears no natural paradigm. An early version was initially conceived under the term "Genetic Annealing" and published in a programmer's magazine [40]. The DE algorithm is extremely simple; the uncondensed C-style pseudocode of the algorithm spans less than 25 lines [40].

According to the classic version of DE, a population of p individuals is randomly dispersed within the DS. The population is denoted as $\mathbf{P_{x,g}}$, as follows:

$$\mathbf{P}_{x,g} = \left(\mathbf{x}_{i,g} \right),\ i = 0,1,...,p-1,\ g = 0,1,...,g_{\max}$$
$$\mathbf{x}_{i,g} = \left(x_{j,i,g} \right),\ j = 0,1,...,N_p - 1. \tag{16}$$

where $\mathbf{P_{x,g}}$= array of p vectors (individuals), $\mathbf{x}_{i,g}$= N_p-dimensional vector representing a solution, i=index for vectors, g=index for generations, j=index for design variables, $g_{\max}$=maximum number of generations and the parentheses indicate an array.

At each evolutionary step (generation), a mutated population $\mathbf{P}_{v,g}$ is formed based on the current population $\mathbf{P}_{x,g}$, as follows:

$$\mathbf{v}_{i,g} = \mathbf{x}_{r0,g} + F\left(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g} \right) \tag{17}$$

where, $r_0 \neq r_1 \neq r_2$ are random indices in $\{0,1,...,p\text{-}1\}$ and F is a scalar DE algorithm parameter. Next, a trial population $\mathbf{P}_{u,g}$ is formed, as follows:

$$\mathbf{u}_{i,g} = \left(u_{j,i,g} \right) = \begin{cases} v_{j,i,g}, & \text{if } \left(rand_j(0,1) \leq Cr \text{ or } j = j_{rand} \right) \\ x_{j,i,g}, & \text{otherwise} \end{cases} \tag{18}$$

where, $rand_j$ is a random number with uniform distribution in $(0,1)$ that is sampled anew each time, j_{rand} is a random index in $\{0,1,...,p\text{-}1\}$ that ensures that at least one design variable will originate from the mutant vector, and Cr is a scalar DE algorithm parameter in the range $(0,1)$. The final step is the selection criterion, which is greedy:

$$\mathbf{x}_{i,g+1} = \begin{cases} \mathbf{u}_{i,g}, & \text{if } OF\left(\mathbf{u}_{i,g}\right) \le OF\left(\mathbf{x}_{i,g}\right) \\ \mathbf{x}_{i,g}, & \text{otherwise} \end{cases} \tag{19}$$

In this study, three variants of DE are examined. The first variant (the classic DE) is denoted as DE1 or "rand/1/bin" [40], where "rand" indicates that base vectors are randomly chosen, "1" means that only one vector difference is used to form the mutated population, and the term "bin" (from binomial distribution) indicates that uniform crossover is employed during the formation of the trial population. The algorithm was described above and features the following properties: (a) p=50 vectors, (b) F=0.5, (c) C_r=0.9.

The second variant is denoted as DE2 or "best/1/bin" [40], where "best" indicates that the base vector used is the currently best vector in the population. Thus, Eq. (17) becomes:

$$\mathbf{v}_{i,g} = \mathbf{x}_{best,g} + F\left(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g}\right) \tag{20}$$

In addition, "jitter" is introduced to the parameter F and Eq. (20) is modified as follows:

$$F_j = F + d\left(rand_j\left(0,1\right) - 0.5\right)$$
$$\mathbf{v}_{i,g} = \mathbf{x}_{best,g} + F_j\left(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g}\right) \tag{21}$$

where, $rand_j$ is a random number with uniform distribution in (0,1) that is sampled anew each time and d is the magnitude of the jitter. The second variant of DE features the following properties: (a) p=50 vectors, (b) F=0.5, (c) C_r=0.9 (d) d=0.001.

Finally, a third variant is also proposed, denoted as DE3 or "rand-best/1/bin". This variant is simply a fixed mix of the DE1 and DE2. Define r_b as the expected ratio of evaluations with "rand/1/bin" as opposed to the ones with "best/1/bin". If $rand_j < r_b$, then evolution is carried out according to DE1. In the opposite case, DE2 is employed. In this study, r_b=0.25 was used.

5   Results

The initial side constraints and reference parameter values are summarized in Table 1. The reference values have been derived in [4] using multiple analyses without limitations in computational time and can be considered to be the "true" values for this problem. The response of the reference system is in very good agreement with the experimental data (Figure 2b). In order to obtain meaningful statistics, the identification results are the mean values of 30 independent runs.

	γ	n	a	F_y [kN]	u_y [m]
Initial lower bound	0.0000	1.0000	0.0000	0.0000	0.0010
Initial upper bound	1.0000	10.0000	1.0000	1000.0000	0.1000
Reference values	1.0000	1.3248	0.0756	420.2557	0.0142

Table 1: Initial side constraints and reference values

In Figure 3, the temporal evolution of the mean MSE of the best individual is presented for SGA, μGA, PSO, the hybrid algorithm and the classic DE (DE1). In terms of average performance, it is observed that the Enhanced PSO variant significantly outperforms the Simple PSO in the early stages of the identification process (Figure 3a). This is mainly due to the dynamic decrease of both the inertia factor and the maximum velocity that enhances the exploitation capabilities of the optimization algorithm. Both variants are outperformed by the DE1, particularly in the early stages of the optimization process. The comparison of the PSO and DE1 with the SGA (Figure 3b) shows that the DE1 and the Enhanced PSO outperform the SGA with either P=25 or P=50 whereas the Simple PSO fails to do so with the case of SGA with P=25. An interesting observation regarding the SGA, is that the best average performance is observed for P=25. Both PSO variants and the DE1 outperform the μGA (Figure 3c), which exhibits the worst performance for the problem under consideration. The Simple PSO is outperformed by the hybrid method. The Enhanced PSO exhibits a more smooth behavior and it manages to outperform the hybrid method at the later stages of identification. The DE1 and the hybrid method exhibit similar performance in the early stages of the optimization process but as optimization progresses the DE1 manages to outperform the hybrid method (Figure 3d). The hybrid method manages to produce very good results at the early stages of the process, as it quickly focuses into the most promising areas of the DS. However, as the size of the DS gets smaller, the hybrid method with the H2 configuration becomes expensive in order to maintain the optimum parameter vector within bounds. Finally, the DE1 produces excellent results with a smooth transition towards the optimum solution as the number of examined solutions increases. This is partly due to the greedy character of the selection operator as it will also be demonstrated later in this paper.

Regarding the Enhanced PSO algorithm, it is observed that the response of the identified system based on the mean results after 5000 analyses is in very good agreement with both the reference identified system and the actual system (Figure 4). This is due to the very good identification of the most sensitive parameters F_y, u_y and a which govern the bilinear skeleton of the response [4].

Next, the Enhanced PSO is compared to the three variants of DE (Figure 5). All DE variants outperformed the Enhanced PSO for this specific problem, in terms of both exploration and exploitation. The second variant, DE2, uses the best population vector as base and therefore is even more greedy than DE1. As a result, it exhibited impressive initial performance, as it required approximately half function evaluations compared to DE1 to reach the same objective function level. However, it

often settled to a near-optimum solution and failed to deliver the "actual" values. The third DE variant (DE3) exhibited the best performance, combining the explorative performance of DE2 and the exploitation capabilities of DE1.
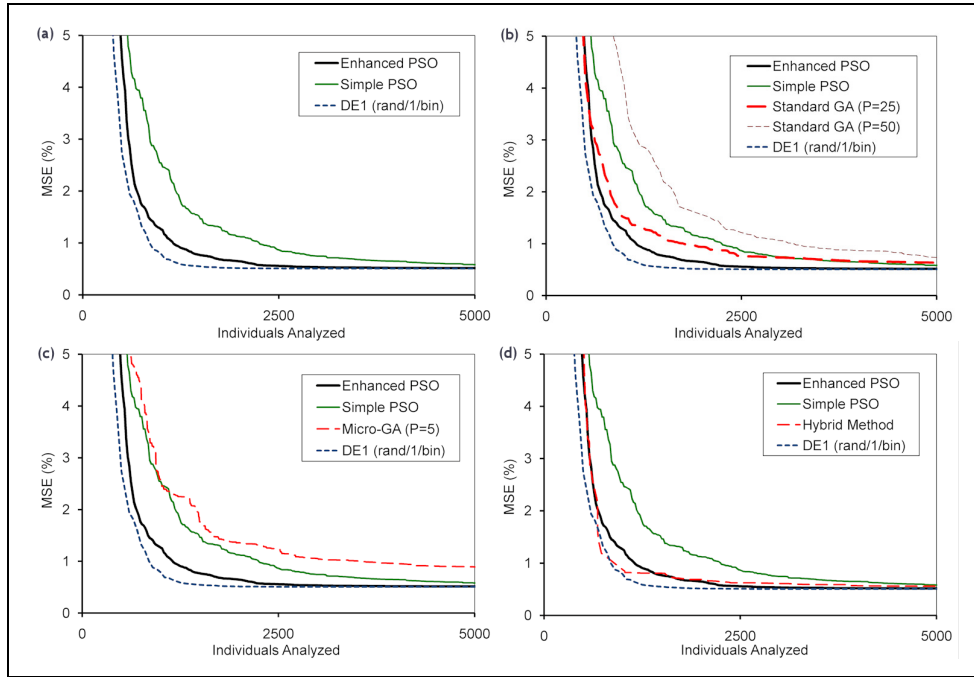
Figure 3: Comparative performance of identification algorithms (a) PSO versus DE1 (b) PSO and DE1 versus SGA with P=25 and P=50 [30] (c) PSO and DE1 versus µGA with P=5 [33], [34] (d) PSO and DE1 versus hybrid method [4]
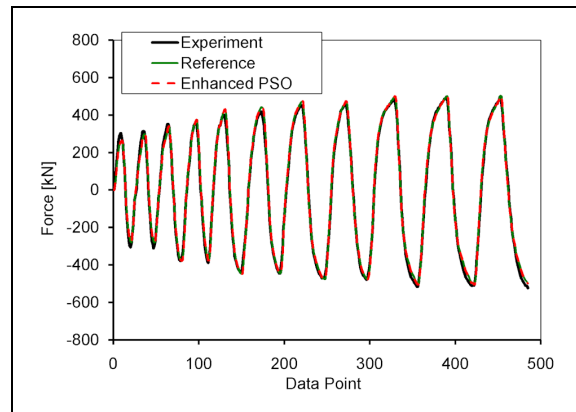
Figure 4: Response of actual system, reference identified system and identified system based on mean Enhanced PSO results after 5000 analyses
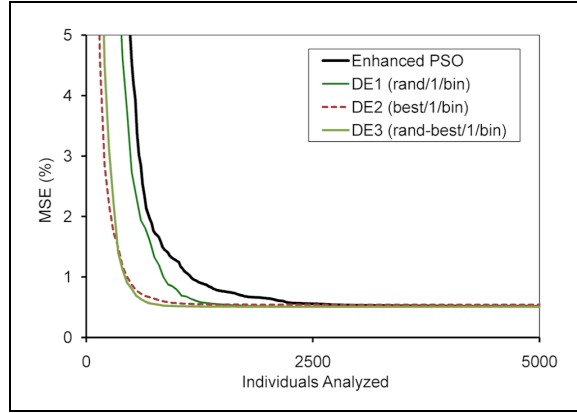
Figure 5: Comparative performance of Enhanced PSO versus DE1, DE2, and DE3

	γ	n	a	F_y [kN]	u_y [m]
Reference values	1.0000	1.3248	0.0756	420.2557	0.0142
SGA (P=25)	0.8717	1.3372	0.0748	409.7100	0.0132
SGA (P=50)	0.8712	1.4320	0.0735	407.0055	0.0132
μGA	0.8342	1.4320	0.0741	402.7696	0.0128
Hybrid Method	0.9591	1.2509	0.0654	429.0323	0.0145
Simple PSO	0.9146	1.3037	0.0770	412.8406	0.0135
Enhanced PSO	0.9358	1.2421	0.0715	420.9948	0.0140
DE1 (random base)	1.0000	1.3247	0.0756	420.2586	0.0142
DE2 (best base)	0.9540	1.2916	0.0727	419.3637	0.0140
DE3 (mixed base)	0.9932	1.3127	0.0750	420.5492	0.0142

Table 2: Identification results after 5000 analyses (mean values)

The identification results after only 5000 function evaluations are summarized in Table 2. It is worth noting the impressive results obtained by DE1, which has practically identified the "actual" parameter values. This is not the product of favorable balancing of estimations around the reference value but rather of impressive algorithm robustness. This conclusion is derived from Table 3, which summarizes the coefficients of variation after 5000 function evaluations. This implies that fine-tuning, unnoticeable in Figure 5, is active with DE1. This is not observed in the case of DE2 where the increased "greediness" results in the derivation of both optimal and near-optimal solutions. Thus, the coefficient of variation is increased considerably as compared to other methods. The DE3 variant, which stochastically transforms the optimization scheme to either DE1 or DE2,

exhibits very good coefficients of variation that fall in between the values observed from DE1 and DE2.

	γ	n	a	F_y	u_y
SGA (P=25)	14.27%	19.58%	27.81%	6.27%	11.36%
SGA (P=50)	13.42%	36.64%	29.25%	6.88%	12.88%
µGA	18.70%	26.86%	39.27%	10.06%	17.19%
Hybrid Method	7.74%	14.28%	23.24%	4.36%	8.28%
Simple PSO	7.76%	13.74%	11.56%	3.40%	6.67%
Enhanced PSO	8.32%	8.08%	7.27%	0.31%	2.86%
DE1 (random base)	0.00%	0.03%	0.04%	0.01%	0.01%
DE2 (best base)	7.95%	13.54%	22.84%	3.58%	6.67%
DE3 (mixed base)	3.31%	4.53%	3.82%	0.35%	0.75%

Table 3: Coefficients of variation after 5000 analyses

5 Conclusions

In this study, several EAs are employed for the identification of an unknown Bouc-Wen hysteretic system that represents a full-scale bolted-welded steel connection. The identification is based on actual experimental data. The algorithms implemented include SGA, µGA, a hybrid method originally presented in [4], two variants of PSO and three variants of DE.

The results indicate that DE is the best algorithm for the specific problem. In particular, the third DE variant, proposed herein, combines impressive exploration and exploitation capabilities. On the other hand, the classic DE variant (DE1) exhibited impressive robustness and produced excellent results after a reasonable number of function evaluations. The Enhanced PSO algorithm also performs satisfactorily. The hybrid method [4] is better suited for more difficult problems, as its bounding method, which gradually diminishes the size of the DS, is hardly even used in this problem. The worst performing algorithm for this problem is µGA.

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