Improved Particle Swarm Optimization for the Determination of Chaboche Model Parameters of the Elastoplastic Behavior Railway Steel

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Abstract:- This paper presents new Particle Swarm Optimization algorithm for the determination of Chaboche model parameter. This is based on the reduction of search-space where the optimal parametersare belonged. The obtained results are compared to other metaheuristic approaches mainly the Genetic Algorithm and standard Particle Swarm Optimization by using the Mean Square Error and optimization time as criteria.The first yielded0.316 for a new approach. Despite this efficiency, the proposed approach has the highest optimization time, which is 787 seconds against 712 seconds for a standard Particle Swarm Optimization, and 615seconds for a Genetic Algorithm.

***Keywords**:- Chaboche model; hardening parameter;genetic algorithm and particle swarm optimization.*

I. INTRODUCTION

Most industrial structures are subjected to variable or fluctuating loadings, which when repeated over a long period of time causes failure by fatigue.When the stresses are relatively high the components fail at low number of cycles, it is then said that the component is subjected to Low-Cycle Fatigue (LCF). In LCF materials experience cyclic plasticity, the behaviors that are generally observed are either the elastic shakedown, the plastic shakedown or the ratcheting. Ratcheting contributes to material damage and reduces fatigue life [1]. Rail- wheel interaction induce multiaxial non-proportional loading that induce most rail failure by ratcheting [2], [3]. To describe the material behavior it is important to choose an appropriate hardening rule.

Structures subjected to multiaxial low cycle amplitude fatigue loading can only be studied on strain- basis. The procedure for LCF life assessment will therefore require the description of the cyclic plasticity behavior of the material. Many models have been developed over the last decades, they range from Prager [4]. Linear kinematic hardening models, to a variety of nonlinear kinematic hardening models. The simpler model is the Armstrong – Frederick hardening rule. Chaboche then modified it by addition of backstress components. Then improvements were brought by Bari- Hassan [5], Ohno-Wang[6] and Abdel-Karim–Ohno [7] and other researchers to better describe the multiaxial non-proportional ratcheting behavior. Yet now-a-days the Armstrong Frederick and the Chaboche models are preferred for their low number of parameters to determine and the presence and simulation software, though they are less accurate [8].

The proper selection of hardening parameters represents an important role both in experimental and numerical calculations. Thus, material hardening parameters obtained from experimental investigations and/or from numerical simulations can be found with a certain precision. Nowadays, soft-computing methods, such as intelligent approaches Fuzzy logic [9], and neural networks [10] have attracted researchers' attention because of their ability to solve inverse problems which are poorly understood or for which deterministic algorithms are not feasible, not complete or give unreliable results. Although the obtained results are efficient in terms of precision and robustness. The values of these parameters, in the case of the Chaboche model, are not optimal. To achieve this issue, meta-heuristic algorithms inspired by biological strategies for solving problems have been implemented. Among them, we have Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) which become more popular approaches that allow the improvement of the magnitudes of material hardening data.

The Chaboche model which is very often used in finite element calculation software is considered to be the most efficient. Compared with the experimental results, it overpredicts the ratchet deformation under uniaxial or multiaxial loading. However, solving this problem using complex and more robust models may result in longer calculation time and the haphazard choice of parameter determination method may seriously affect the prediction results. The genetic algorithm is aersatile optimization method that allows you to find the slightest discrepancy between simulation results and ratcheting tests. The Chaboche parameters can be extracted from the hysteresis curves of experimental uniaxial cyclic compression tests [11].

The appropriate choice of the method for determining optimal parameters is essential for modeling cyclic plasticity in the case of small deformations and displacements. The estimation of the optimal parameters of the material from the curves of the experimental data can be done from the inverse problem which minimizes the deviation of the behavior of the simulated material compared to the real behavior, in the plasticity regime, without taking into account the interdependence of material parameters[12].Zhang used an improved genetic algorithm for the choice of constituent compositions in the development of microstructures in order to determine the optimal material properties necessary for their working conditions[13].Mahmoudi used a modified single objective genetic algorithm S.O.GA for the determination of the parameters of the Chaboche model of carbon steel CS1026. The S.O.GA model overpredicted the ratcheting for certain experiments. To solve this problem, they used a multi objective Genetic Algorithm to predict the ratcheting phenomenon by determining the material parameters under strain control conditions in the case of uniaxial and multiaxial loading [14].

The second approach PSO is employed compared to other evolutionary computation algorithms like Genetic Algorithms, PSO has some attractive features including simple implementation, small computational load, and fast convergence. Many researchers have used the classical PSO algorithm in order to identify the parameters of the Chaboche model [15], [11]. They convergence to the optimal value remain very low as shown by Barisal [16], who proposed an Improved Particle Swarm Optimization (IPSO),which has proven their efficiency in the determination of parameters and the optimization of the generation control of multi-source [17], [18] and [19].Whenever, this approach does not test if the obtained optimal value belongs to the dynamic reduce search-space.To solve this issue, we propose a new approach of PSOin order to find a suitable optimal parametersof the Chaboche model to predict the Low Cycle of Fatigue. The obtained results are compared to the GA and standard PSO, in term of optimization time and mean square error (MSE). This paper is organized, by the next section on Material and method where we develop the mathematic model of chaboche and proposed algorigthm, follow by a presentation of the main results and ended by a conclusion

II. MATERIALS AND METHODS

A. Material Properties and Modelling

➢ *Material properties*

There are four profiles of rails on the Cameroonian railway namely: 30kg/m, 36kg/m, 50kg/m and 54kg/m. Since they are progressively replaced by the 54 kg/m, it is the one considered in this study. The rail wheel assembly has been modelled on the Abaqus software. The material is assumed isotropic and homogenous. The different characteristics mainly the chemical composition in Tab. I and Physical and Mechanical properties [20] in Tab. II are presented below.

Table 1: Chemical composition

C	***Si***	***Mn***	***P max***	***S max***
0.6-0.8	0.1-0.5	0.8-1.3	0.04	0.04

Table 2: Physical and Mechanical properties

Parameter	Definition	Unit	Value
E	The young modulus	**GPa**	206
σ_y	The yield stress	C	379
γ'_f	The fatigue ductility	(%)	15.45
c	The fatigue ductility index		-0.559

➢ *Elastoplastic hardeningmodel*

By considering the Chaboche model with Ncomponents,we have:

$$da = \sum_{i=1}^{N} da_i \tag{1}$$

Where

$$da_i = \frac{2}{3} C_i d\varepsilon_p - \gamma_i a_i dp \tag{2}$$

Moreover, the von Mises surface is given by:

$$f(\sigma - a) = \sqrt{\frac{3}{2}(s-a):(s-a)} \tag{3}$$

Strain rate can increase yield strength and must be taken into account. The following equation describes the plastic strain rate.

$$\dot{\bar{\varepsilon}}^{pl} = \dot{\varepsilon}_0 \langle \frac{\bar{\sigma}-\sigma^0}{K} \rangle^n \tag{4}$$

Due to the fact that we do not considered the temperature propagation, the hardening laws for each backstress are [21].

$$\dot{\alpha}_k = C_k \frac{1}{\sigma_0}(\sigma - \alpha)\dot{\bar{\varepsilon}}^{pl} - \gamma_k \dot{\bar{\varepsilon}}^{pl} \alpha_i - \xi_k \left(\frac{|\alpha_k|}{R_k}\right)^{m_k - 1} \alpha_k \tag{5}$$

and the overall backstress is computed from the relation:

$$\alpha = \sum_{k=1}^{N} \alpha_k \tag{6}$$

where N is the number of backstresses, and C_k, γ_k, ξ_k, R_k and m_k are material parameters that must be calibrated from cyclic test data. $C_{k,}$ is the initial kinematic hardening moduli, and γ_k determines the rate at which the kinematic hardening occurs.

The isotropic hardening of the material is defined by *Re* yield stress at zero plastic strain and Q_∞ and b which are material parameters.

$$\sigma^0 = R_e + Q_\infty \left(1 - e^{-b\bar{\varepsilon}^{pl}}\right) \tag{7}$$

More details and specifications related to Chabochemodel can be found in a book from J. Lemaitre and J.L. Chaboche [22] that describes elastoplasticity and related material behaviors in great detail.

- *Description of evolutionnary algorithm for identification of the material parameters*

The selection of plasticity model parameters, even in the case of the classic Chaboche model, is a complex task. This section presents the procedure for selecting the model parameters by using an optimization process. Indeed, the identification of the model's parameters is performed by adopting a step-by-step procedure. Initial values of the parameters are estimated by processing the experimental data. These initial values are then used in an optimization routine solver available in MATLABthrough metaheuristic algorithms Particle swarm optimization and Genetic Algorithm.

- Particle Swarm Optimization

Adapting from the social characteristics of schooling and bird Pocking, the particle PSO is one of the most popular bio-inspired and population-driven evolutionary algorithms. PSOs are unique in that they do not require gradients or differential forms of the objective function; they simply need the objective function along with a few hyperparameters. PSO is known for its simplicity, stability, and superior computing abilities, particularly when it is applied to nonlinear, large dimensional, and multioptimal problems.

In this method, the position and speed of each particle in each iteration are evaluated for a new particle position that minimizes the cost function. The members are selected or ranked based on best fitness value as indicated by minimized the objective function given by equation (11)[23].This team working activity is mathematically explained in an equation, which presents the new position of the member as:

$$x_i^{new} = x_i^{old} + v_i^{new} \tag{8}$$

where, x_i^{new} is the optimum solution for a member in the population, in our case the x_i^{new} is the latest Chaboche parameter that is minimized in objective function given by equation (11)

$$F(x_k) = \frac{1}{2}\sum_i^N \left(\sigma(x_k)_i^{num} - \sigma(x_k)_i^{exp}\right)^2 \tag{09}$$

x_i^{old} is the previous position and v_i^{new} is the velocity (direction) of member that can be described as:

$$v_i^{new} = \omega v_i^{old} + t_1 r_1 \left(x_i^{local} - x_i^{old}\right) + t_2 r_2 \left(x_i^{global} - x_i^{old}\right) \tag{10}$$

where, v_i is the velocity of the particle, ω is the inertial coefficient and r_1 is a random number between 0 and 1.

In this case,the position mechanism of the particle in the search space is updated by adding the velocity vector to its position vector to get an updated position. Over the course of iterations, the positions of particles (solutions) are updated by their positions and the velocity vectors, then converge to an optimal solution, the whole diagram is shown on Fig. 1.

In our context, we proposed a new algorithm in order to accelerate the convergence by improving the choice of optimal parameter of each Chaboche parameters describe by the flow diagramFig. 2. Generally, the main goal of PSO is to converge quickly to the optimal value by considering given constraints. Now let us consider the following assumptions:

The value of $x_{j,n}^{(it)}$ is not comprised in $\left[K_{i,min}^{it+1} \quad K_{i,max}^{it+1}\right]$ we redefine a new value of $x_{j,n}^{(it)}$ such as:

$$\text{If } x_{j,n}^{(it)} < K_{i,min}^{it+1}, \tag{11}$$

Then

$$x_{j,n}^{(it)} = K_{i,max}^{it+1} + \frac{K_{i,min}^{it+1} - K_{i,max}^{it}}{K_{i,max} - K_{i,min}} \left(x_{j,n}^{(it)} - K_{i,max}^{it}\right) \tag{12}$$

$$\text{If } x_{j,n}^{(it)} > K_{i,max}^{it+1}, \tag{13}$$

then

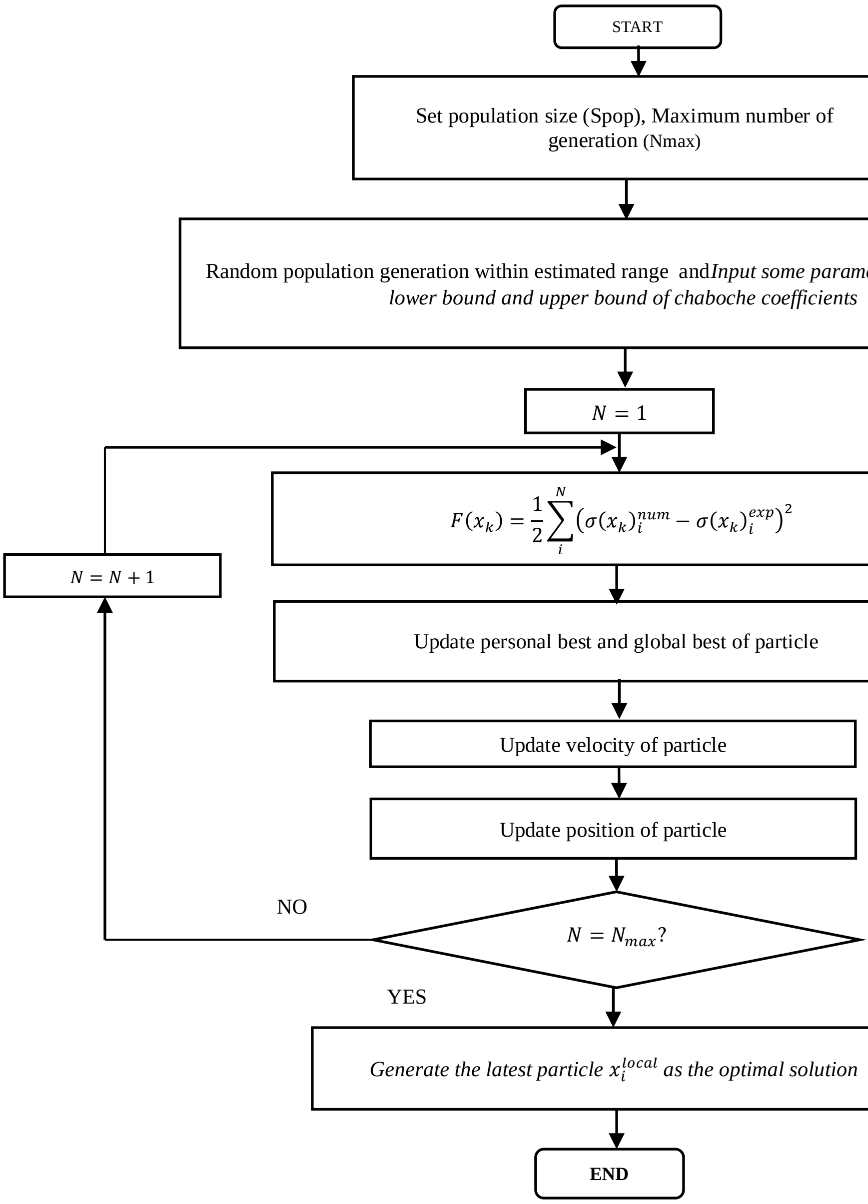

Fig. 1: Flow diagram of PSO technique process

$$x_{n,j}^{(it)} = K_{i,min}^{it} + \frac{K_{i,max}^{it+1} - K_{i,max}^{it}}{K_{i,max} - K_{i,min}}\left(x_{n,j}^{(it)} - K_{i,min}^{it}\right) \tag{14}$$

- The boundaries must be updated in order to facilitate fastest convergence to accelerate the optimization process, by using the following equations :

$$K_{i,min}^{it+1} = K_{i,min}^{it} + \frac{\left(g_n^{(it)} - K_{i,min}^{it}\right)^2}{K_{i,max} - K_{i,min}} \tag{15}$$

$$K_{i,max}^{it+1} = K_{i,max}^{it} + \left(-g_n^{it} - K_{i,max}^{it}\right) \times \frac{K_{i,max}^{it} - g_n^{it}}{K_{i,max} - K_{i,min}} \tag{16}$$

ISSN No:-2456-2165

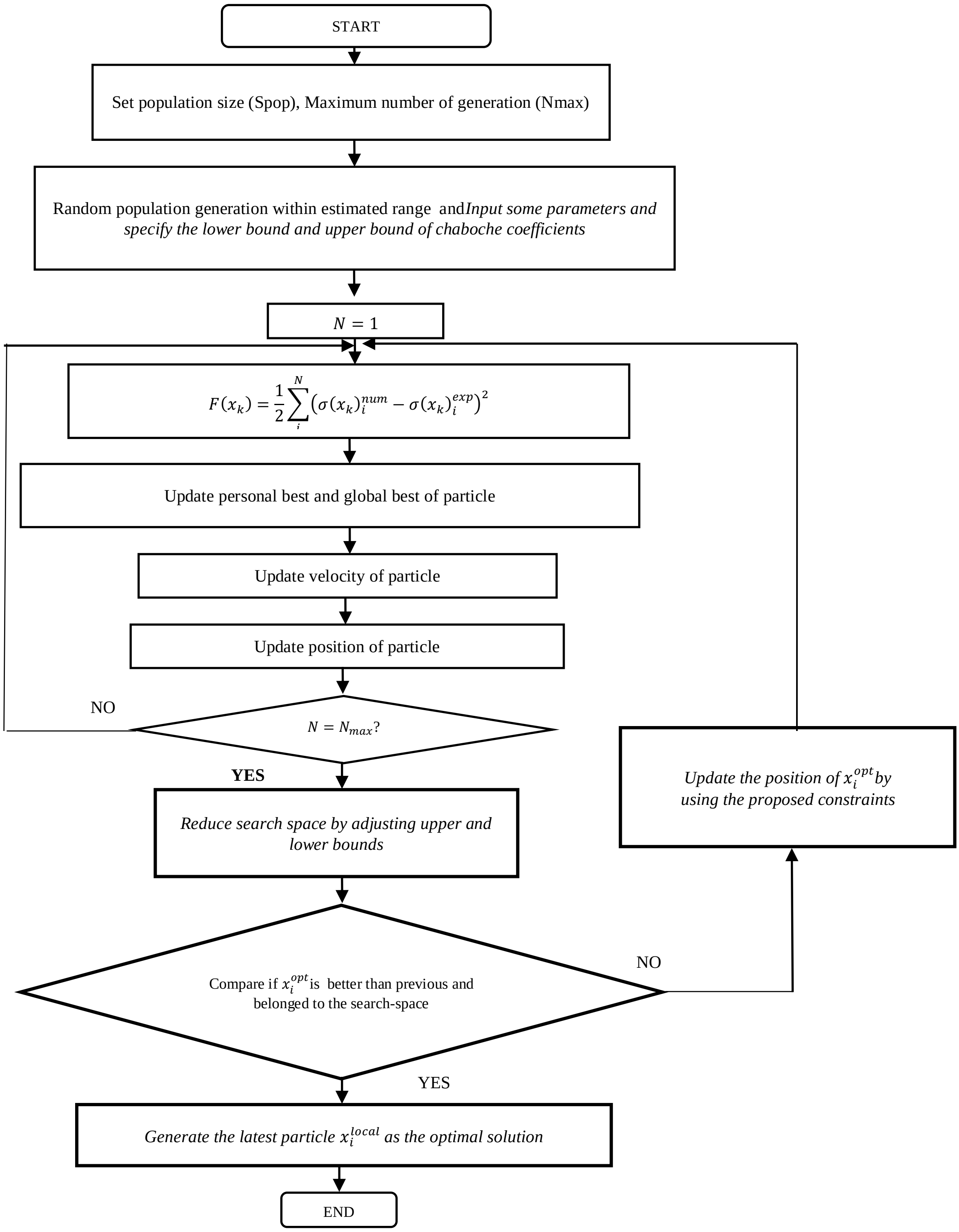

Fig. 2: Flow diagram of Proposed PSO technique process

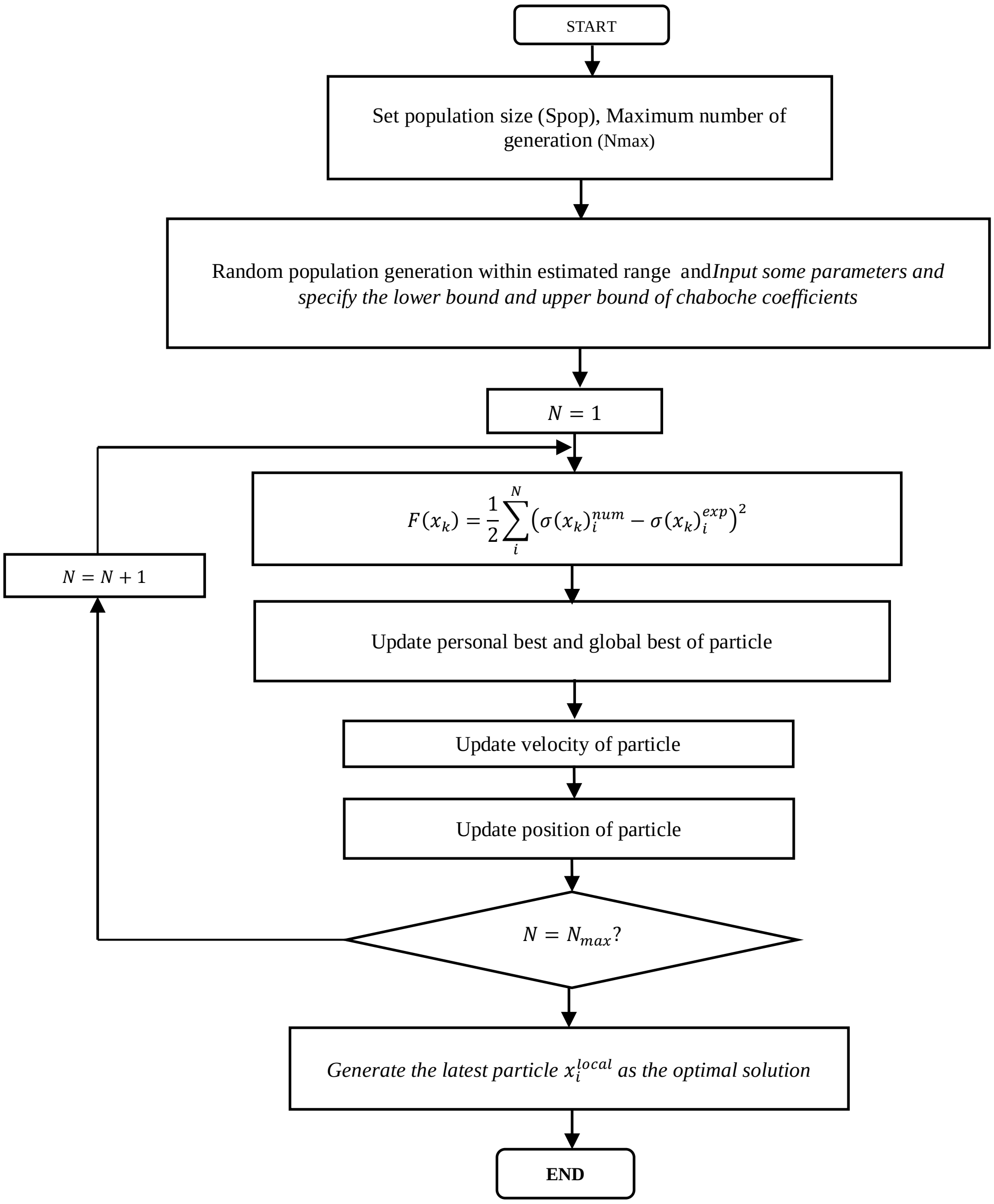

Fig. 3: Flow diagram of PSO technique process

➢ *The Genetic Algorithm*

Genetic Algorithm is an metaheuristic approach which has been inspired throught the biological phenomena mainly the crossing over, selection,and mutation. This is generally adopted as a method to identify parameters of physical models to satisfy the cost function [24] . The principle of our approach is developped in [11] , therefore a flowchart diagram is presented in the below Fig. 3

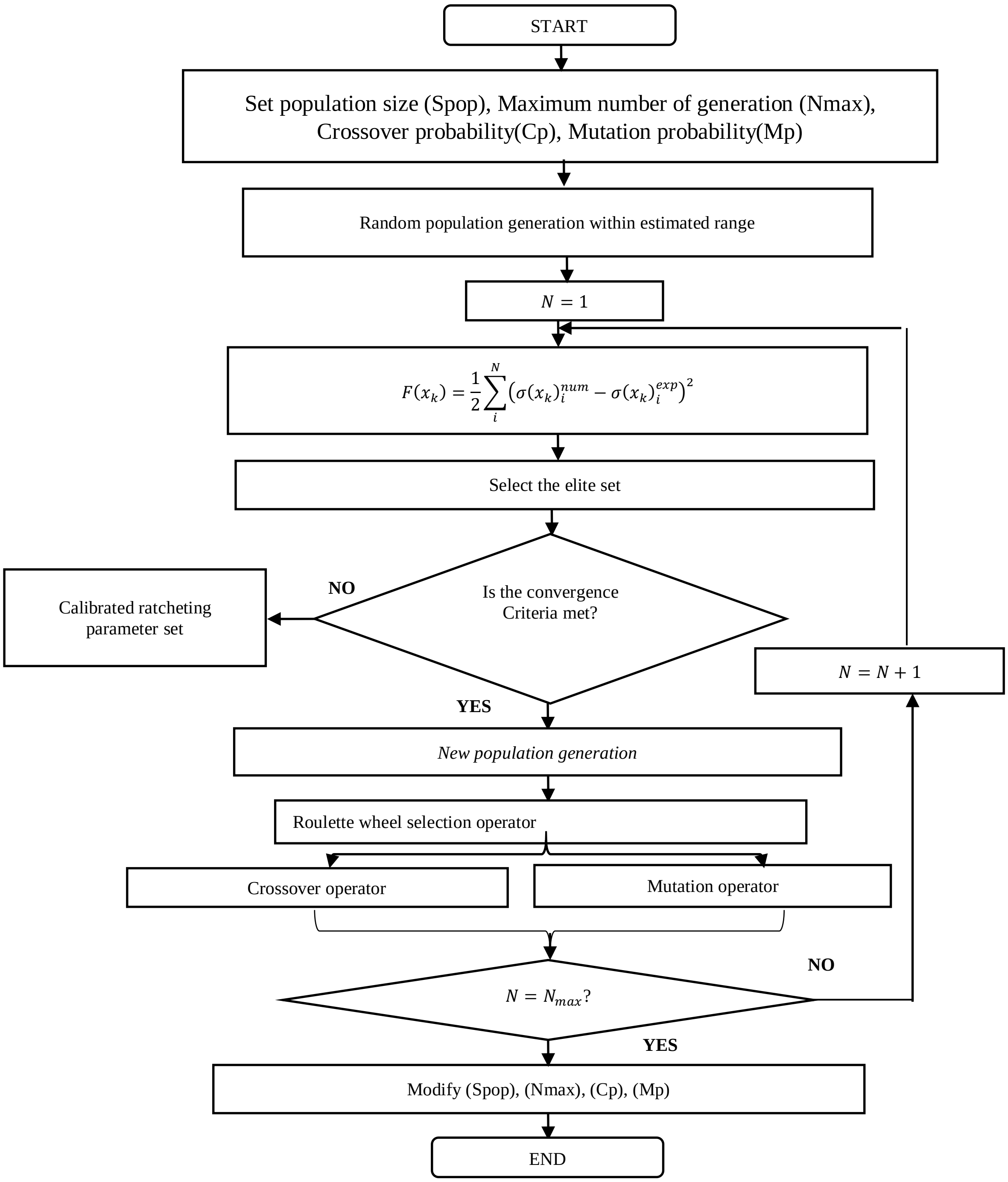

Fig. 3: Flow diagram of Genetic Algorithm

The optimization process is based on following parameters which are constituted of lower and upper values listed in Tab. III.

Table 3: Parameter limits of Chaboche model

	C_1**(MPa)**	C_2**(MPa)**	C_3**(MPa)**	γ_1	γ_2	γ_3
Upper values	700285	**96437**	301387	6010	4063	16
Lower values	507111	240728	1265	2280	816	0

III. RESULTS AND DISCUSSION

The stress-plastic strain parameters of Chaboche model is determined by using the GA,PSO and PPSO schemes are calculated and listed in Tab. IV:

Table 4: GA, PSO, and PPSO calibration for post-stabilized monotonic curve

Type	**GA**	**PSO**	**PPSO**
C_{1-3}	424658; 56437; 3285	281526 ; 38064 ; 20533	312812 ; 91951 ; 26515
γ_{1-3}	3438 ; 3449 ; 0	2223 ; 2173 ; 0	5020 ; 930 ; 0

The assessment of the different approaches is done by determining of the mean square error (MSE) and optimization time error between the experimental model and theoretical result obtained by the setof optimal values.

Table 5: Evaluation Criteria

Methods	GA	PSO	PPSO
Optimization time	615	712	787
MSE	0.475	0.632	0.316

The curves obtained by these approaches are shown by the following figures (Fig.4 and Fig.5) where the evolution of stress and strain phenomena are presented:

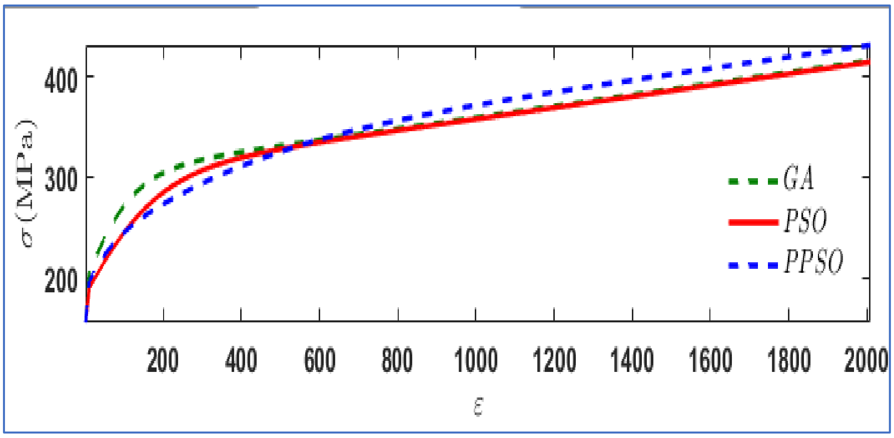

Fig. 4: Comparison of Chaboche model curves according to different optimization approaches

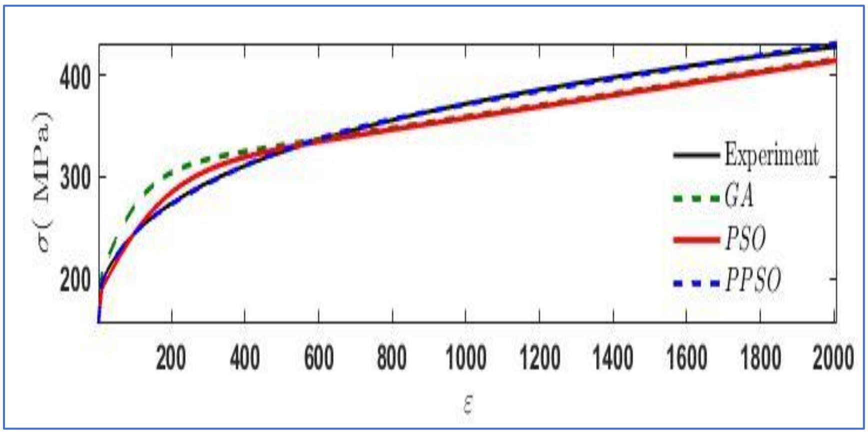

Fig. 5: Comparison of Chaboche model curves according to different optimization approaches and experimentation

The above curve presented are based on the set of optimal parameters obtained by the following approach based on PPSO, GA and PSO. Thus, we have plotted inFig. 4 the evolution of the behavior of stress and strain variables. To assess the obtained results, we have consideredthe experimental results obtained by [25]which is shown in Fig.5. We notice a very good fitting of PPSO to the experimental curve, follow by the GA approach and PSO. Furthermore, optimization time and mean square error have been calculated and presented in Tab. V.The optimization time of PPSO is highest than optimization time of GA and PSO. This due to the fact that, the determination of optimal parameters by this require the checking at each iteration, the belonging of optimal values to the new research-pace. Whenever, the MSE of PPSO yield the lowest value than the other approaches. This criteria confirm the suitable fitness of curve obtained by using the optimal set parameters of PPSO algorithm.

IV. CONCLUSION

In summary, the determination of hardening parameters of Chaboche model remain complex and tridious task. In this study, we proposed a metaheuristic approach based on PSO. The dynamic squeeze space-research has been improved in order to accelerate the convergence to a set of optimal value. The obtained results have been compared in terms of MSE and optimization time to other algorithm from literature such as Genetic algorithm and standard PSO. The first criteria has proven their efficiency by itssuitable fitness to the experimental results than other (GA and PSO), with MSE equal to 0.475, 0.632 and 0.316 respectively for GA, PSO and PPSO. Despite, this relevant asset, the main inconvenient of this new approach is the optimization time which remained highest than other. For the future, we will assess hardening parameters of Chaboche model by considering the effect of the loading and unloading process.

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