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Particle Swarm Optimisation of hardness in nickel diamond electro composites

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ABSTRACT

Purpose: This paper presents an efficient and reliable swarm intelligence-based approach, namely particle swarm optimization [PSO] technique, to optimize the hardness and the parameters that affect the hardness in the Ni-Diamond composite coatings.

Design/methodology/approach: Particle swarm optimizers are inherently distributed algorithms, in which the solution for a problem emerges from the interactions between many simple individuals called particles. Nickel-diamond composite coatings are produced by electro deposition using sedimentation technique on mild steel substrate at various cathode current densities, pH and temperatures. Electro deposition was carried out from a conventional Watts bath. Natural diamond powder of 6-12 μm size was used in the study .

Findings: The hardness value of composite coated specimens were measured using Vickers micro indentation technique. Non linear Regression model was developed using experimental data and was used as an objective function for optimizing hardness and their influencing parameters. The optimized hardness of Ni-diamond metal matrix was found to be 431VHN at pH = 2.5, Current density = 1 A/dm^2 and temperature = 300°C.

Research limitations/implications: The key advantage of PSO is its computational efficiency and less parameter required to be adjusted in order to get the optimum result compared to related techniques. A non linear regression model was developed for the unconstrained optimization of hardness in Ni-diamond composite coated metal matrix using experimental data and it was used as objective function in the maximization problem.

Originality/value: The proposed approach utilizes the global exploration capabilities of PSO to search for the optimal solution.

Keywords: Ni-diamond composite coatings; Vickers Hardness (VHN); Regression model; Particle Swarm Optimisation (PSO)

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METHODS OF ANALYSIS AND MODELLING

1. Introduction

Composite coatings offer synergistic properties over any of the single material. The maintenance related downtime due to higher rate of the wear part is minimized. Nickel-diamond composite coating provides excellent wear resistance, hardness, corrosion resistance, and increased thermal transfer property which subsequently result in increase in tool life. It substitutes more expensive material such as titanium carbide coated on less expensive metals like aluminum and steel. Diamond coated tool produced using various techniques such as PVD, CVD [1, 2] and electro deposition with nickel [3-6] have been reported in the literature.

The extent of diamond particles codeposited with nickel and the corresponding hardness of the composite coatings are decided by operating parameters like the operating current density, pH, temperature of the electrolyte used and concentration of diamond particles dispersed in the electrolyte. Since hardness is dependent on numerous variables, it is essential to optimize them to produce a coating with a maximum hardness. To achieve this, a modern non traditional intelligence technique called as Particle swarm optimization (PSO) was employed in this investigation.

2. Particle swarm optimization

2.1. Introduction

Particle Swarm Optimization is an evolutionary computation technique that was first developed by Kennedy and Eberhart [7]. The particle swarm idea originated as a simulation of a simplified social system, the graceful but unpredictable choreography of a flock of birds. The word ‘swarm’ is used after a paper by Millonas, who developed several models in artificial life and considered certain principles in swarm intelligence. The selection of the term ‘particle’ comes from mechanics and is justified by the fact that positions and velocities are applied to the population elements, despite them being considered to have zero mass and volume. Kennedy and Eberhart’s first original idea was to simulate the social behaviour of a flock of birds in their endeavor to reach, when flying through the field (search space), their unknown destination (fitness function), e.g. the location of food resources. In PSO, each problem solution is a bird of the flock and is referred to as a particle. In this algorithm, birds evolve in terms of their individual and social behaviour and mutually coordinate their movement towards their destination.

To this end, each bird keeps track of its coordinates in the problem space and aims at a specific direction: the best solution (best local position) it has achieved so far. Birds also communicate among them and are able to identify the bird in the best position. In a coordinated way each bird evolves by changing its velocity so that it accelerates towards both its best position and the best position obtained so far by any bird in the flock (best global position). This enables each bird to explore in the search space from its new location. The process is repeated until the best bird reaches certain desired location. It is worth noting here that, according to the description, the process involves not only intelligent behavior but also social interaction. This way, birds learn both from their own experience (local search) and from the group experience (global search).

PSO exhibits common evolutionary computation features including:

- Initialization with a population of random solutions
- Search for optima by updating generations
- Particles evolution through the problem space by following some specific strategies.

Thus, the process initially starts with a group of particles, which have been randomly generated, representing different solutions of the problem. The i^{th} particle is represented by its location in an s-dimensional space, where s corresponds to the number of variables of the problem. Any set of values of the s variables, determining the particle location, represents a candidate solution for the optimization problem.

PSO shares with other evolutionary techniques that it does not guarantee the global optimum. But, on the other hand, PSO does not need specific operators (such as crossover and mutation in the case of Genetic Algorithms, or pheromone updating in Ant Colony Optimization, amongst others), since particles update themselves with internal velocity. They also have memory and receive information only from the best particle in history, which is a simpler mechanism of information transmission than those used in Genetic Algorithms, for example. Particles try to converge to the best solution quickly, but PSO’s main drawback is that it is difficult to keep good levels of population diversity and to balance local and global search. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called **pbest**. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called **lbest**. When a particle takes all the population as its topological neighbors, the best value is a global best and is called **gbest**.

After finding the two best values, the particle updates its velocity and positions with following equation (1) and (2).

V [] = w* v [] + c1 * rand () * (pbest [] - present []) + c2 * rand () * (gbest [] - present []) (1)

Present [] = present [] + v [] (2)

where

W is the inertia weight v [] is the particle velocity,

Present [] is the current particle (solution).

pbest [] the particle’s best

gbest[] the global best.

rand () is a random number between (0, 1).

c1, c2 are learning factors.

The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its pbest and lbest locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations.

In past several years, PSO has been successfully applied in many research and application areas. Optimization of waste water collection network and multi purpose reservoir operation was done by PSO in the field of civil engineering [8, 9]. PSO optimization was earlier used in the flow shop problem and for flow shop scheduling [10, 11]. Modified PSO algorithm was used for solving planar graph coloring problem [12]. Multi-objective particle swarm optimization was carried out for generating optimal trade-offs in reservoir operation [13]. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement. In this study particle swarm optimization is used to optimize the hardness of nickel-diamond electro composites.

2.2. PSO parameter control

In PSO, followings are the parameter need to be tuned in. (i) The number of particles (ii) Dimension of particles (iii) Range of particles (iv) Vmax (v) Learning factors (vi) Stopping Criteria. The values of parameters used in the present study are as detailed in the Table 1.

Table 1.
Parameters of PSO

No of particles	20
Dimensions of particle	3 (Current density, pH vale and temperature)
Range of particles	Current density, i = 1 – 3 A/dm^2 PH value = 2.5 – 4.5 Temperature, T = 30 - 60 ^{0}C
Learning factor c1 and c2	[1.49, 1.49]
Inertia factor (W)	0.8
No of iterations	500
No of cycles	5

2.3. PSO algorithm

1. Initialization of position and velocity vectors of the swarm: Each decision variable represents a parameter to be optimized in the model. The initial positions of all particles have to be generated randomly within the limits specified for each decision variable Each particle is initialized with random position vectors, *X*, and random velocity vectors, *V*, for all *i*=1, 2….., *N*.
2. Initial evaluation of fitness function: The fitness of each particle is evaluated using the objective function of the problem. Then the best value out of all the fitness values is searched. Two "best" values are defined, the global best and the particle best. The global best gbest is the highest fitness value among all the particles in an entire run (best solution so far) and the particle best pbest is the highest fitness value of a specific particle up to the current iteration.
3. Modification of each searching point: Using the global best of each particle up to the current iteration, the searching point of each particle is modified using the change in velocity as given by equation (1) and the positions of the particles are updated using equation (2).
4. Evaluation of fitness function: After modification of the particle positions, the fitness of each particle is evaluated using the objective function of the problem.
5. Updating the global and the particle bests: The gbest and pbest values have to be updated according to the new fitness values. If the best fitness value of a particular particle in the swarm is better than the current gbest, then gbest is to be changed to the value of the searching point of the corresponding particle contributing to this best fitness value. Similarly the local best of other particles in the population should be changed accordingly if the present fitness function value is better than the previous.
6. Termination criteria: Repeat steps 3 to 6 until either the pre-set maximum number of iterations is reached or no significant improvement is observed over a pre specified number of iterations.

3. Experimental procedure

3.1. 3^K Factorial design for three factors

3^k factorial design is the most widely used factorial design having three levels for each of 'k' factors. The three levels of factors are referred to as low (-1), intermediate (0) and high (+1). If there are three factors under study and each factor is at three levels arranged in a factorial experiment, then this constitutes a 3^3 factorial design. Each main effect has two degrees of freedom; each two-factor interaction has four degrees of freedom. If they are *n* replicates, then there are (n x 3^3 – 1) degrees of freedom and 3^3(n-1) degrees of freedom for error. This investigation is designed as above. Ni-diamond electro composite coating was obtained for the combination of three different process variables and their designation is shown in the Table 2.

Table 2.
Level designation of process variables

Level	i (A/dm^2)	pH	T (^{0}C)
-1	1	2.5	30
0	2	3.5	45
1	3	4.5	60

3.2. Preparation of bath for Nickel-diamond electro composite coating

10 liters of the conventional watts bath containing nickel sulphate: 250g/l, nickel chloride: 30g/l, Boric acid: 40g/l was prepared and was purified in the conventional manner for removal of organic and inorganic impurities [14]. The pH of the electrolyte was adjusted electrometrically using dilute H_2SO_4 or NaOH. 0.01-g/l sodium lauryl sulphate was added to the electrolyte as surface active agent. The temperature of the electrolyte was maintained up to 60^{0}C using a thermostat. To remove the organic impurities, activated charcoal treatment was given. For removing inorganic impurities i.e., metallic impurities dummy electrolysis was carried out using corrugated stainless steel cathode and nickel anode. The formation of white nickel deposited on the corrugated cathode was taken as indication of freedom from inorganic impurities.

3.3. Plating procedure

Deposition was carried out on a 500ml capacity using sedimentation technique. Nickel anodes and mild steel cathodes were used. The cathodes of 7.5×2.5cm area were mechanically polished, degreased and bent to 90°. They were suitably masked to expose an effective plating area of 6.25cm^2, electro cleaned, first cathodically and then anodically, washed rinsed and then introduced into the plating electrolyte with the area to be plated in the horizontal plane closer to the bottom of the cell facing the anode. A bagged nickel anode bent similarly was placed above the area to be coated. Diamond powder (6 to 12 µm) was added to the electrolyte in the form of slurry. The solution was stirred using a magnetic stirrer. Stirring was given initially for 30s to bring all the diamond powder into the suspension and then stopped. The deposition was continued for 15 minutes to allow the particles to settle on the substrate while the deposition proceeded. The same process was repeated to obtain deposit thickness of 25µm. The experimental setup used for Nickel-diamond electro deposition by sediment co deposition technique (SCED) is shown in Fig. 1.

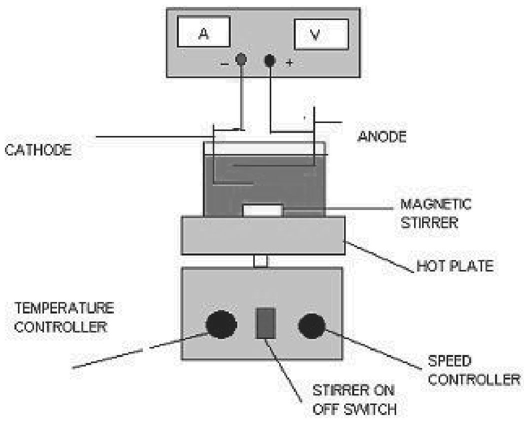

Fig. 1. Experimental setup for SCED

3.4. Ni-diamond deposition

Natural grade polycrystalline diamond powder of 6–12µm sizes was used. Prior to the co-deposition, the diamond particles were ultrasonically dispersed in the bath for 10 min. Experiments were conducted at a fixed diamond concentration of 5 g/l, while the plating parameters like temperature, pH, and current density were varied. Ranges of coating parameters in the coating process were as follows: Current density, i = 1 – 3A/dm^2; pH value = 2.5 – 4.5; Temperature = 30 to 60^{0}C. The hardness of the coated specimens was measured using Vickers micro hardness tester.

4. Objective function (Hardness)

To maximize the hardness using PSO, an objective function is to be developed and a non linear regression equation was formed for this purpose using the practical data obtained at different combinations of process parameters such as pH, and current density and temperature. The developed regression equation for hardness is:

Hardness (VHN) = $1370.83\,pH^{-0.054}\, i^{-0.0241}\, T^{-0.325}$

5. Implementation

5.1. The pseudo code of the procedure is as follows

```
For each particle
   Initialize particle
END
Do
   For each particle
      Calculate fitness value
      If the fitness value is better than the best fitness value (pbest)
in history
         set current value as the new pbest
   End
   Choose the particle with the best fitness value of all the
particles as the gbest
   For each particle
      Calculate particle velocity according equation (1)
      Update particle position according equation (2)
   End
While maximum iterations or minimum error criteria is not
attained
```

6. Results and discussion

Effect of PSO on hardness: To optimize the hardness (VHN) of Ni-diamond composite coated specimens and their influencing parameters in PSO, a programme was written and executed in MATLAB software. Particle swarm optimization was done for the particle size of 20 and for 500 iterations. The results of Particle swarm optimization for 5 cycles are given in the Table 3.

Table 3.
Results of Particle Swarm Optimization

No. of cycles	pH value	Current density (A/dm^2)	Temperature (^{0}C)	Hardness (VHN)	No. of iteration
1.	2.5000	1.0000	30.0000	431.9470	334
2.	2.5000	1.0000	30.0000	431.9470	336
3.	2.5000	1.0000	30.0000	431.9470	322
4.	2.5000	1.0000	30.0000	431.9470	324
5.	2.5000	1.0000	30.0000	431.9470	322

The results were converged at around 150th iteration among 500 iterations for all the five cycles and it is shown in the Fig. 2.

7. Conclusions

This paper presents an efficient and reliable evolutionary based approach to optimizing the hardness of Ni-Diamond composite coating under unconstraint manner. The proposed approach utilizes the global exploration capabilities of PSO to search for the optimal solution.

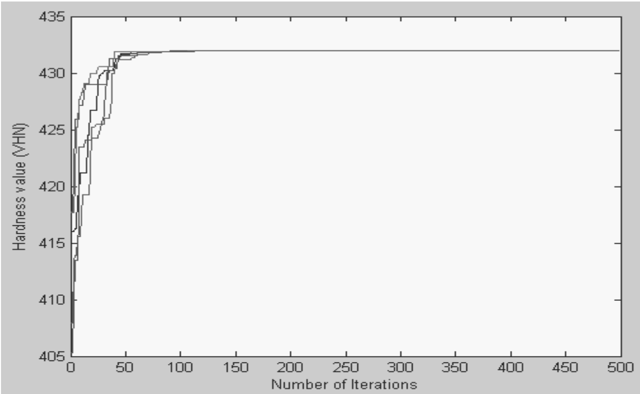

Fig. 2. PSO results for five cycles

The key advantage of PSO is its computational efficiency and less parameter required to be adjusted in order to get the optimum result compared to related techniques. A non linear regression model was developed for the unconstrained optimization of hardness in Ni-diamond composite coated metal matrix using experimental data and it was used as objective function in the maximization problem. For maximizing hardness and to estimate the affecting parameters such as pH, current density and temperature, a modern intelligent technique known as Particle swarm optimization (PSO) approach was carried out. PSO programme was written and run using MATLAB software. Within the range of input variables for the present case (pH = 2.5 to 4.5; current density (i) = 1 to 3 A/dm^2; temperature (T) = 30 to 60^{0}C), the parameters that maximized the hardness are pH=2.5, i=1 A/dm^{2}and T=30^{0}C and the maximized hardness is 431.947 VHN.

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