Chapter two

Micro-electromechanical systems & particle swarm optimization overview

2.1. Literature Review:

A number of robust optimization methods have been applied to design MEMS devices. Robust optimizations for MEMS have been reported as:

- **Gyroscopes:[10]**They made robust optimal design of shape and size is formulated for vibratory microgyroscopes that can reduce the effect of variations from uncertainties in micro-electromechanical systems fabrication, **[11]** it discusses a simple and effective robust optimization formulation and illustrates its application to MicroElectroMechanical Systems (MEMS) devices by minimizing a gradient index (GI) and **[12]**They focus in reduce the influence of microfabrication errors on the design performance of a tuning fork vibratory micromachined gyroscope, and to enhance the performance robustness in the volume production environment.
- **Accelerometer: [13]**It reports on the optimization and robust design of a MEMS accelerometer using the genetic algorithm technique and **[14]**it studies a robust optimization approach for a MEMS accelerometer to minimize the effects of temperature variations.
- **Quartz crystal microbalance:[15]** it presents method for the design of quartz crystal microbalance (QCM) by using the finite element analysis (FEA) software.
- **Resonator: [16]**itprovides a stability analysis and design method for MEMS resonators for the single material and multi-layer structures.
- **Cantilever:[17]** it take design considerations into mechanical as well as the electrical properties of a unimorph piezoelectric cantilever.

- **Micro-mirror: [18]**it discusses the applicability of a reliability- and performance-based multi-criteria robust design optimization technique for micro-electromechanical systems with example of the optimization carried out for micro-mirror by finite element model.
- **Filters:[19]**it discuss optimal structure for MEMS in the field of telecommunication.
- **Magnetometers: [20]** it discuss Optimal design of a resonating MEMS magnetometer for a multi-physics model for a beam subject to current flow in a magnetic field proposed which takes into account thermal and non-linear geometrical effects applied to the study Lorentz-force in MEMS magnetometer and**[21]**discuss optimization with a new z-axis Lorentz force microelectromechanical systems magnetometer design and optimized for sensors.
- **Electrostatic actuator: [22]** it discusses structure optimizationand modeling technique for electroststic micro devices by genetic algorithm.
- **Electrothermal actuator:[2]**it discuss optimal design using entropy for v-beam micro actuator by finite element modeling and**[3]** it proposes a method to optimize the fillet radius of the electrothermal V-beam microactuatorsdueto bent beam connected with electrical pad by genetic algorithm combines with the finite element.

This research proposes optimal method PSO (particle swarm optimization) to design fillet shape of electrothermal V-beam microactuator by decreasing beam entropy generation rate and simulation the results by MATLAB and investigated parameters do not achieve in the past designs developing more effective optimizer with accurate results agree with calculations.

2.2. MEMS definition:

Micro-electromechanical systems (MEMS) are a process technology used to create tiny integrated devices or systems that combine mechanical and electrical components. They are fabricated using integrated circuit (IC) batch processing techniques and can range in size from a few micrometers to millimeters. These devices (or systems) have the ability to sense,Control and actuate on the micro scale, and generate effects on the macro scale**[1]**.

While the device electronics are fabricated using 'computer chip' IC technology, the micromechanical components are fabricated by sophisticated manipulations of silicon and other substrates using micromachining processes. Processes such as bulk and surface micromachining, as well as high-aspect-ratio micromachining (HARM) selectively remove parts of the silicon or add additional structural layers to form the mechanical and electromechanical components. While integrated circuits are designed to exploit the electrical properties of silicon, MEMS takes advantage of either silicon's mechanical properties or both its electrical and mechanical properties**[1].**

In the most general form, MEMS consist of mechanical microstructures, microsensors,Microactuators and microelectronics, all integrated onto the same silicon chip. Microsensors detect changes in the system's environment by measuring mechanical, thermal, magnetic, chemical or electromagnetic information or phenomena. Microelectronics processes this information and signals the microactuators to react and create some form of changes to the environment.

MEMS devices are very small; their components are usually microscopic. Levers, gears,pistons, as well as motors and even steam engines have all been fabricated by MEMS Figure (2.1). However, MEMS is not just about the miniaturization of mechanical components ormaking things out of silicon (in fact, the term MEMS is actually misleading as manymicromachined devices are not mechanical in any sense). MEMS is a manufacturingtechnology; a paradigm for designing and creating complex mechanical devices and systemsas well as their integrated electronics using batch fabrication techniques**[1].**

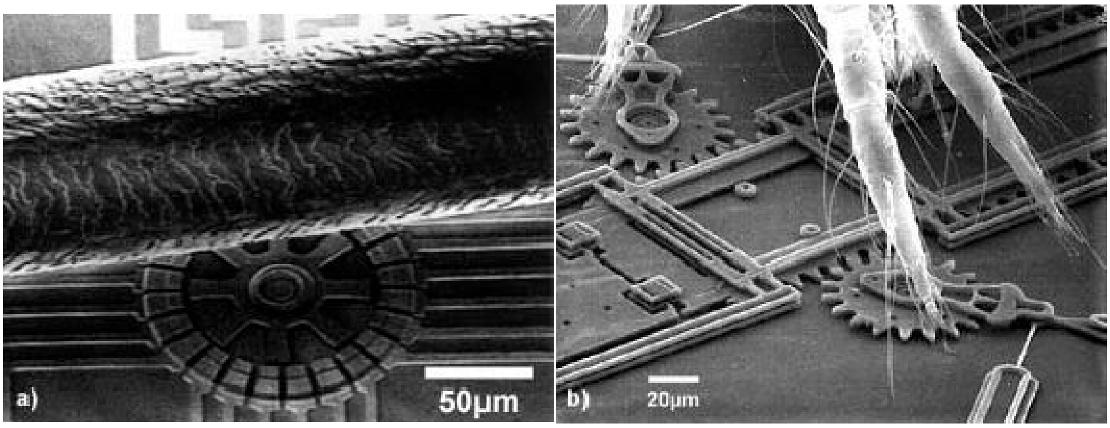

Figure (2.1) (a) A MEMS silicon motor together with a strand of human hair **[23],** and (b)the legs of a spider mite standing on gears from a micro-engine **[24]**

MEMS have several distinct advantages as a manufacturing technology. In the first place, theInterdisciplinary nature of MEMS technology and its micromachining techniques, as well asits diversity of applications has resulted in an unprecedented range of devices and synergiesacross previously unrelated fields (for example biology and microelectronics). Secondly,MEMS with its batch fabrication techniques enables components and devices to be manufactured with increased performance and reliability, combined with the obviousadvantages of reduced physical size, volume, weight and cost. Thirdly, MEMS provides thebasis for the manufacture of products that cannot be made by other methods. These factorsmake

MEMS potentially a far more pervasive technology than integrated circuit microchips.However, there are many challenges and technological obstacles associated withminiaturization that need to be addressed and overcome before MEMS can realize itsoverwhelming potential**[1].**

2.2.1. MEMS Classifications:

Figure (2.2) illustrates the classifications of microsystems technology (MST). Although MEMSis also referred to as MST, strictly speaking, MEMS is a process technology used to createthese tiny mechanical devices or systems, and as a result, it is a subset of MST.

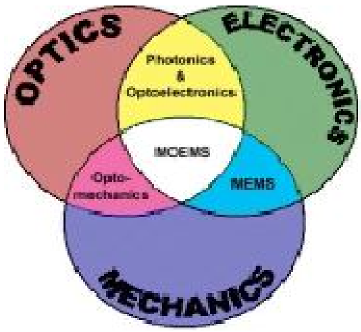

Figure (2.2)Classifications of microsystems technology **[25].**

Micro-optoelectromechanical systems (MOEMS) is also a subset of MST and together withMEMS forms the specialized technology fields using miniaturized combinations of optics,electronics and mechanics. Both their microsystems incorporate the use of microelectronicsbatch processing techniques for their design and fabrication. There are considerable overlapsbetween fields in terms of their integrating technology and their applications and hence it isextremely difficult to categories MEMS devices in terms of sensing domain and/or theirsubset of MST. The real difference between MEMS and MST is that MEMS tends to usesemiconductor processes to create a mechanical part. In contrast, the deposition of a materialon silicon for example, does not constitute MEMS but is an application of MST.

2.2.1.1. Transducer

A transducer is a device that transforms one form of signal or energy into another form. Theterm transducer can therefore be used to include both sensors and actuators and is the mostgeneric and widely used term in MEMS.

2.2.1.2.Sensor

A sensor is a device that measures information from a surrounding environment and providesan electrical output signal in response to the parameter it measured. Over the years, thisinformation (or phenomenon) has been categorized in terms of the type of energy domains but MEMS devices generally overlap several domains or do not even belong in any one category. These energy domains include:

- Mechanical - force, pressure, velocity, acceleration, position.
- Thermal - temperature, entropy, heat, heat flow.
- Chemical - concentration, composition, reaction rate.
- Radiant - electromagnetic wave intensity, phase, wavelength, polarization, reflectance, refractive index, transmittance.
- Magnetic - field intensity, flux density, magnetic moment, permeability.
- Electrical - voltage, current, charge, resistance, capacitance, polarization **[26,27, 28, 29].**

2.2.1.3. Actuator

An actuator is a device that converts an electrical signal into an action. It can create a force tomanipulate itself, other mechanical devices, or the surrounding environment to perform someuseful function.

2.2.1.3.1. Electrothermal Actuator:

The actuator is deflect according to thermal expansion caused by omhic heating caused in microstructure when the current pass through anchors .

The electrothermal actuators have been known as their large displacement and high force output (DeVoe 2002)The V-beam actuator (Gianchandani and Najafi 1996; Que et al. 2001) and U-shaped actuator (Pan and Hsu 1997; Huang and Lee 1999) are the two most cited and characterized electrothermal actuators, while two new sorts of electrothermal actuators, i.e., X-shaped and H-shaped electrothermal actuators, have been reported recently (Lee and Yeh 2005; Lee 2006a)**[2].**

2.2. 2. MEMS Applications:

Today, high volume MEMS can be found in a diversity of applications across multiplemarkets .Table (2.1).

Table (2.1) Applications of MEMS **[30].**

Automotive	Electronics	Medical	Communications	Defence
Internal navigation sensors	Disk drive heads	Blood pressure sensor	Fibre-optic network components	Munitions guidance
Air conditioning compressor sensor	Inkjet printer heads	Muscle stimulators & drug delivery systems	RF Relays, switches and filters	Surveillance
Brake force sensors & suspension control accelerometers	Projection screen televisions	Implanted pressure sensors	Projection displays in portable communications devices and instrumentation	Arming systems
Fuel level and vapour pressure sensors	Earthquake sensors	Prosthetics	Voltage controlled oscillators (VCOs)	Embedded sensors
Airbag sensors	Avionics pressure sensors	Miniature analytical instruments	Splitters and couplers	Data storage
"Intelligent" tyres	Mass data storage systems	Pacemakers	Tuneable lasers	Aircraft control

2.2.3.Established MEMS Applications [1]:

2.2.3.1. Automotive airbag sensor:

Automotive airbag sensors were one of the first commercial devices using MEMS. They arein widespread use today in the form of a single chip containing a smart sensor, oraccelerometer, which measures the rapid deceleration of a vehicle on hitting an object. Thedeceleration is sensed by a change in voltage. An electronic control unit subsequently sends asignal to trigger and explosively fill the airbag.

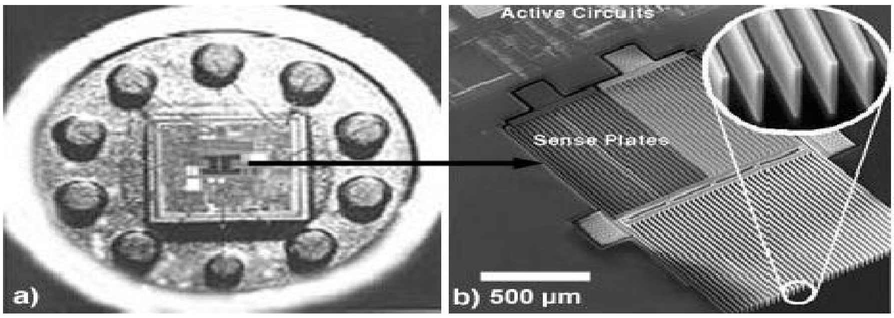

Figure (2.3) (a) the first commercial accelerometer from AnalogDevices (1990); its size is less than 1 cm2 (left) **[31],** and (b)capacitive sense plates, 60 microns deep (right) **[32].**

2.2.3.2. Medical pressure sensor:

Another example of an extremely successful MEMS application is the miniature disposable pressure sensor used to monitor blood pressure in hospitals. These sensors connect to a patient’s intravenous (IV) line and monitor the blood pressure through the IV solution.

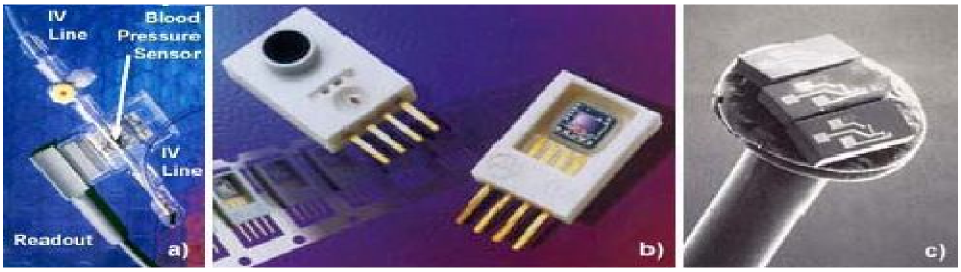

Figure (2.4) (a) Disposable blood pressure sensor connected to an IV line **[33],** (b) disposable blood pressure sensors (as shipped) **[34],** and (c) intracardialcatheter-tip sensors for monitoring blood pressure during cardiaccatheterisation, shown on the head of a pin **[32].**

2.2.3.3. Inkjet printer head:

One of the most successful MEMS applications is the inkjet printer head, superseding evenautomotive and medical pressure sensors. Inkjet printers use a series of nozzles to spray drops of ink directly on to a printing medium. Depending on the type of inkjet printer the droplets of ink are formed in different ways; thermally or piezoelectrically.

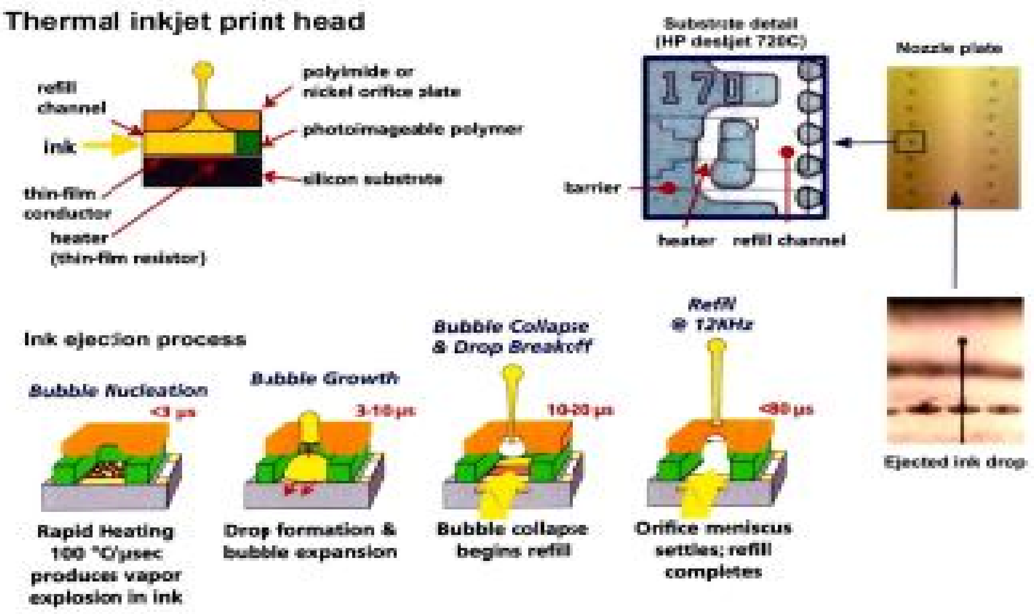

Figure (2.5)Thermal inkjet print technology **[35]**

2.3. Optimization Techniques:

The aim of optimization is to determine the best-suited solution to a problem under a given set of constraints. Several researchers over the decades have come up with different solutions to linear and non-linear optimization problems. Mathematically an optimization problem involves a fitness function describing the problem, under a set of constraints representing the solution space for the problem.

Unfortunately, most of the traditional optimization techniques are centered around evaluating the first derivatives to locate the optima on a given constrained surface. Because of the difficulties in evaluating the first derivatives, to locate the optima for many rough and discontinuous optimization surfaces, in recent times, several derivative free optimization algorithms have emerged.

The optimization problem, now-a-days, is represented as an intelligent search problem, where one or more agents are employed to determine the optima on a search landscape, representing the constrained surface for the optimization problem **[36].**An optimization problem is made up of the following basic components**[7]:**

- The quantity to be optimized (maximized or minimized), termed the objective function.
- The parameters that may be changed in the search for the optimum, called design parameters.
- The restrictions on allowed parameter values, known as constraints.

The optimization process finds the values (design parameters) that minimize or maximize (optimize) the objective function while satisfying constraints. Thus, the general optimization problem may be stated mathematically as:

$$\text{minmize} \quad f(x), \quad x = (x_1, x_2 \dots, x_n)^T$$

$$\text{subject to} \quad c_i(x) = 0 \quad i = 1,2, \dots, m'$$

$$c_i(x) \geq 0, \qquad i = m' + 1, \dots, m$$

Where $f(x)$ is the objective function, x is the column vector of n independent design parameters, and $c_i(x)$ is the set of constraint functions. Constraint equations of the form $c_i(x) = 0$ are termed equality constraints, and those of the form $c_i(x) \geq 0$ are inequality constraints.

Generally, optimization techniques or algorithms can be broadly classified into deterministic, such as the steepest descent method, and stochastic, such as the local search method **[37].** A deterministic algorithm progresses toward the solution by making deterministic decisions. On the other hand, stochastic algorithms make random decisions in their search for a solution. Therefore, deterministic algorithms produce the same solution for a given problem instance, whereas this is not the case for stochastic algorithms.

Evolutionary algorithms (EA) are search methods that take their inspiration from natural selection and survival of the fittest in the biological world. EA differ from more traditional optimization techniques in that they involve a search from a "population" of solutions, not from a single point. Each iteration of an EA involves a competitive selection that removes poor solutions. Evolutionary computation

(EC), evolution strategies (ES), Particle Swarm Optimization (PSO), and genetic algorithms (GA) may be considered as EAs **[38].**

EAs and other stochastic search techniques seem to be a promising alternative to traditional or deterministic techniques. First, EA do not rely on analytic assumptions such as differentiability or continuity. Second, they are capable of handling problems with nonlinear constraints, multiple objectives, and time-varying components. Third, they have shown superior performance in a variety of real-world applications**[7].**

2.3.1. Particle Swarm Optimization (PSO):

PSO is a population-based stochastic optimization technique developed by Kennedy and Eberhart**[5,6],** and it has been inspired by the behavior of schools of fish and flocks of birds. Unlike other heuristic techniques of optimization, PSO has a flexible and well-balanced mechanism to enhance and adapt to the global and local exploration abilities. PSO has its roots primarily in two methodologies. Perhaps more obvious are its ties to artificial life (A-life) and the behavior of flocks of birds, schools of fish, and swarms in particular. It is also related to evolutionary computation and has ties to genetic algorithms and evolutionary strategies **[39].**

In general, PSO is based on a relatively simple concept and can be implemented in a few lines of computer code. It requires only simple mathematical operators and is computationally inexpensive in terms of both memory requirement and speed. It exhibits some evolutionary computation attributes; for example, it is initialized with a population of random solutions, it searches for optima by updating generations, and updating is based on the previous generations**[7].**

PSO has also been proved to perform well in test functions used in EA and may be used to solve many problems similar to those in EA. It appears to be a promising approach, and early testing has found the implementation to be effective with complex practical problems. However, PSO does not suffer from some of the difficulties of EAs. For example, a PS system has memory, which the genetic algorithms (GA) do not have. In PSO, individuals who fly past optima are pulled to return toward them, and knowledge of good solutions is retained by all particles **[40].** Whereas a GA can handle combinatorial optimization problems, PSO was initially used to handle continuous optimization problems. Subsequently, PSO has been expanded to handle combinatorial optimization problems and those involving both discrete and continuous parameters as well. Efficient treatment of mixed-integer nonlinear optimization problems (MINLP) is a rather difficult issue in the optimization field. Unlike other EC techniques, PSO can be realized using only a short program in MINLP. This feature of PSO is one of its main advantages when compared with other optimization techniques **[41].**

2.3.1.1. The Structure of PSO:

The PSO algorithm consists of the following basic components **[39, 40, and 42]:**

• **Particle position vector X:** This vector contains the current location of the solution for each particle in the search space.

• **Particle velocity vector V:** It represents the amount by which vector (both vectors have consistent units) will change in magnitude and direction in the next iteration. The velocity is the step size, the amount by which the changing of the values changes the particle direction through the search space; that is, it causes the particle to make a turn. The velocity vector is used to control the range and resolution of the search.

• **Inertia weight w (t):** This is a control parameter that is used to control the impact of the previous velocities on the current velocity. Hence, it influences the trade-off between the global and local exploration abilities of particles.

• **Best solution pbest:** This is the best solution of the objective function that has been discovered thus far by a particular particle.

• **Best global solution gbest:** This is the best global solution of the objective function that has been discovered by all particles of the population.

PSO can be expressed mathematically for a given problem of D-dimensions i.e., D-design parameters for each particle i and each channel d = [1… D], using:

$$V_{id} = W * V_{id} + \sigma_1 * rand_1[P_{best} - X_{id}] + \sigma_2 rand_2[g_{best} - X_{id}] \quad (2.1)$$

$$X_{id} = X_{id} + V_{id} \quad (2.2)$$

$$W = W_{max} - \frac{W_{max} - W_{min}}{iteration_{max}} \times iteration_{current} \quad (2.3)$$

Where

• W is the inertia factor

• V_{id} is the value of channel d in the velocity vector for particle i

• σ_1 is the cognitive learning rate

• σ_2 is the social learning rate

• rand1 and rand2 are random values in the range of [0–1] (accelerating), giving the current position of particle i along dimension d.

2.3.1.2. The Trajectory of a Particle

The heart of the PSO algorithm is the process by which is modified in Equation (2.1), forcing the particles to search through the most promising areas of the solution space again and again adding its velocity vector to its location vector to obtain a new location. Without modifying the values in, the particle would simply take uniform steps in a straight line through the search space and beyond. In each iteration, the previous values of constitute the momentum of a particle.

The momentum is essential, as it is this feature of PSO that allows particles to escape local optima. The velocities of the particles in each dimension are clamped to a maximum velocity Vmax, which is an important parameter. It determines the fineness or the objective function value with which the regions between the present position and the best target position thus far are searched. If Vmax is too high, the particles might fly past good solutions. On the other hand, if Vmax is too small, the particles might not explore sufficiently beyond locally good regions. In fact, they could become trapped in local optima, unable to move far enough to reach a better position in the problem space**[7].**The acceleration constants σ_1 and σ_2 in Equation (2.1) represent the weighting factors of the stochastic acceleration terms that direct each particle toward the pbest and gbest positions. Early experience with PSO has led to setting both the acceleration constants σ_1 and σ_2 to 2.0 for almost all applications**[7].**Vmax is thus the only parameter to be adjusted by the user, and it is often set to a value of about 10 to 20% of the dynamic range of the parameter in each dimension **[43].**

The selected population size is problem-dependent, and a population size of 20–50 is quite common. It was found early on that smaller populations that were common for other EAs (such as GAs and evolutionary programming) were optimal for PSO in terms of minimizing the total number of evaluations (population size times the number of generations) needed to obtain a sufficient solution **[44].** A flowchart for the PSO optimization process is given in Figure (2.6).

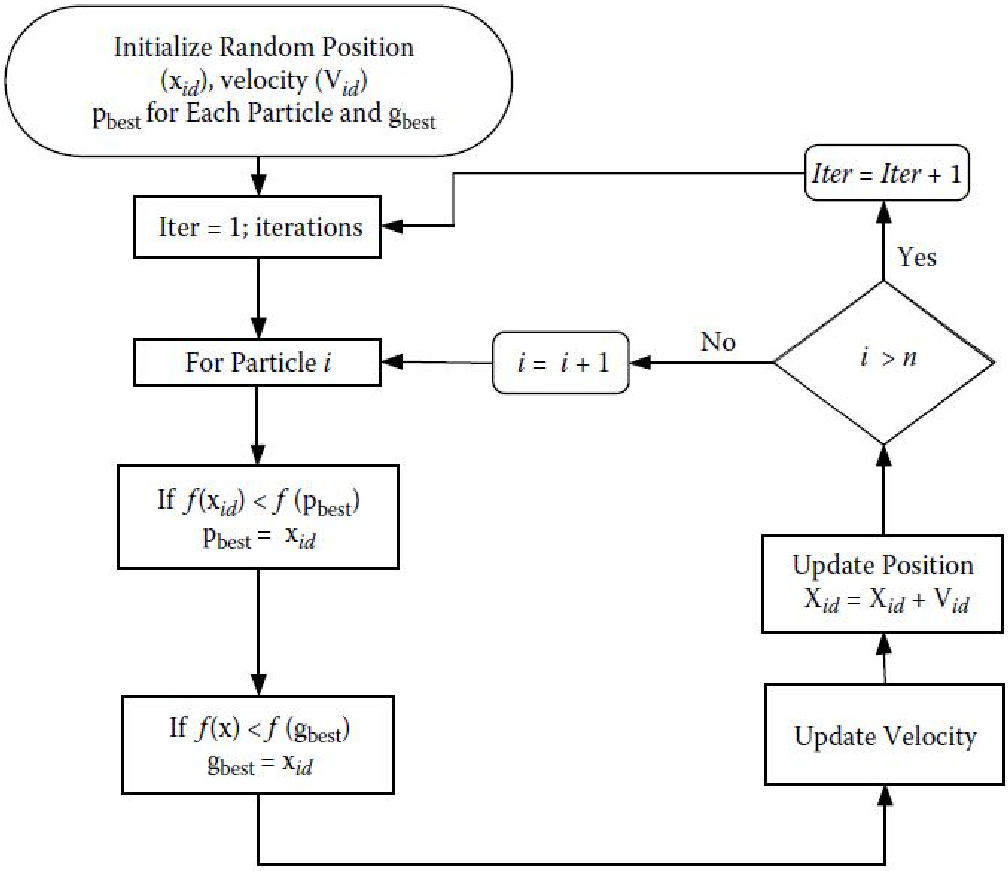

Figure (2.6) PSO flow chart **[7]**