Published by
NIGERIAN SOCIETY OF PHYSICAL SCIENCES
Available online @ https://journal.nsps.org.ng/index.php/jnsps

J. Nig. Soc. Phys. Sci. 6 (2024) 2180

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Journal of the Nigerian Society of Physical Sciences

Availability optimization of bolts manufacturing plant using particle swarm optimization and genetic algorithm

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Abstract

Availability plays an imperative role in the effectiveness investigation and performance evaluation of any manufacturing plant. The bolt manufacturing industry is one such plant. The present study is conducted with the motto of building a novel stochastic model of a bolt manufacturing plant (BMP) to derive availability along with its optimisation using metaheuristic approaches. The Markov birth-death process is adopted to build the stochastic model, as the breakdown and restore rates of the parts exhibit constant behaviour. The availability function is treated as an objective function of the optimisation problem, considering breakdown and restore rates as determination parameters. The availability function is optimised using particle swarm optimisation (PSO) and a genetic algorithm (GA) to forecast the optimal availability and estimated parametric values. The highly susceptible part of the system is observed after a 10% deviation in breakdown and restoration rates. It is viewed that the PSO algorithm predicts the optimal value of availability as 0.999429 after 30 iterations at 100 swarm size, while GA reached only up to 0.94791544 at a population size of 1000 after 100 iterations. The convergence rate of PSO is very fast in predicting the availability of plants. These results are valuable for organisational engineers and maintenance engineers to propose maintenance strategies. The suggested approach can be employed to predict the availability of other process industries.

DOI:10.46481/jnsps.2024.2180

Keywords: Bolt manufacturing plant, Particle swarm optimization, Markov Birth-Death process, Genetic algorithm, Availability

Article History :
Received: 07 June 2024
Received in revised form: 24 July 2024
Accepted for publication: 11 August 2024
Published: 24 August 2024

Communicated by: B. J. Falaye

1. Introduction

Today's era is the era of science and technology, and now technological advancements are seen in every sphere of human life. All the equipment, including industrial, mechanical, electrical, and communication, now depends on the technology. The use of such equipment is increasing day by day in human life. Whether it is from making a small electric board to launching a big satellite, to launch any satellite, even a small component of it plays a big role. The complexity of such equipment is constantly increasing. In the manufacturing of such equipment, a lot of components are utilised; those are assembled with the help of a small component, namely a bolt. A bolt is a solid cylindrical fastener used with a nut and has a circular cross section. The failure of the bolt may result in the complete failure of the equipment. So, quality and reliability of the bolt are very essential, and in this situation, investigation of the reliability of

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the bolt manufacturing process becomes crucial. So, the extensive applicability of bolts in industries and the importance of their availability in plant operation motivate us to investigate the bolt manufacturing plant.

Several works have been performed related to the operation of the mechanical procedure of the bolt. Mojtabaei *et al.* [1] optimised cold-formed steel (CFS) beams for seismic performance and explained the CFS codes. Kang *et al.* [2] developed an algorithm for bearing torque screwed up by bolt friction and analysed the association between the external assets and the subsequent frictional torque. Shakeri *et al.* [3] investigated the impact of manufacturing defects on wind turbines using fatigue life and fatigue crack growth. The testing methodology included the physical data and exhaustion test setup, classification of thread root defects, EBSD trial, factors for determining design curves, and statistical analysis of fatigue crack expansion. Toribio [4] reviewed the stress intensity factor solution for cracking of grooved members in bolts. He used displacement of quarter-point nodes and transposition of adjacent nodes to increase the stickiness of the result. He *et al.* [5] did the experiment on a quasi-NPR steel bolt and analysed the shear performance under different normal stresses using a shear test. The study was performed under the setup of two types of steel bolts to compare and analyse shear strength. The testing programme included the segments of bolt preparation, disposition of bolted joint samples, and shear test procedures. Shaheen *et al.* [6] used the FE model to increase the flexibility and strength of bolt connections up to 2.6 and 2.5 times, respectively. The study focused on a single-story frame for analysis. Zou *et al.* [7] presented details about hole-making process selection in the aircraft industry, especially CERP/Ti single-lap bolted joints, and introduced a 3D numerical simulation model for the measurement of hole size. Selvaraj *et al.* [8] experimented on a total of 72 PFRP bolt connections and described their combined failure modes. Pandey *et al.* [9] designed an ISO standard M16 bolt using polylactic acid and acrylonitrile butadiene styrene material. After comparing both bolts, it is learned that the bolts achieved by polylactic acid are competent in excellence as assessed to acrylonitrile butadiene styrene.

It is revealed that mechanical and chemical properties of bolts investigated in literature extensively. Though more intensive efforts are still required to study the reliability aspects of the bolt manufacturing process. For this, reliability and availability are the key effectiveness measures. Several studies were conducted for the reliability evaluation of various industries. Garg [10] opted for fuzzy methodology and PSO for optimisation of reliability measures. Kumar and Malik [11] used reliability measures to investigate the performance of computer systems, utilising the concepts of priority in repair disciplines. Kumar *et al.* [12] conducted a probabilistic investigation of various reliability measures of redundant systems under time-dependent repair and breakdown laws. Hu *et al.* [13] used hybrid metaheuristic approaches for forecasting load requirements in the papermaking process. Kumar [14] proposed a stochastic model for performance prediction and optimisation of rice mills using particle swarm optimization. Saini *et al.* [15] extended a mathematical model using the Markovian birth-death process to investigate and optimise the availability of urea decomposition plants using GA and PSO. Saini *et al.* [16] suggested a stochastic model for the availability investigation of condenser units in turbine power plants and optimised it using GA and PSO. Kumar *et al.* [17] developed a stochastic construction for the e-waste management factory to enhance its availability using numerous metaheuristic approaches like a GA, PSO, and DE. Saini *et al.* [18] suggested a statistical simulation using the Markovian birth-death process to investigate and optimise the availability of biological and chemical units in a sewage treatment plant using GA and PSO. Maihulla and Yusuf [19] analysed the RAMD characteristics of a solar photovoltaic system. Huang *et al.* [20] considered availability as an important effectiveness measure for information transmission and analysed that where reliability and availability for information sharing are high, management performance in the supply chain will also be better, which will give more benefits to supply chain members. Kumar *et al.* [21] developed an efficient stochastic model using the Markovian birth-death process to optimise the availability of cooling tower plants using GA and PSO. Peixer *et al.* [22] proposed a model for a magnetic air conditioner and optimised the system for minimal power consumption and total assembly cost using a genetic algorithm. Gopal and Panchal [23] suggested a framework based on reliability for predicting the failure pattern in milk plants. It is observed that the investigation about availability prediction of bolt manufacturing plants using nature-inspired algorithms is not so extensively conducted.

By keeping the facts and figures stated earlier in mind, the present study is conducted with the motto of building a novel efficient stochastic model of a bolt manufacturing plant (BMP) to derive availability along with its optimisation using metaheuristic approaches. The Markov birth-death process is adopted to build the stochastic model, as the breakdown and restore rates of the parts exhibit constant behaviour. The availability function is treated as an objective function of the optimisation problem, considering breakdown and restore rates as determination parameters. The availability function is optimised using particle swarm optimisation (PSO) and a genetic algorithm (GA) to forecast the optimal availability and estimated parametric values. The highly susceptible part of the system is observed after a 10% deviation in breakdown and restoration rates. It is viewed that the PSO algorithm predicts the optimal value of availability as 0.999429 after 30 iterations at 100 swarm size, while GA reached only up to 0.94791544 at a population size of 1000 after 100 iterations. The convergence rate of PSO is very fast in predicting the availability of plants. These results are valuable for organisational engineers and maintenance engineers to propose maintenance strategies. The suggested approach can be employed to predict the availability of other process industries.

The whole manuscript is divided into five sections, including the present introductory part. The second section incorporates material and methods; availability analysis of bolt manufacturing plants is given in Section 3; the fourth section includes results and discussion; and a conclusion is appended in the fifth section.

2. Material and methods

In this section, the nomenclature, system description, search space and metaheuristic algorithms required for the study are discussed:

2.1. Notations

The nomenclature (Table 1) is utilized for the development of transition diagram and mathematical model of bolt manufacturing plant.

2.2. System description

Here, the working process of the bolts' manufacturing plant is discussed. It is a very complex system having seven units namely, blank cutting, CNC 1^{st} side, CNC 2^{nd} side, hex milling, threading, plating, and final inspection & dispatch. As all the subsystems connected in series, so failure of anyone causes complete system failure.

2.2.1. Blank cutting (BC)

After checking the quality of raw material, manufacturing process proceed to the 1^{st} stage, i.e., blank cutting. In blank cutting, the coil wire is cut into a particular size. It can be done in transformative and including subtractive method. Blank cutting is a single unit component. The failure and repair rate of it follows exponential distribution. If we found all things are good, then move to the next step.

2.2.2. CNC 1^{st} side

After BC, size of the blank is checked and if size is correct, blank is clamped in the machine. According to the desired size, fixed in the machine, the bolt prepared from one side. It is also a single unit subsystem having exponential distribution failure and repair laws.

2.2.3. CNC 2^{nd} side

To process from the second side, the item received from previous subsystem clamped from other side on machine. It is also a single unit subsystem having exponential distribution failure and repair laws.

2.2.4. Hex milling

After the completion of CNC process, the hex of the part is machined. Here, the item clamped on polygon machine from one side and prepare hex according to the size from the other side. It comprises two parallel smart machines. The failure and repair rate of both machines are same and exponentially distributed.

2.2.5. Threading

To make thread on the processed item it put in the machine from the side from which thread are required and feed the programme in the machine according to the size. After the thread is made, item is checked by putting it on the gauge, if thread is fine, then budge it for the next process and if the part is not good, then will mark with red colour and put it in the box of defective items. It is also a single unit subsystem having exponential distribution failure and repair laws.

2.2.6. Plating

According to the demand and type of plating mentioned by the consumer, plating will be done on the part through burl machine. It is also a single unit subsystem having exponential distribution failure and repair laws.

2.2.7. Final inspection

In the last check the part according to the size given for manufacturing in the drawing. If all the dimensions are according to the given tolerance, then our part is fine as shown in Figure 1. We will also check the part visually that there are no burrs, lines, plating, and scratch marks. As per the given method, if everything is in order then our part is packed and ready for dispatch. On the basis of subsystems of BMP a state transition diagram is developed as shown in Figure 2.

2.3. Particle Swarm Optimization (PSO)

Kennedy and Eberhart [24] developed PSO as a metaheuristics algorithm to simulate the behaviour of birds' flock flying in search of food. As an effective strategy birds follow the one which is near to any food source. Birds in PSO act as particles that move towards achieving their common goal in search space. Birds initialized with the group of random particles known as swarm/population. In the said algorithm all particles have fitness value which is assessed by objective/fitness function. Each particle has its own personal best (p-best) position and the global best (g-best) position achieved by any particle in the group. The best particle is treated as leader. The speed that directs the flying of particle is referred to as velocity. PSO algorithm converges when the terminating criteria satisfy. The fundamental equation of PSO is defined in Equation (1).

$$y_j(t+1) = y_j(t) + v_j(t+1). \tag{1}$$

Here $y_j(t)$ indicates the location of a element j in the hunt space at time t. Whereas, $v_j(t)$ specifies the velocity of element j at time t. The new location of element is reached by adding the velocity to the current location, as stated in Equation (1). The velocity $v_j(t+1)$ takes into account several other components viz. inertia coefficient, cognitive component, and the social component.

$$v_j(t+1) = w.v_j(t) + c_1\left(p_j(t) - \mathrm{y}(t)\right) + c_2\left(g(t) - y_j(t)\right). \tag{2}$$

Here, w , $p_j(t), g(t), v_j(t), c_1$ and c_2 represent inertia coefficient, personal best, global best, initial velocity, and acceleration coefficients.: The detailed working process of PSO is shown by flowchart given in Figure 3.

Genetic algorithm is an adopative heuristic search algorithm developed by Goldberg and Holland [25] which is based on genetic and natural selection. It is used to find high quality solutions to an optimization problem. Possible solution for a given problem is individual and group of individuals is termed as population. It works on four operators namely, selection, crossover, mutation and encoding. In selection, fittest individuals (parents) are select from the initial population for the mating process. Reproducing to generate new offspring is termed as crossover whereas mutation is done to find new population solutions. GA

Table 1. Nomenclature BMP model.

Sub-system	Code		Failure rate/hr. γ_i	Repair rate/hr. ζ_i
	Operative Mode	Failed Mode		
Blank cutting	A	a	γ_1	ζ_1
CNC 1^{st} side	B	b	γ_2	ζ_2
CNC 2^{nd} side	C	c	γ_3	ζ_3
Hex milling	D	D’	$2\gamma_4$	ζ_4
	D’	d	γ_4	ζ_4
Threading	E	e	γ_5	ζ_5
Plating	F	f	γ_6	ζ_6
Final inspection	G	g	γ_7	ζ_7

∘ : Operative state ◯ :Partially failed state
□ : Failed state

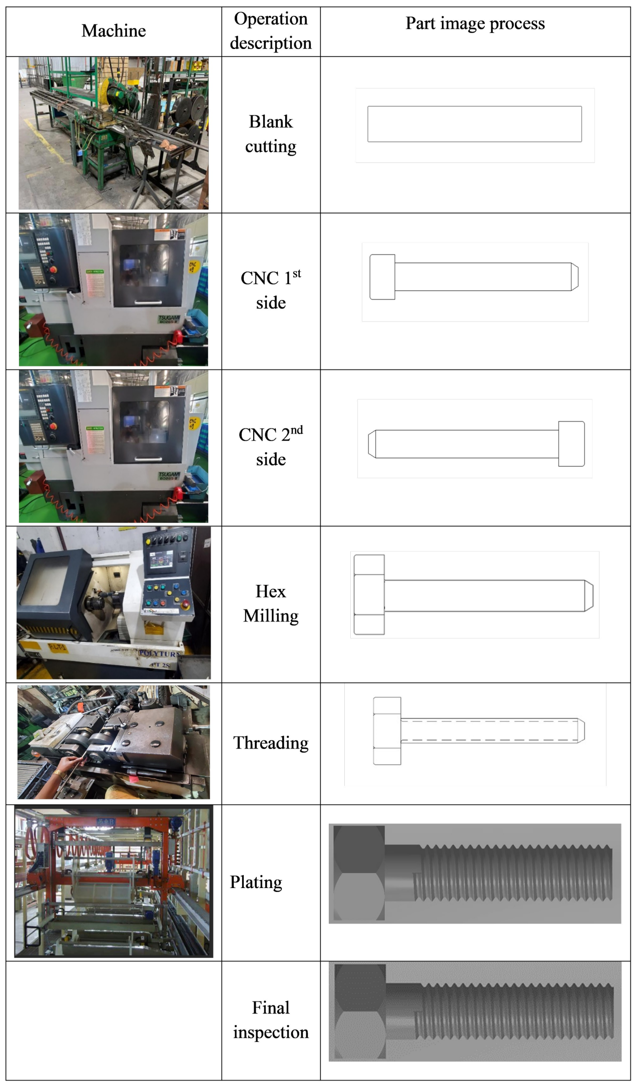

Figure 1. Visualisation of BMP manufacturing process.

algorithm converges when the terminating criteria satisfy. The detailed working of genetic algorithm is shown by flowchart in Figure 4.

3. Availability modeling of BMP system

Among all system effectiveness characteristics, availability is the most decisive measure that is highly persuaded by its breakdown and restoration rates, as well as by time. So,

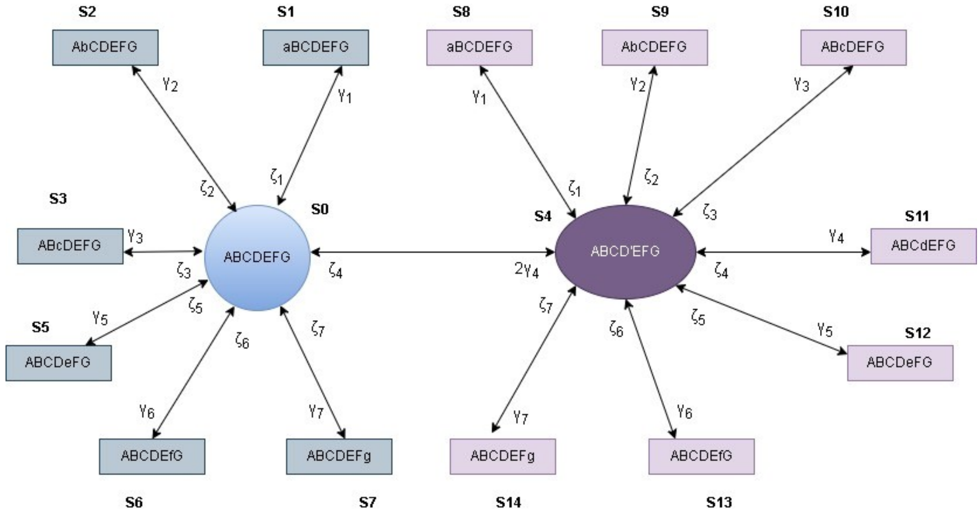

Figure 2. State transition diagram of BMP.

Table 2. Parameters values of BMP.

Subsystems	Availability and Markov Analysis Base values		Search Space	
	Failure Rates	Repair rates	Failure Rates	Repair rates
Blank cutting	γ_1 = 0.00221	ζ_1= 0.1052	[0.00011-0.933]	[0.00021-1.762]
CNC 1st	γ_2 = 0.00118	ζ_2 = 0.8054	[0.00031-0.891]	[0.00045-2.945]
CNC 2nd	γ_3 = 0.00825	ζ_3 = 0.8238	[0.00023-0.954]	[0.00031-1.865]
Hex milling	γ_4 = 0.00734	ζ_4 = 0.4732	[0.00042-0.817]	[0.00051-1.854]
Threading	γ_5 = 0.00228	ζ_5= 0.2929	[0.00001-0.956]	[0.00021-2.923]
Plating	γ_6 = 0.00159	ζ_6 = 0.2811	[0.00041-0.947]	[0.00051-1.768]
Final inspection	γ_7 = 0.00637	ζ_7 = 0.728	[0.00022-0.917]	[0.00041-2.981]

Table 3. Parameter values for metaheuristics.

Algorithm	Parameters
Genetic Algorithm	Population size =10, 20, 50, 100, 200, 500, 1000; Number of maximum iterations =200; crossover rate=0.8; mutation factor=0.9
Particle Swarm Optimization	Population size=10, 20, 50, 100, 200, 500, 1000; Number of maximum iterations=200; inertia weight=0.99; damping ratio=0.8; personal best=1.789; global best=2.684

Table 4. Influence of failure rates on BMP availability w.r.t failure rate γ_1.

γ_1	Base values	γ_2+10% of γ_2	γ_3+10% of γ_3	γ_4+10% of γ_4	γ_5+10% of γ_5	γ_6+10% of γ_6	γ_7+10% of γ_7
0.00221	0.947737412	0.947603603	0.946833309	0.947651398	0.947032619	0.947226435	0.946948437
0.00321	0.939275562	0.939144132	0.938387524	0.939191077	0.938583294	0.938773667	0.938500608
0.00421	0.930963478	0.930834364	0.930091081	0.930880482	0.930283404	0.930470424	0.930202173
0.00521	0.922797218	0.922670359	0.921940052	0.922715672	0.922129019	0.922312774	0.922049206
0.00621	0.914772979	0.914648316	0.913930648	0.914692845	0.914116345	0.914296921	0.914037914
0.00721	0.906887088	0.906764565	0.90605921	0.906808329	0.906241722	0.9064192	0.906164636
0.00821	0.899135996	0.899015559	0.898322203	0.899058578	0.898501611	0.89867607	0.898425836

Table 5. Influence of repir rates on BMP w.r.t repair rate ζ_1.

ζ_1	Base values	ζ_2+10% of ζ_2	ζ_3+10% of ζ_3	ζ_4+10% of ζ_4	ζ_5+10% of ζ_5	ζ_6+10% of ζ_6	ζ_7+10% of ζ_7
0.1052	0.947737412	0.947857007	0.948556039	0.947809198	0.948373658	0.948199357	0.948452433
0.2052	0.957023003	0.957144953	0.957857758	0.957096203	0.957671782	0.957494048	0.95775211
0.3052	0.960265984	0.960388762	0.961106408	0.96033968	0.960919168	0.960740226	0.961000042
0.4052	0.961916681	0.962039881	0.962759997	0.96199063	0.962572114	0.962392555	0.962653265
0.5052	0.962916647	0.963040104	0.963761719	0.962990751	0.963573444	0.963393513	0.963654765
0.6052	0.963587319	0.963710948	0.964433569	0.963661526	0.964245031	0.964064849	0.964326465
0.7052	0.964068358	0.96419211	0.964915453	0.964142639	0.964726727	0.964546364	0.964808242

it becomes essential to examine the steady-state availability of the system before reaching any judgement about its execution. Thus, a mathematical model for the bolt manufacturing plant is proposed. The Markov birth-death process is applied to derive the availability expression of the system. A state transition diagram is prepared and shown in Figure 2. The transition between states happened at a constant rate. Using simple probabilistic arguments and a changeover diagram, the mathematical model has been developed. The differential equations have been described as follows:

$$P_0(x+\delta x) = (1-\gamma_1-\gamma_2-\gamma_3-2\gamma_4-\gamma_5-\gamma_6-\gamma_7)\,P_0(x)\,\delta x + \zeta_1 P_1(x)\,\delta x + \zeta_2 P_2(x)\,\delta x + \zeta_3 P_3(x)\,\delta x + \zeta_4 P_4(x)\,\delta x$$

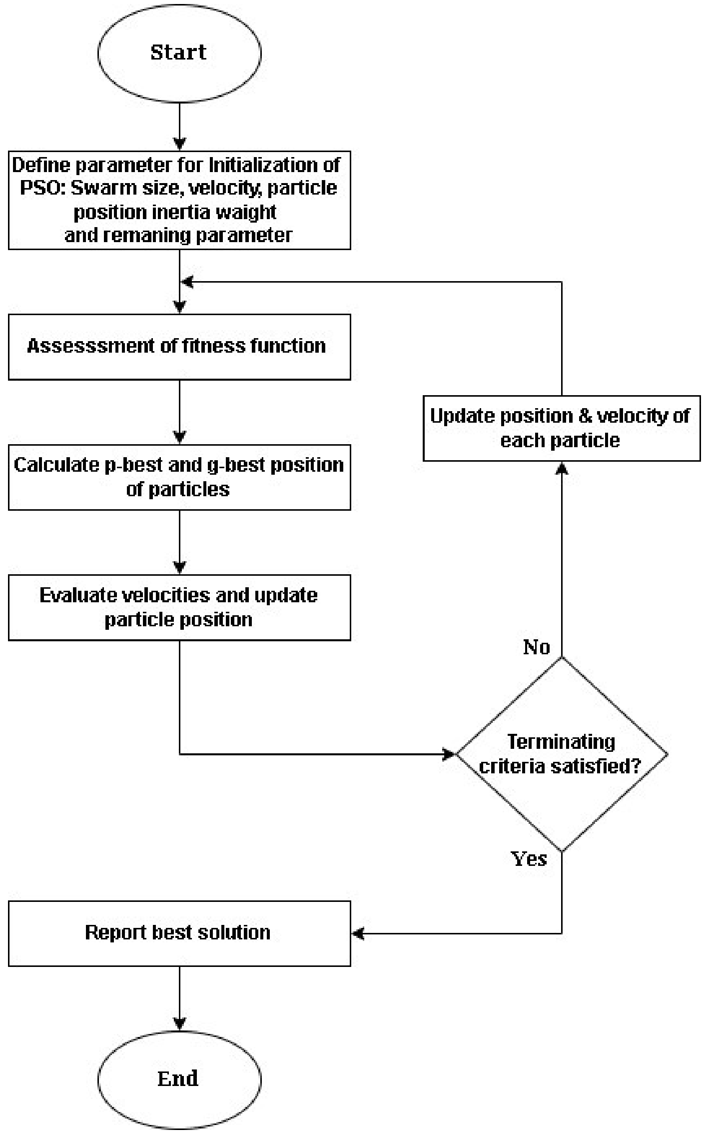

Figure 3. Flowchart of particle swarm optimization.

Table 6. Predicted availability of BMP at various population sizes on various iterations using PSO and GA.

	iter\NP	10	20	50	100	200	500	1000
PSO	10	0.700944903	0.858029114	0.875806296	0.990594675	0.96760625	0.99804745	0.99915923
	30	0.999132941	0.999412442	0.999411642	0.999429844	0.99942983	0.99942984	0.99942984
	50	0.999429793	0.999429844	0.999429844	0.999429844	0.99942984	0.99942984	0.99942984
	80	0.999429844	0.999429844	0.999429844	0.999429844	0.99942984	0.99942984	0.99942984
	100	0.999429844	0.999429844	0.999429844	0.999429844	0.99942984	0.99942984	0.99942984
	200	0.999429844	0.999429844	0.999429844	0.999429844	0.99942984	0.99942984	0.99942984
GA	10	0.648587811	0.793086249	0.862996038	0.837989257	0.85003865	0.93146411	0.91249012
	30	0.872315186	0.800997415	0.833399715	0.856732966	0.85352130	0.92293249	0.92067114
	50	0.830476333	0.858206543	0.906430717	0.897345884	0.81546764	0.91559903	0.94364405
	80	0.793144981	0.685248847	0.80123703	0.852529099	0.92440968	0.92579323	0.93463340
	100	0.775117876	0.865098597	0.886126282	0.880369928	0.90810800	0.94770550	0.94791544
	200	0.924234029	0.804154667	0.878194425	0.927305879	0.93433147	0.93034191	0.91398290

$$+ \zeta_5 P_5(x)\,\delta x + \zeta_6 P_6(x)\,\delta x + \zeta_7 P_7(x)\,\delta x,$$

$$\Rightarrow \frac{P_0(x+\delta x) - P_0(x)}{\delta x} = (-\gamma_1 - \gamma_2 - \gamma_3 - 2\gamma_4 - \gamma_5 - \gamma_6 - \gamma_7)\,P_0(x) + \zeta_1 P_1(x) + \zeta_2 P_2(x) + \zeta_3 P_3(x) + \zeta_4 P_4(x) + \zeta_5 P_5(x) + \zeta_6 P_6(x) + \zeta_7 P_7(x).$$

Taking limit δt→0, we get

$$\Rightarrow P_0'(x) = (-\gamma_1 - \gamma_2 - \gamma_3 - 2\gamma_4 - \gamma_5 - \gamma_6 - \gamma_7)\,P_0(x) + \zeta_1 P_1(x)\,\zeta_2 P_2(x) + \zeta_3 P_3(x) + \zeta_4 P_4(x) + \zeta_5 P_5(x) + \zeta_6 P_6(x) + \zeta_7 P_7(x). \quad (3)$$

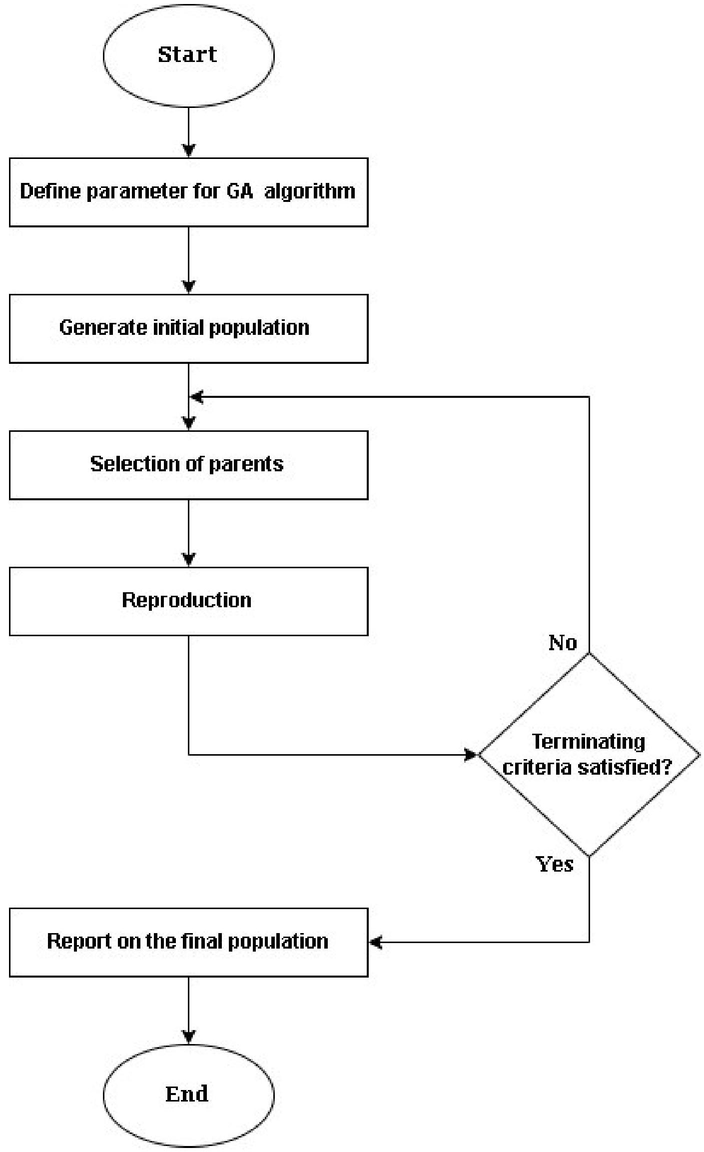

Figure 4. Flowchart of genetic algorithm.

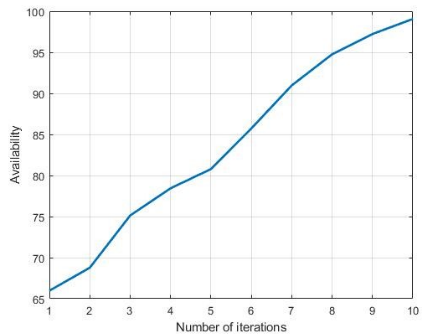

Figure 5. Availability at 100 population size after 10 iterations using PSO.

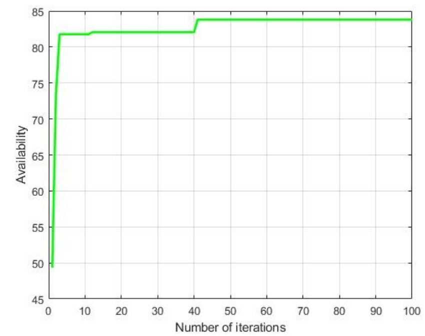

Figure 6. Availability at 100 population size after 10 iterations using GA.

Similarly,

$$P_i^{'}(x) = -\zeta_i P_i(x) + \gamma_i P_0(x) \;\; ; i = 1, 2, 3, 5, 6, 7. \quad (4)$$

Table 7. Estimated values of various failure and repair rates of the BMP after 10 iterations using PSO and GA.

Number of populations		10	20	50	100	200	500	1000
PSO	γ_1	0.490047508	0.00011	0.00011	0.00011	0.00011	0.000431236	0.00011
	γ_2	0.225127707	0.225006408	0.196673832	0.00031	0.264424676	0.00031	0.00031
	γ_3	0.00023	0.005105267	0.043613151	0.011583277	0.00023	0.00023	0.00023
	γ_4	0.198322104	0.29612961	0.206007458	0.023822047	0.00042	0.07477856	0.004476907
	γ_5	0.223605493	0.107926167	6.56E-01	1.00E-05	1.00E-05	0.000314514	1.00E-05
	γ_6	0.014482912	0.00041	0.027503439	0.003950468	0.004504199	0.00041	0.00041
	γ_7	0.740031319	0.624629799	0.078205002	0.007293779	0.001427145	0.00022	0.00022
	ζ_1	1.585821	1.172052115	0.795879061	0.514663058	1.387572389	1.019157293	1.104411681
	ζ_2	1.598942284	2.265967233	2.679058718	0.643590694	2.596909511	1.919445566	1.693367174
	ζ_3	0.315962611	1.404192242	1.515361236	1.022239537	1.197714023	1.082379099	1.297703018
	ζ_4	1.373508852	1.073987853	1.722776524	1.063182693	1.09283969	1.854	1.306447662
	ζ_5	1.377554576	2.412718502	2.87360297	2.204724862	1.959977356	1.715423284	1.639471954
	ζ_6	0.982830611	1.731180836	1.448979685	1.17572706	1.27107478	0.751497137	1.393246072
	ζ_7	1.506318062	2.03092576	1.656931984	2.768862764	1.91543751	2.201632094	1.485408757
GA	γ_1	0.109790936	0.009566051	0.024186636	0.008282914	0.071459514	0.003403429	0.029555235
	γ_2	0.119114744	0.092542683	0.055522083	0.082578522	0.161100443	0.096442155	0.101737153
	γ_3	0.020519934	0.032392022	0.01514898	0.007202904	0.013816109	0.015493226	0.001435538
	γ_4	0.072340107	0.001556462	0.087026365	0.063351672	0.01531819	0.133205808	0.010413869
	γ_5	0.003366448	0.007223519	0.004481304	0.006225799	0.005189041	0.004308944	0.014953297
	γ_6	0.00471446	0.022664636	0.085212252	0.066937417	0.029661771	0.002321772	0.04774658
	γ_7	0.500465891	0.410195603	0.11988607	0.070744954	0.009037315	0.002265881	0.012387755
	ζ_1	0.360791935	0.588798132	1.287026821	0.383204672	1.094521295	0.593341705	0.878506193
	ζ_2	2.566048048	0.579696537	0.584577418	0.434792986	0.713685741	1.52407272	1.252637622
	ζ_3	0.17402971	4.055879388	0.323078016	1.860313384	1.01726314	0.201332755	0.118272585
	ζ_4	0.156238636	0.344775193	1.359104189	0.61281857	1.574837446	3.183478466	0.125605969
	ζ_5	0.487578771	0.333028472	0.481556507	0.133253332	0.68382519	0.260977909	0.417180611
	ζ_6	0.160177647	0.162053319	0.713615162	0.490390221	0.271093619	0.498974908	0.905928848
	ζ_7	0.680042002	1.0853462	1.384902432	0.744542976	0.648937246	0.340844027	1.210254859

Table 8. Estimated values of various failure and repair rates of the BMP after 50 iterations using PSO and GA.

Number of populations		10	20	50	100	200	500	1000
PSO	γ_1	0.00011	0.00011	0.00011	0.00011	0.00011	0.00011	0.00011
	γ_2	0.00031	0.00031	0.00031	0.00031	0.00031	0.00031	0.00031
	γ_3	0.00023	0.00023	0.00023	0.00023	0.00023	0.00023	0.00023
	γ_4	0.00042	0.00042	0.00042	0.00042	0.00042	0.00042	0.00042
	γ_5	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05
	γ_6	0.00041	0.00041	0.00041	0.00041	0.00041	0.00041	0.00041
	γ_7	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022	0.00022
	ζ_1	1.761814	1.761999	1.762	1.762	1.762	1.762	1.762
	ζ_2	2.944865	2.945	2.945	2.945	2.945	2.945	2.945
	ζ_3	1.864998	1.865	1.865	1.865	1.865	1.865	1.865
	ζ_4	1.568362	1.853908	1.854	1.854	1.854	1.854	1.854
	ζ_5	2.922648	2.922997	2.923	2.923	2.923	2.923	2.923
	ζ_6	1.768	1.768	1.768	1.768	1.768	1.768	1.768
	ζ_7	2.980877	2.981	2.981	2.981	2.981	2.981	2.981
GA	γ_1	0.124752	0.029087	0.009295	0.046095	0.023504	0.006865	0.015292
	γ_2	0.317911	0.003643	0.050665	0.05606	0.063412	0.09589	0.217262
	γ_3	0.03215	0.001965	0.044504	0.033063	0.001562	0.048578	0.000831
	γ_4	0.005322	0.011271	0.021715	0.003348	0.038016	0.114976	0.000479
	γ_5	0.005101	0.001403	0.001167	0.001398	0.004644	0.006033	0.003847
	γ_6	0.019138	0.035117	0.024932	0.012608	0.000793	0.013228	0.033711
	γ_7	0.267769	0.312576	0.150308	0.215131	0.333981	0.150807	0.066609
	ζ_1	0.759203	0.794587	0.851584	1.475923	0.090942	0.502792	2.775891
	ζ_2	2.807557	0.777309	0.903846	1.344482	0.494852	0.723914	4.34301
	ζ_3	1.559552	2.937016	0.943066	3.687249	0.102516	1.807518	1.978709
	ζ_4	0.483269	0.039449	1.661361	0.443595	1.949969	1.379402	4.388048
	ζ_5	0.22286	1.259845	1.884823	0.964533	1.402132	1.295596	0.225634
	ζ_6	0.543743	0.888068	0.598119	0.541979	0.038102	0.694939	0.618509
	ζ_7	1.818853	1.013324	1.400166	0.986767	4.537921	2.862869	3.312466

$$P_j^{'}(x) = -\zeta_j P_j(x) + \gamma_j P_4(x)\ ;\ j = 8, 9, 10, 11, 12, 13, 14. \quad (5)$$

$$P_4^{'}(x) = (-\zeta_4 - \gamma_1 - \gamma_2 - \gamma_3 - \gamma_4 - \gamma_5 - \gamma_6 - \gamma_7) P_4(x) \quad (6)$$
$$+ 2\gamma_4 P_0(x) + \zeta_1 P_8(x) + \zeta_2 P_9(x) + \zeta_3 P_{10}(x)$$
$$+ \zeta_4 P_{11}(x) + \zeta_5 P_{12}(x) + \zeta_6 P_{13}(x) + \zeta_7 P_{14}(x).$$

Now taking limit x→∞ on Equations (4) – (6) and using normalization properity $\sum_{k=0}^{14} P_k = 1$, we get

$$P_0 = \left(1 + \frac{\gamma_1}{\zeta_1} + \frac{\gamma_2}{\zeta_2} + \frac{\gamma_3}{\zeta_3} + \frac{2\gamma_4}{\zeta_4} + \frac{\gamma_5}{\zeta_5} + \frac{\gamma_6}{\zeta_6} + \frac{\gamma_7}{\zeta_7} \right. \quad (7)$$
$$+ + 2\left(\frac{\gamma_1}{\zeta_1}\right)\left(\frac{\gamma_4}{\zeta_4}\right) + 2\left(\frac{\gamma_2}{\zeta_2}\right)\left(\frac{\gamma_4}{\zeta_4}\right) + 2\left(\frac{\gamma_3}{\zeta_3}\right)\left(\frac{\gamma_4}{\zeta_4}\right)$$
$$\left. + 2\left(\frac{\gamma_4}{\zeta_4}\right)\left(\frac{\gamma_4}{\zeta_4}\right) + 2\left(\frac{\gamma_5}{\zeta_5}\right)\left(\frac{\gamma_4}{\zeta_4}\right) + 2\left(\frac{\gamma_6}{\zeta_6}\right)\left(\frac{\gamma_4}{\zeta_4}\right) + 2\left(\frac{\gamma_7}{\zeta_7}\right)\left(\frac{\gamma_4}{\zeta_4}\right)\right)^{-1}.$$

Similarly, probability at state are as follows

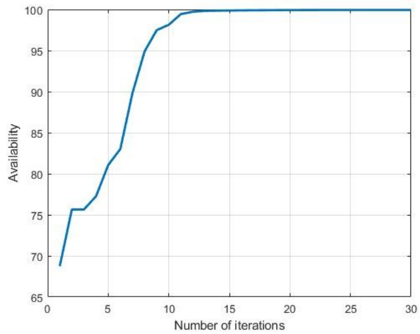

Figure 7. Availability at 200 population size after 30 iterations using PSO.

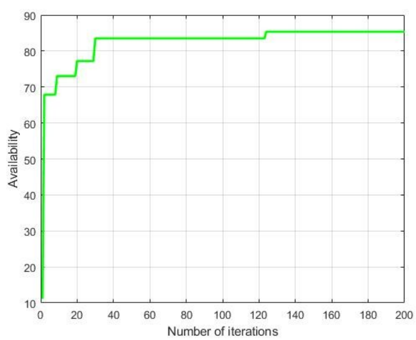

Figure 8. Availability at 200 population size after 30 iterations using GA.

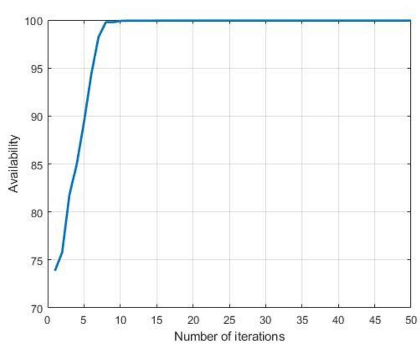

Figure 9. Availability at 500 population size after 50 iterations using PSO.

$$P_i = \frac{\gamma_i}{\zeta_i} P_0 \;;\; i = 1, 2, 3, 5, 6, 7. \tag{8}$$

$$P_{j+7} = 2\left(\frac{\gamma_j}{\zeta_j}\right)\left(\frac{\gamma_4}{\zeta_4}\right) P_0 \;;\; j = 1, 2, 3, 4, 5, 6, 7. \tag{9}$$

$$P_4 = 2\left(\frac{\gamma_4}{\zeta_4}\right) P_0. \tag{10}$$

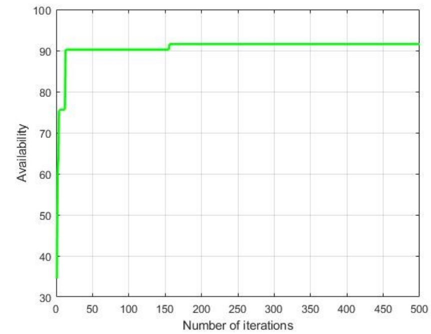

Figure 10. Availability at 500 population size after 50 iterations using GA.

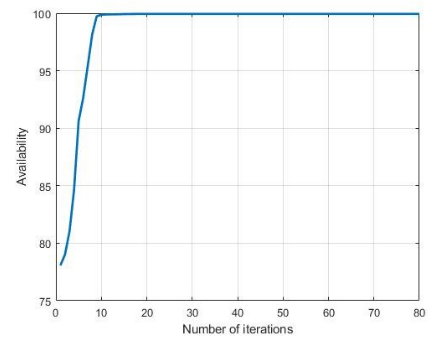

Figure 11. Availability at 1000 population size after 80 iterations using PSO.

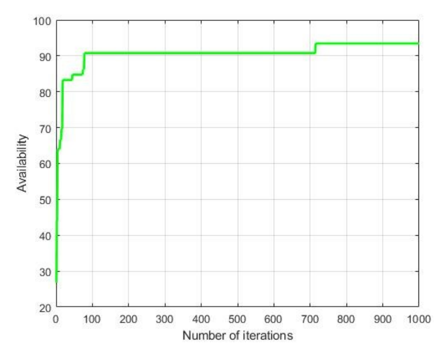

Figure 12. Availability at 1000 population size after 80 iterations using GA.

The initial conditions associated with the Markov model are

$$P_z(x = 0) = \begin{cases} 1 & if\ z = 1 \\ 0 & if\ z \neq 1 \end{cases}. \tag{11}$$

By using the differential difference equations and initial conditions mentioned earlier, an algebraic solution has been derived for a particular case using MATLAB R2021b. The SSA of the plant is:

SSA = P_0+P_4

$$= (1 + 2\frac{\gamma_4}{\zeta_4})\{1 + \frac{\gamma_1}{\zeta_1} + \frac{\gamma_2}{\zeta_2} + \frac{\gamma_3}{\zeta_3} + \frac{2\gamma_4}{\zeta_4} + \frac{\gamma_5}{\zeta_5} + \frac{\gamma_6}{\zeta_6} + \frac{\gamma_7}{\zeta_7} \tag{12}$$

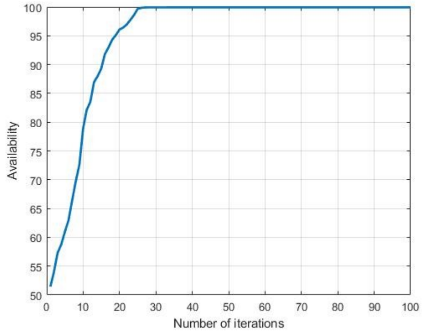

Figure 13. Availability at 20 population size after 100 iterations using PSO.

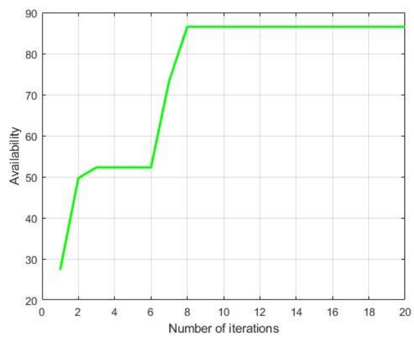

Figure 14. Availability at 20 population size after 100 iterations using GA.

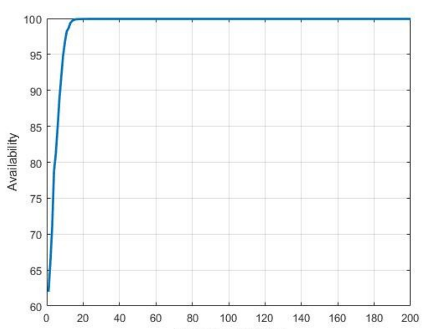

Figure 15. Availability at 100 population size after 200 iterations using PSO.

$$+2\left(\frac{\gamma_1}{\zeta_1}\right)\left(\frac{\gamma_4}{\zeta_4}\right)+2\left(\frac{\gamma_2}{\zeta_2}\right)\left(\frac{\gamma_4}{\zeta_4}\right)+2\left(\frac{\gamma_3}{\zeta_3}\right)\left(\frac{\gamma_4}{\zeta_4}\right)+2\left(\frac{\gamma_4}{\zeta_4}\right)\left(\frac{\gamma_4}{\zeta_4}\right)$$

$$+2\left(\frac{\gamma_5}{\zeta_5}\right)\left(\frac{\gamma_4}{\zeta_4}\right)+2\left(\frac{\gamma_6}{\zeta_6}\right)\left(\frac{\gamma_4}{\zeta_4}\right)+2\left(\frac{\gamma_7}{\zeta_7}\right)\left(\frac{\gamma_4}{\zeta_4}\right)\}^{-1}.$$

4. Results and discussion

For a particular case, the steady state availability of the BMP is derived by considering the failure and repair rates as given in Table 2. The prediction of the optimal availability of BMP and estimation of the parameters is also made in the search space given in Table 3. The values of the parameters in

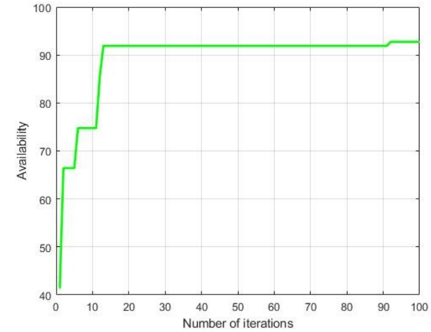

Figure 16. Availability at 100 population size after 200 iterations using GA.

search space are considered with the plant personnel help. As well as the impact of variation in various failure and repair rates on steady state availability is also investigated by making 10% variation in the failure rates of all the subsystems of BMP. It is revealed from Table 4 that, the steady state availability sharply declined with respect to the failure rate of blank cutting subsystem. It is observed that 10% increment in failure rate of Ist CNC resulted the decline in availability of BMP plant from 0.947737412 to 0.947603603. It is observed that failure rate γ_7 is very crucial.

Table 5 showed the influence of repair rates of various subsystems on the availability of the BMP. The base value of the availability is derived by using initial values of the parameters given in Table 2. After making 10% variation in repair rates, it is identified that IInd CNC subsystem is very sensitive. Here, availability inclined sharply from 0.947737412 to 0.948556039. It is revealed that availability increased from 0.947737412 to 0.964068358 by changing values of ζ_1.

After the availability evaluation an effort has been made to predict the optimal availability of BM plant. For this purpose, metaheuristic algorithms namely PSO and GA applied on the objective function given in Equation (12). The simulation study is performed at various population sizes between 10 to 1000 and different iterations between 10 to 200. It is noticed that GA provides the maximum value of availability as 0.9479154486 at a population size 1000 after 100 iterations. The PSO algorithm predict that BM plant attains the optimal availability 0.99942984 after 30 iterations at 100 swarm size. It is revealed from Table 6 that rate of convergence of PSO algorithm is very faster than GA in prediction of availability of process industries like BMP. The estimated values of the failure and repair rates for prediction of optimal availability is appended in Tables 7 and 8 after 10 and 50 iterations.

5. Conclusion

In the designing and operational phases of any process industry, like bolt manufacturing plants, reliability characteristics play an extremely crucial role, and their continuous evaluation is necessary for the performance of the industry. Here, the impact of failure and repair rates of various subsystems of the bolt manufacturing plant is observed on its availability by making a 10% increment in various parameters. The numerical results of the availability presented in Tables 4 and 5 acknowledged that the availability of bolt manufacturing plants sharply declined with respect to the increment in failure rate, while availability increased with respect to the repair rate. The predicted value of availability and estimated parameters are appended in Tables 6, 7 and 8, and a graphical representation of predicted availability at various population sizes after certain iterations is shown in Figures 5 – 16. It is observed that the PSO algorithm predicts the optimal availability as 0.99942984 at 100 swarm sizes after 30 iterations. While the genetic algorithm reached up to 0.9479154 at a population size of 1000 after 100 iterations, The convergence rate of PSO is very fast in predicting the availability of bolt manufacturing plants in accordance with the attainment of optimal value. The derived results are beneficial for plant designers and maintenance engineers to implement new maintenance plans for plants for effective operation. The present investigation is performed on a small-scale plant under the assumption of constant failure rates, no simultaneous failures, and sufficient repair facilities. In further investigation, it can be extended to large-scale industries under arbitrary life testing distributions, and more advanced metaheuristic approaches may be adopted for availability prediction. It is also recommended that the same methodology be used in other plants of similar kind.

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