International Journal of Industrial Engineering, 29(6), 794-804, 2022

AN INDUSTRIAL APPLICATION OF IMPROVED PARTICLE SWARM OPTIMIZATION: AVAILABILITY ASSESSMENT OF ELECTROSTATIC PRECIPITATOR

Pouya Bolourchi[1,*] and Mohammadreza Gholami[2]

[1]Department of Electrical and Electronic Engineering
Final International University
Girne, Mersin 10, Turkey
[*]Corresponding author's e-mail: pouya.bolourchi@final.edu.tr

[2]Department of Electrical and Electronic Engineering
Near East University
Lefkosa, Mersin 10, Turkey

The Electrostatic Precipitator (ESP) is common equipment used in thermal power plants and industrial mining plants such as steel, copper, and cement. ESP is installed to capture the dust in the exhaust gas of boilers or furnaces. The availability of ESP is vital for plants since any interruption in this device causes serious process problems and environmental pollution. As a result, the availability of ESP is crucial, and a comprehensive study in this area must be performed for maintenance activities. This paper presents a novel method for assessing complex equipment availability, such as ESP, based on improved dynamic particle swarm optimization (IDPSO). To evaluate the availability of ESP, all related systems, sub-systems, and all components of ESP must be considered. Availability assessment of ESP, consisting of many series-parallel sections and components, can be challenging and time-consuming. An IDPSO is used to search for the most probable states among numerous possible states. In addition, IDPSO overcomes shortcomings of standard PSO, such as falling into local optimums. The proposed method is applied to the actual data of an ESP installed at a copper factory. The results show the proposed method achieved an accuracy of 99.54 % in availability assessment.

Keywords: Air Pollution Control Systems; De-Dusting System; Availability; Electrostatic Precipitator; Meta-Heuristic Algorithms; Particle Swarm Optimization.

(Received on July 19, 2022; Accepted on November 16, 2022)

1. INTRODUCTION

Proper operation of air pollution control systems is essential in pollutant industries. Due to their advantages, such as low maintenance cost and ability to work at high temperatures and flow rate, Electrostatic Precipitator (ESP) is the best and sometimes the only option for plant designers to capture the dust from exhaust gases of boilers and furnaces. Two main reasons make ESP the best and sometimes the only option for plant designers. Firstly, the ESP can operate at a high-temperature working point, between 300°C and 400°C, making ESP the only choice for designers. In contrast, other de-dusting equipment, such as Bag-houses, should operate at lower temperatures. Secondly, the low differential pressure across the ESP is about 2 mbar, which is remarkably lower than other devices, typically between 10 and 15 mbar. Higher differential pressure leads to installing an exhaust fan with higher capacity (in KW) and significantly higher electrical energy cost. An ESP uses static electricity to capture the dust using the force of an induced electrostatic between collecting plates and discharge electrodes. Any interruption in the operation of ESP can result in severe problems in these plants. Air pollution and staff health matter is the first significant result of ESP interruption and improper operation. The second result of ESP interruption is an imbalance in the exhaust fan's impeller due to a large volume of dust. In addition, economically, dust is more valuable than raw material for plants and can be used in the production line. Considering the aforementioned reasons, assessing the availability of ESP and identifying the weak points of this equipment is essential to improve its availability. The problems associated with ESP in industries can be categorized as process, mechanical, and electrical issues. Severe process issues can occur because of dust coating through internal sections and components, significant corrosion, and false air. Problem-related with mechanical sub-systems such as collecting and discharge rapping systems and conveying systems results in ESP operation failures. In addition, any failure in electrical components, such as high-voltage rectifiers and control

DOI: 10.23055/ijietap.2022.29.6.8477 ISSN 1943-670X

panels case, instantly stops the operation of ESP. All the above-mention can lead to failure in ESP operation and the whole plant process.

Most studies in this area have focused on the operation and efficiency of ESP. A few papers have proposed solutions to improve the efficiency of ESP. To the authors' best knowledge, no research has been conducted on assessing the availability and identifying the weak points. In (Wei *et al*., 2020), an improved transformer-based converter is proposed to enhance the collection efficiency of ESP by reducing the ac resistance. A real-time optimization method is proposed to minimize the energy consumption of ESP (Zheng *et al*., 2020). The proposed intelligent optimization system and coordination control logic are compared with proportion-integral-derivative (PID) and manual control methods. An experimental investigation is done to analyze the collecting efficiency of ESP. Due to the high volume and nature of the dust in the copper factory, the functionality of ESP is more significant than other mining factories, such as cement and steel. As a result, to improve the reliability of ESP, using any control systems that can work on both PID and optimal intelligent-based systems is most suitable for copper factories. In addition, intelligent optimization algorithms such as PSO and genetic algorithms, which have shown their high performance in dealing with high-dimension and NP-hard problems, are suitable for the copper factory.

This study shows that ESP can collect dust particles for a velocity range of 1-4 m/s with high efficiency. Savita Naik and M. S. Aspalli (2015) proposed a new 16-bit microcontroller that uses a true spark sensing method. The microcontroller is maintenance-free and enhances the performance of ESP. In (Remaoun *et al*., 2014), the authors designed a home-made and cost-efficient ESP., the half-scale ESP, which includes a high voltage supplier consisting of a static converter and a ferrite transformer. However, the efficiency of their proposed ESP is not high. Still, it has been suggested to be used in places without air pollution control devices, such as medical waste incinerators. A comprehensive description of the performance of ESP is given in (Parker, 2016). The authors reviewed the basics of ESP, such as corona discharge, particle charging, theoretical migration velocity, and efficiency. Furthermore, new technologies such as pulsed energization and wet ESP are proposed in this paper.

On the other hand, meta-heuristic algorithms (MAs) have been applied widely to nonlinear optimization problems. Among many MAs, PSO has shown high efficiency and performance. The main idea of PSO was proposed by Kennedy and Eberhart (Clerc, 2010). The idea was based on analyzing traveling to find the destination. In this regard, a possible solution to the problem is simulated by a "Particle," as one member in a group called a "Swarm" or "Population." Every particle includes the necessary information required to solve the problem.

However, the first population is generated randomly. For every particle, a fitness function is calculated based on the mathematical model of the problem. Then, the particle moves and follows others for a better solution. They move toward their best memory and the leader. After meeting stopping criteria which can be specific iterations, the particles find the best solution. The main equations regarding the improvement of particles are given in Eq. 1 and Eq. 2, respectively:

$$v_{ij}^{(t+1)} = w\, v_{ij}^{(t)} + c_1\, r1_{ij}(t) \times \left(y_{ij}(t) - x_{ij}(t)\right) + c_2\, r2_{ij}(t) \times \left(\hat{y}_i(\mathrm{t}) - x_{ij}(t)\right) \tag{1}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \tag{2}$$

where, $v_{ij}^{(t)}$ is the velocity in dimension j at time t. $x_{ij}(t)$ is the position at time t. w, c_1 and c_2 are inertia weight and controlling parameters termed cognitive and social coefficients, respectively. $r1_{ij}$ and $r2_{ij}$ are random numbers ~ $U(0{,}1)$. $\hat{y}_i(\mathrm{t})$ and $y_{ij}(t)$ represent the best position of the individual and neighborhood, and finally $x_{ij}^{(t+1)}$ is the new position at time t+1.

Regarding the convergence of the PSO algorithm, the mathematical relationship between control parameters given in Eq. 3 should be met as follows:

$$c_1 + c_2 < \frac{24\,(1 - w^2)}{7 - 5w} \tag{3}$$

Because of the advantages of PSO, such as simplicity in implementation, few controlling parameters, flexibility, and fast convergence, researchers applied this algorithm to solve many real-world engineering problems (Li *et al*., 2021; Kim and Lee, 2017; Keshavarzi *et al*., 2016; Tanweer *et al*., 2016; Al-Maamari and Omara, 2015; Sudheer *et al*., 2014; Pousinho *et al*., 2011). However, some drawbacks are related to the PSO, such as too fast convergence and a high probability of falling into the local optimum. Many researchers have proposed improved PSO algorithms, including solutions to overcome these shortcomings (Zhang *et al*., 2022; Liang and Yi, 2022; Dai *et al*., 2021).

To improve standard PSO's performance, we first added a mutation operation to the algorithm. Regarding this operator, for every particle, a random value is generated and compared with the probability of mutation (pm). If the random value is less than the pm, the randomly selected values are set to the particle. Second, we updated the movements of the particle. The randomly selected particles move not only toward their best experiences and leaders but also follow the opposite position of the worst particles (Eq. 4). As a third enhancement, to overcome the problem associated with finding the global solution, we considered dynamic control parameters in IDPSO. After some specific iterations, the setting parameters mentioned above, such as pm, c1, c2, and c3, are changed according to (Eq. 5).

$$\begin{aligned}&if\ rand < p_{move}:\\&v[new] = v[old] + c_1 \times rand \times (p_{best} - present) + c_2 \times rand \times (g_{best} - present) +\\&c_3 \times rand \times (present - g_{worst})\end{aligned} \tag{4}$$

where g_{worst} is the particle with the worst fitness function. p_{move} is a small value considering for probability of moving particles toward the worst particle, and c_3 is a parameter to control the movement of particles toward the opposite side of g_{worst}.

$$\begin{cases} if\ iter < specific_{iter}:\ pm, c_1, c_2, c_3 = pm, c_1, c_2, c_{3(base)} \times \dfrac{(iter\_max + iter)}{iter\_max} \\ if\ iter > specific_{iter}:\ pm, c_1, c_2, c_3 = pm, c_1, c_2. c_{3(base)} \times \dfrac{(iter_{max} - iter)}{iter\_max} \end{cases} \tag{5}$$

where pm is the mutation parameter. $\mathrm{pm_{base}}$ is the initial value for pm. iter_maxis the maximum iteration number, and iter is the variable that shows the number of algorithm iterations. Considering Eq.4, at the first iteration, the number of pm is increasing, which means that more random particles are generated to search sufficiency among all problem search spaces. After specific iterations, the random particle movements can be limited by decreasing the value of pm in each step. Besides the improvements above, the main limitation associated with applying IDPSO is the control parameters' dependency on problem size. A problem with a smaller size is more likely to be divergence. However, in this study, because of a large number of components, the possible states (2^{40}) are large enough, which does not affect the convergence.

Considering the advantages and wide range of improved PSO, we selected this powerful optimization algorithm in our study. Regarding the availability studies, some researchers have used PSO to improve the availability of systems. In (Mellal and Zio, 2022), a hybrid PSO and cuckoo optimization algorithm (COA) are used to solve a multi-objective optimization problem. Both availability and cost are considered fitness functions for a series-parallel system consisting of six sub-systems with high failure dependencies. In (Chaudhary *et al*., 2019), PSO is utilized to find the optimum values of failure rate and repair rates of condenser manufacture and evaluate the effects of these parameters on the availability of the system.

Still, the availability assessment of complex systems, which consist of many sub-systems and components, requires high computational time. Therefore, in this paper, we applied PSO to assess the availability of ESP as a complex system including 40 components. A two states condition (up and down) is used for all ESP components. The failure and repair rates of ESP components are chosen based on the actual reports from a copper plant. The accurate availability of the ESP should be evaluated by considering all possible states based on components failure and repair rates. Because of the complexity and high required time computational to consider all possible states, the PSO is applied to assess the availability, considering the fact that the probability of occurrence in many states is too low and can be ignored in availability assessment. For instance, the probability that all components are in a failure state is too low. In the proposed method, PSO searches among all possible states and finds the most probable states. The high probable states are evaluated and states that cause failure in the system is chosen for availability evaluation. The main advantage of applying PSO on ESP is reducing the feature space remarkably. Another advantage of the proposed method is finding weak points for further maintenance activity and availability improvements.

The remainder of this paper is as follows. The components and operation of ESP are described in section 2. The methodology used in this paper is detailed in section 3, and the results of applying the proposed method to real ESP data are given in section 4. This section consists of results related to both availability assessment and most probable failure as two highlight findings of the method. Finally, the conclusion and future work suggestions are provided in section 5.

2. ESP COMPONENTS AND OPERATIONS

ESP is a highly efficient air pollution control device. An ESP can capture dust with an efficiency of more than 99 percent. The problems associated with ESP in industries can be categorized as process, mechanical, and electrical. Severe process issues can occur because of dust coating through internal sections and components, significant corrosion, and false air. Problem-related with mechanical sub-systems such as collecting and discharge rapping systems and conveying systems results in ESP operation failures. In addition, any failure in electrical components, such as high-voltage rectifiers and control panels case, instantly stops the operation of ESP. All the problems mentioned above can lead to failure in ESP and the whole plant process. In this paper, all systems and components related to the ESP (Both mechanical and Electrical) are selected to have an accurate assessment of availability. An ESP is classified into three main sections: mechanical sections, electrical sections, and other sections. Each main section is further divided into many subsections. The mechanical section involves a gas distribution system (GDS), collecting plats (CP), discharge electrodes (DE), collecting rapping system (CRS), discharge rapping system (DRS), and conveying system (CS). The electrical section includes electrical panels (EP), touch panels (TP), supporting insulators (SI), control systems (CoS), and cables. Other sections, such as casing and accessories, do not affect the system's availability and, therefore, are not considered in this paper. Some related photos and the main sections of an ESP are illustrated in Figures 1 and 2, respectively.

Gas distribution systems, called screens or perforated plates, are installed at the inlet and outlet of ESP to distribute the input dust evenly. The problems related to GSD directly affect the efficiency of ESP. Collecting plates are installed to collect dust passing through ESP. The number, length, material, and other factors related to collecting plates are determined by designers based on the characteristics and volume of inlet gas and dust. Discharge electrodes are connected to the DC voltage output of high-voltage rectifiers to generate an electrostatic field between each collecting and discharge electrode. Discharge electrodes are used in different shapes based on design factors. The collected dust should be removed from collecting plates and discharge electrodes. Rapping systems remove captured dust from collecting plates and discharge electrodes. Depending on the brand and design of ESP, different types and numbers of rapping systems are used in ESPs. Generally, a rapping system consists of a gear motor, a shaft, and some hammers installed at the shaft. The removed dust is stored in hoppers and returned to the production line using the conveying system. The conveying systems consist of a rotary airlock, a drag chain, and an electromotor. Electrical systems include high voltage rectifiers (HVR), electrical panels, and control systems. The role of the electrical system is to supply discharge electrodes by a high dc voltage and control the operation of ESP.

3. ASSESSMENT OF ESP AVAILABILITY USING THE PROPOSED PSO-BASED METHOD

The availability of an ESP can be defined as the ability of ESP to capture dust without any interruption. Generally, an ESP consists of two or three fields. Each field can capture dust independent of other fields. Any interruption in ESP operation leads to the whole production process interruption. Generally, the installed ESPs in plants consist of three independent fields. The interruption of ESP because of failure in one field or two fields is a decision that operators should make. Operation of ESP with a failure of two fields is practically possible but causes severe environmental issues. Due to the importance of environmental problems, this paper considers two scenarios for three fields of ESP. In the first scenario, the interruption of two fields out of three simultaneously is regarded as ESP interruption. In the second scenario, the interruption of all three fields is considered the whole system interruption.

The flowchart of the proposed method is shown in Figure 3. The input data includes experimental values of failure and repair rate of all mechanical and electrical subsections, such as collecting rapping system and supporting insulators, PSO parameters such as C1, C2, and population size. Be noted that each subsection is further divided into different components. For instance, a collecting rapping system consists of a gear motor, shaft, and hammer. These inputs are fed to PSO. PSO randomly generates binaries (zero and ones) for each component at the first population. Binary numbers are chosen to represent the status of equipment availability. If the equipment is available (upstates), the number 1 is allocated. Otherwise, the number 0 is shown in the statues. A particle represents one possible state of the availability of all ESP equipment. The length of each particle, n, is the number of ESP components in three fields and the gas distribution system as a component for the whole ESP (Table 1). 2n is the number of all possible states or dimensions of PSO search space. For example, as shown in Table. 2, rotary airlock of conveying system, gear motor of collecting rapping system, and supporting insulator in fields one and three are considered downstate (downstate component=0). Other components are upstate (upstate component=1). The explained particle is shown in three different tables.

The fitness function for each particle (possible state) is calculated based on the probability of that state (Eq. 6)

$$p_j = \prod_{j=1}^{n} sp_j \tag{6}$$

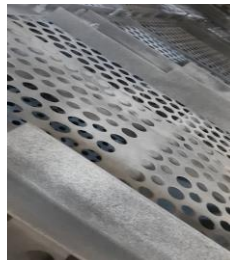
where sp_j stands for state probability of jth particle as defines as follows:

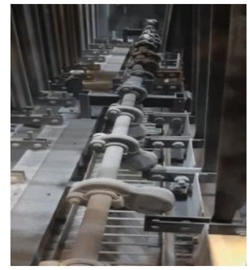
$$sp_j = \begin{cases} availibility_j & if\ component\ is\ in\ upsatate\ mode \\ 1 - availibility_j & if\ component\ is\ in\ downsatate\ mode \end{cases} \tag{7}$$

where

$$availibility_j = \frac{\mu_j}{\lambda_j + \mu_j} \tag{8}$$


a) A three fields ESP


b) Gas Distribution


c) Collecting Rapping


d) Collecting plates


e) Electrical panel


f) Conveying system

Figure 1. Some Photos of ESP's Components

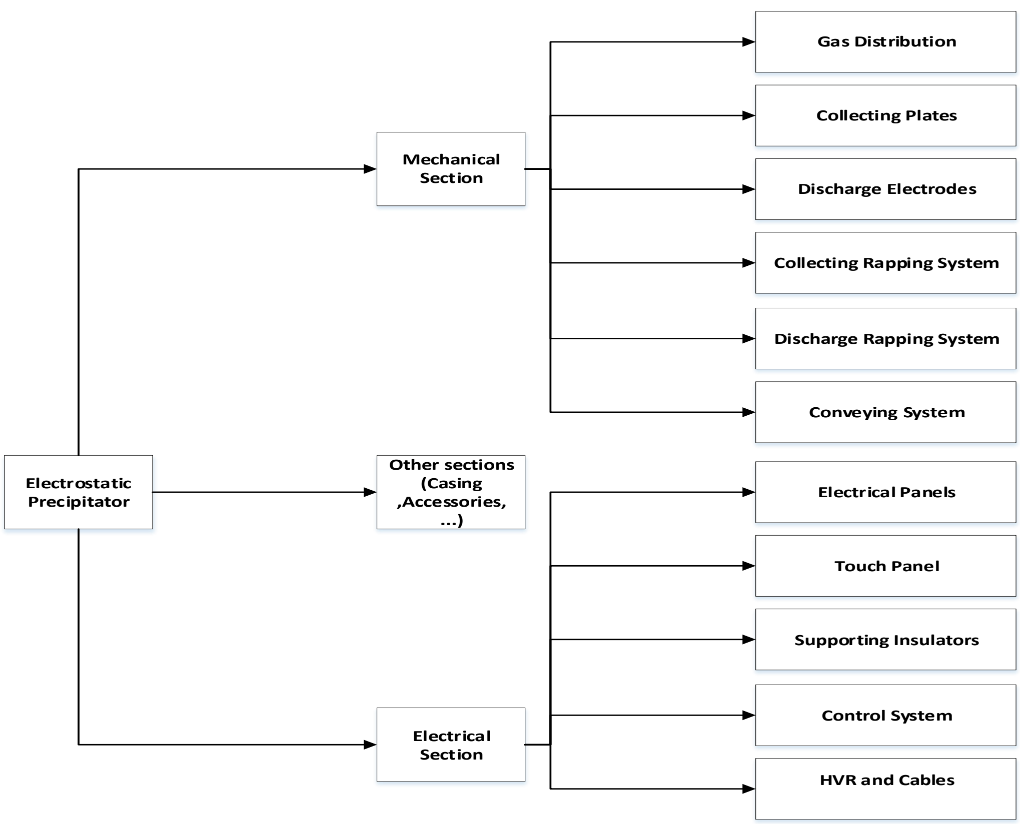


Figure 2. Main Sections of an ESP

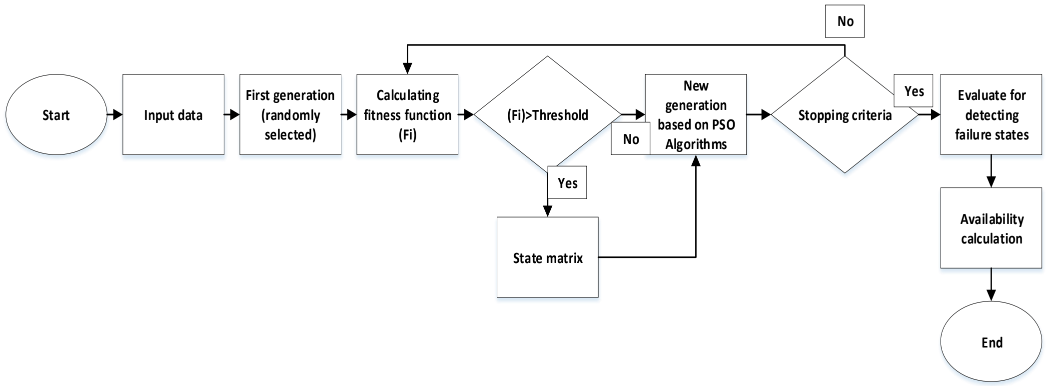


Figure 3. Schematic of the Proposed Method

Table 1. A particle Representation of a Sample State with Four Components in Each Field (comp stands for components)

Status of Components in field 1				Status of Components in field 2				Status of Components in field 3			
Comp1	Comp2	Comp3	….	Comp1	Comp2	Comp3	…	Comp1	Comp2	Comp3	…
1(up)	1(up)	0(down)	….	0(down)	0(down)	1(up)	…	1(up)	0(down)	1(up)	….

Table 2. A Particle Representation of a Sample State General Approach- all Components are in Upstate

All sub-systems and components of field 1													
Gas Distribution System	Collecting Plates	Discharge Electrodes	Gear Motor-CRS	Shaft-CRS	Hammers-CRS	Gear Motor-DRS	Shaft-DRS	Hammers -DRS	Rotary Air lock - CS	Drag Chain - CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
1	1	1	0	1	1	1	1	1	0	1	1	0	1

All sub-systems and components of field 2												
Collecting Plates	Discharge Electrodes	Gear Motor CRS	Shaft-CRS	Hammers CRS	Gear Motor DRS	Shaft-DRS	Hammers DRS	Rotary Air lock CS	Drag Chain CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
1	1	1	1	1	1	1	1	1	1	1	1	1

All sub-systems and components of field 3												
Collecting Plates	Discharge Electrodes	Gear Motor CRS	Shaft-CRS	Hammers CRS	Gear Motor-DRS	Shaft-DRS	Hammers DRS	Rotary Air lock CS	Drag Chain CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
1	1	0	1	1	1	1	1	0	1	1	0	1

To calculate the probability of states, the availability of all components should be calculated considering the failure rate and repair rate of components. Therefore, the status of components in each state, failure rate, and repair rate are the parameters needed to be specified to calculate the fitness function.

PSO is used to search all possible states to find the states with a high probability. To reduce the computational cost, we consider a threshold value. Only states with higher values than threshold values will be selected and saved in a state matrix. Those values less than the given threshold value follow the same steps as those with higher values, except they do not keep in the state matrix. The threshold considered in this study is 1e-15, which is found experimentally. A new generation of possible states continues until PSO meets the stopping criteria, determined as specific numbers of iterations. The saved states are evaluated as failure or success states in the next step. For example, in the first scenario, the unavailability of the gear motor from the first field rapping system does not cause any interruptions of the whole ESP. While in the second scenario, any interruption in the rapping system is considered an interruption of the entire ESP. Finally, the availability of ESP is calculated using the sum of the probability of failure states. Note that the total number of states for all possible combinations of m components of three fields ESP is n=2^3m=8^m. The proposed algorithm can determine the availability by selecting much fewer states than 8^m with an acceptable level of accuracy. Furthermore, as mentioned as the advantages of the proposed algorithm, the most probable failure states are investigated for suggestions regarding the availability improvement of ESP.

4. RESULTS AND DISCUSSIONS

The proposed method is applied to an installed ESP in a copper plant. The availability of each subsection and component determined based on the recorded failure and repair data during a year is given in Table 3. Eq.8 is applied to the recorded failure and repair data to achieve the availability of components. It should be noted that the data is collected after the main overhaul of the equipment in which all components are repaired or renewed. As a result, the average values of availability are relatively high. The failure rate of the components will be increased by aging the system.

The following parameters are set for the IDPSO part of the algorithm: Population Size= 100, C1=1.8, C2 = 3.1 and C3=2.2. A particle consists of 40 variables, including the 13 components for each field, and one variable specifies the status of the gas distribution system. The total possible states are $n = 2^{(3*13)+1} = 2^{40}$.

Table 3. The Availability of each Component for the Case Study as Input Data

Component	Gas Distribution System	Collecting Plates	Discharge Electrodes	Gear Motor-CRS	Shaft-CRS	Hammers CRS	Gear Motor-DRS	Shaft-DRS	Hammers DRS	Rotary Air lock - CS	Drag Chain - CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
F1	0.998	0.995	0.995	0.995	0.995	0.991	0.995	0.995	0.992	0.996	0.994	0.997	0.99	0.997
F2	…	0.995	0.995	0.997	0.997	0.997	0.997	0.997	0.993	0.996	0.996	0.997	0.99	0.997
F3	….	0.998	0.998	0.997	0.997	0.997	0.997	0.997	0.995	0.997	0.997	0.997	0.995	0.997
F1= Field 1, F2= Field 2, F3= Field 3														

4.1 ESP Availability Assessment

The results for different scenarios and iterations of PSO are shown and compared in Table 4. The result of IDPSO is compared with the exact availability amount of the given sample calculated by considering all possible states. An Intel (R) Core(TM) i7-7700HQ CPU @ 2.80GHz with 16 GB is used to run the algorithm. The results show that IDPSO can calculate the availability of the whole ESP by sampling much fewer states. By sampling 430,675 states, the accuracy of 99.54 and 99.58 is obtained after 100000 Iterations for the first and second scenarios, respectively, as shown in Table 5. Also, as the applied algorithm uses failure states to obtain the availability, PSO's availability is more significant than the actual value, which means that some failure states are not sampled by PSO or saved in the state matrix. It is crucial to remark that the input data are based on the specific installed ESP and may vary for other plants. Also, all the most frequently failed components are considered in this study. However, other components can be added to other cases.

Table 4. The Results for Different Scenarios and Iterations of PSO

Iterations	First Scenario		Second Scenario	
	Availability%	Number of Samples	Availability%	Number of Samples
20,000	99.81	85,136	99.86	85,136
50,000	99.6	210,145	99.68	210,145
100,000	99.46	430,670	99.54	430,670

Moreover, to show the efficiency of the proposed method (IDPSO), we deployed three most well-known optimization algorithms, including genetic algorithm (GA), simulated annealing (SA), and standard PSO, which are summarized in Table 6. The results validate the higher performance of IPSO compared to other algorithms.

Table 5. The Results of PSO Compared with Considering All Possible States

Method	First Scenario		Second Scenario		Run Time (hour)
	Availability %	Accuracy	Availability %	Accuracy	
PSO, after 100000 iterations	99.46	99.54	99.54	99.58	3.3
All possible states	99.01		99.13		37

Table 6. The Comparison of IDPSO Performance with Other Optimization Methods

Method	Accuracy		Number of Samples	Run Time (hour)
	First Scenario	Second Scenario		
IDPSO	99.54	99.58	430,670	3.3
GA	99.21	99.14	400,659	3.9
Standard PSO	98.43	97.86	386,951	4.5
SA	97.67	97.56	345,049	2.9

All availability values for ESP are calculated based on the data which is collected after maintenance activity and renewing the components for one year. Obviously, the lower availability value is expected to be achieved for an ESP as the time of operation increases and the components reach the end of their life cycles.

4.2 Most Probable State and Availability Improvement

The most probable failure states for the first and second scenarios are given in Tables 7 and 8, respectively. As an advantage of the presented method, analysis of the most probable failure states shows that supporting insulators and hammers of the discharge rapping system have the most impact on the availability of ESP in this case.

Table 7. The Most Failure Probable States Sampled by PSO for the First Scenario

Component	Gas Distribution System	Collecting Plates	Discharge Electrodes	Gear Motor-CRS	Shaft-CRS	Hammers CRS	Gear Motor-DRS	Shaft-DRS	Hammers DRS	Rotary Air lock - CS	Drag Chain – CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
Field 1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
Field 2		1	1	1	1	1	1	1	1	1	1	1	0	1
Field 3		1	1	1	1	1	1	1	1	1	1	1	1	1

Table 8. The Most Failure Probable States Sampled by PSO for the Second Scenario

Component	Gas Distribution System	Collecting Plates	Discharge Electrodes	Gear Motor-CRS	Shaft-CRS	Hammers CRS	Gear Motor-DRS	Shaft-DRS	Hammers DRS	Rotary Air lock - CS	Drag Chain - CS	Electrical Panels	Supporting Insulators	HVR-CS and cables
Field 1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
Field 2		1	1	1	1	1	1	1	1	1	1	1	0	1
Field 3		1	1	1	1	1	1	1	0	1	1	1	1	1

As a result, the proper maintenance activities and performing a daily checklist to audit these devices can improve the availability of ESP. Practically, the availability of ESP can be enhanced remarkably by auditing and fixing the hammers of the discharge system during planned interruptions. In addition, supporting insulators play an essential role in the operation of ESP. They hold and isolate the discharge system from ESP's other parts. Mechanical misalignment, electrical arcs, and thermal tensions are the three most common reasons for problems regarding the supporting insulators. Mechanical misalignments are caused by installation mistakes which can be checked and solved in overhaul activities. Periodic cleaning of supporting insulators and checking the sealing of these components can solve problems related to the electrical arcs. Using electrical elements or a purge air system, especially at least 6 hours before every commissioning of ESP, is the best solution to avoiding thermal tensions in supporting insulators. The primary duties of installing a purge air system are to deliver the hot air to the supporting insulators and clean the surface of supporting insulators by purging the air. The most mistakes related to the purge air system are problems in mechanical installation, such as weak welding points and improper insulation, and design problems which can lead to low efficiency of the purge air system.

5. CONCLUSION AND SUGGESTIONS

ESP is one of the most essential air pollution control devices in mining plants. Availability of ESP is vital as any interruption of this device causes severe problems for both the environment and the production line. Calculating the availability of ESP, as complex equipment consists of series-parallel sections and components, can be a challenging and time-consuming problem due to the numerous components involved. In this paper, a PSO-based method was proposed to estimate the availability of ESP. Totally, 40 components are considered for three fields installed ESP. The proposed method can obtain availability by sampling the most probable failure states significantly less than all possible ones at an accurate level. For the evaluation of the states, two different scenarios are defined. The interruption of two fields and three fields simultaneously was considered ESP interruption in the first and second scenarios. The results show that the availability of ESP has an accuracy of 99.54 and 99.58, which is obtained after 100000 iterations for the first and second scenarios, respectively. In addition, the most probable failure state is chosen and analyzed for availability improvement of the device.

The main achievements of the proposed method are the availability assessment of complicated systems and equipment and finding the probable failure states, which are useful for both researchers and industrial experts in maintenance planning. The authors suggest calculating the availability of other complex devices, including more sections and components such as boilers and furnaces, for future work. In addition, applying different optimization algorithms is suggested to increase the efficiency of the performance.

REFERENCES

Al-Maamari, A. and Omara, F. A. (2015). Task Scheduling Using PSO Algorithm in Cloud Computing Environments. *International Journal of Grid and Distributed Computing*, 8(5): 245–256. DOI: Https://Doi.Org/10.14257/Ijgdc.2015.8.5.24

Chaudhary, R., Tewari, P. C., and Modgil, V. (2019). System Availability Assessment and Optimization of Repairable Cooling Module of HVAC System Using PSO Algorithm. *Journal of Physics: Conference Series*, 1240(1). DOI: Https://Doi.Org/10.1088/1742-6596/1240/1/012139

Clerc, M. (2010). Particle Swarm Optimization. Particle Swarm Optimization, 1942–1948. DOI: Https://Doi.Org/10.1002/

9780470612163.

Dai, Q., Zhang, H., and Zhang, B. (2021). An Improved Particle Swarm Optimization Based on Total Variation Regularization and Projection Constraint with Applications in Ground-Penetrating Radar Inversion: A Model Simulation Study. *Remote Sensing*, 13(13). DOI: Https://Doi.Org/10.3390/Rs13132514

Keshavarzi, R., Akhlaghi, M., and Emami, F. (2016). Binary PSO Algorithm Assisted to Investigate The Optical Sensor Based Plasmonic Nano-Bi-Domes. *Optik*, 127(19): 7670–7675. DOI: Https://Doi.Org/10.1016/J.Ijleo.2016.05.098

Kim, J. and Lee, J. (2017). Particle Swarm Optimization Based Inventory Policy for Wholesale Business in Devs-Based Medicine Supply Chain. *International Journal of Industrial Engineering : Theory Applications and Practice*, 24(2): 146–161.

Li, C., Zhao, G., Meng, J., Zheng, Z., and Yu, S. (2021). Multi-Objective Optimization Strategy Based on Entropy Weight, Grey Correlation Theory, and Response Surface Method in Turning. *International Journal of Industrial Engineering : Theory Applications and Practice*, 28(5): 490–507. DOI: Https://Doi.Org/10.23055/Ijietap.2021.28.5.7327

Liang, Z. D. and Yi, W. J. (2022). Application of Improved Particle Swarm Optimization Algorithm in TDOA. *AIP Advances*, 12(2). DOI: Https://Doi.Org/10.1063/5.0082778

Mellal, M. A. and Zio, E. (2022). Multi-Objective Availability and Cost Optimization by PSO and COA for Series-Parallel Systems With Sub-Systems Failure Dependencies. *Microprocessors and Microsystems*, 89(February 2021): 104422. DOI: Https://Doi.Org/10.1016/J.Micpro.2021.104422

Parker, K. R. (2016). Electrostatic Precipitation. *Particle Technology and Applications*, 7(5): 281–300. DOI: Https://Doi.Org/10.1201/Noe0849398438.Ch20

Pousinho, H. M. I., Mendes, V. M. F., and Catalão, J. P. S. (2011). A Hybrid Pso-Anfis Approach for Short-Term Wind Power Prediction in Portugal. *Energy Conversion and Management*, 52(1): 397–402. DOI: Https://Doi.Org/10.1016/J.Enconman.2010.07.015

Remaoun, S. M., Miloua, F., Tilmatine, A., Hammadi, N., Zouzou, N., and Dascalescu, L. (2014). Optimization of A Cost-Effective "Wire-Plate"-Type ESP for Installation in A Medical Waste Incinerator. *IEEE Transactions on Industry Applications*, 50(2): 1391–1396. DOI: Https://Doi.Org/10.1109/TIA.2013.2272607

Savita Naik and M. S. Aspalli. (2015). Enhancement of ESP Performance Using 'ARECA' Microcontroller. *International Journal of Engineering Research and Technology* (IJERT), V4(08): 495–499. DOI: Https://Doi.Org/10.17577 /Ijertv4is080575

Sayem, A. S. M., Khan, M. M. K., Rasul, M. G., Wolfs, P., Hassan, N. M. S., and Sneath, B. (2018). Experimental Study of A High Voltage (HV) Electrostatic Precipitator to Achieve Higher Collection Efficiency. *2017 Australasian Universities Power Engineering Conference*, AUPEC 2017, 2017-Novem, 1–4. DOI: Https://Doi.Org/10.1109/AUPEC.2017.8282433

Sudheer, C., Maheswaran, R., Panigrahi, B. K., and Mathur, S. (2014). A Hybrid SVM-PSO Model for Forecasting Monthly Streamflow. *Neural Computing and Applications*, 24(6): 1381–1389. DOI: Https://Doi.Org/10.1007/S00521-013-1341-Y

Tanweer, M. R., Suresh, S., and Sundararajan, N. (2016). Dynamic Mentoring and Self-Regulation Based Particle Swarm Optimization Algorithm for Solving Complex Real-World Optimization Problems. *Information Sciences*, 326, 1–24. DOI: Https://Doi.Org/10.1016/J.Ins.2015.07.035

Wei, X., Shen, Z., Ye, Y., Leng, J., Xu, Z., and Jin, L. (2020). Optimization and Design of A High-Voltage Supply for Electrostatic Precipitators. *ECCE 2020 - IEEE Energy Conversion Congress and Exposition*, 2268–2275. DOI: Https://Doi.Org/10.1109/ECCE44975.2020.9235595

Zhang, J., Zhai, Y., Han, Z., and Lu, J. (2022). Improved Particle Swarm Optimization Based on Entropy and its Application in Implicit Generalized Predictive Control. *Entropy*, 24(1). DOI: Https://Doi.Org/10.3390/E24010048

Zheng, C., Zhao, Z., Guo, Y., Zhao, H., Weng, W., Zhu, W., Yu, B., and Gao, X. (2020). A Real-Time Optimization Method for Economic and Effective Operation of Electrostatic Precipitators. *Journal of The Air and Waste Management Association*, 70(7): 708–720. DOI: Https://Doi.Org/10.1080/10962247.2020.1767227