1. Ghalem Abdelhak, 2. Naceri Abdellatif, 3. Djeriri Youcef

1.2 Department of Electrotechnics, Faculty of Electrical Engineering, Interaction Networks-Converters-Machines Laboratory, Djillali Liabes University, Sidi Bel-Abbes, Algeria
3. Department of Electrotechnics, Faculty of Electrical Engineering, Intelligent Control and Electrical Power Systems Laboratory, Djillali Liabes University, Sidi Bel-Abbes, Algeria

doi:10.15199/48.2023.10.20

Optimisation of a renewable energy system by hybridisation PSO algorithm and Artificial Neural Network

***Abstract**. Artificial intelligence is poised to revolutionise the energy sector. Its data-based learning capabilities enable both energy production and consumption optimization. Energy needs are better assessed to support the energy transition. This digital innovation is necessary to implement the development policies for preserving the environment. There are many projects in this direction. They concern the oil industry as well as gas extraction or the intelligence of electrical networks. In fact, artificial intelligence is gradually becoming the tool that optimizes energy production and consumption.*

***Streszczenie.** Sztuczna inteligencja może zrewolucjonizować sektor energetyczny. Jego możliwości uczenia się w oparciu o dane umożliwiają zarówno optymalizację produkcji energii, jak i jej zużycia. Potrzeby energetyczne są lepiej oceniane, aby wesprzeć transformację energetyczną. Ta cyfrowa innowacja jest niezbędna do realizacji polityki rozwoju na rzecz ochrony środowiska. Projektów w tym kierunku jest wiele. Dotyczą one zarówno przemysłu naftowego, jak i wydobycia gazu czy inteligencji sieci elektrycznych. W rzeczywistości sztuczna inteligencja stopniowo staje się narzędziem optymalizującym produkcję i zużycie energii. (**Optymalizacja systemu OZE poprzez hybrydyzację algorytmu PSO i sztucznej sieci neuronowej**)*

Keywords: New Energy; Optimisation; PSO; Artificial Neural Networks; Photovoltaic Generator; Wind Turbines; Battery.
Słowa kluczowe: Nowa Energia; Optymalizacja; obowiązek publiczny; Sztuczne sieci neuronowe; generator fotowoltaiczny; Turbiny wiatrowe; Bateria.

Introduction

The developed new technology in the world needs new energy to satisfy the unprecedented increase of the demand for energy. This energy is the assembly of an advance hybrid control system and a hybrid power system of renewable and conventional energy sources. The new energy is an efficient and nature-friendly solution to increase the independence from fossil fuels and, most importantly, a free primary source such as wind, sun, water, sea and biomass [1].

Hybrid Renewable Energy Systems (HRES) are formed by one or multiple renewable sources in addition of one or more conventional sources, mostly used in stand-alone also as a grid-connected mode [2].

HRES are growing in popularity for stand-alone users due to their advanced technologies, good installation cost, movability and most importantly: Electronic converters; That convert their randomly generated power into a stable power for the loads. A major feature of HRES is to combine different renewable sources to extract the most energy of their operating characteristics and obtain a higher efficiency.

Photovoltaic and wind systems are the principal sources of energy. This energy is accessible with large quantities but variable in its nature, and site-specific. The sources are connected to a DC bus through converters to obtain a regulated power output and a constant voltage. The converters used for PV/wind systems are usually two DC-DC converters, one for maximum power tracking and the other for voltage regulation. Similarly, the loads are connected to the DC bus through DC-DC and DC-AC converters dependent on the needs of the charge [3].

However, this study focuses on a full HRES system that uses tow renewable energy sources (PV and Wind) and a diesel generator as a conventional source. The power generated by the PV generators depends on the array's operating voltage and the maximum power point (MPP) that varies with solar insolation and temperature. The MPP is a specifies point to extract the maximum power from the PV characteristic.

Similarly, for the wind turbine systems the MPP varies with the wind speed and direction. At the MPP, both wind and PV operate at their highest efficiency. Therefore, many methods have been developed to track the MPP [4].

Materials and Methods

A. Particle swarm optimisation (PSO)

The PSO algorithm is a stochastic, population-based optimisation technique that simulates the behaviour of social animals as insects, fish and birds. These swarms perform collaborative tasks to search for food, where each element change the search pattern according to its own experiences and also based on the global best position explored by swarm, these particles hold information about their existence and potential value. They provide information to each other to find the most optimal results. [5, 6, 7, 8].

Millonas [9] proposed five principles to construct a swarm of artificial life systems when studying the behaviour of social animals using the artificial life theory, that become guiding principles for establishing the swarm artificial life system (van den Bergh, 2001) [10]:

- ✓ It should be able to carry out simple space and time computations.
- ✓ It should be able to detect and respond to changes in environmental quality.
- ✓ It shouldn't limit how it gets the resources from narrow areas.
- ✓ It should not change its behaviour mode with every environmental change.
- ✓ It should change its behaviour mode when this change is worthwhile.

In PSO, all particles update their positions and velocity based on the actual velocity and it best explored position, also, according to environmental changes (swarm best global) [11].

Particles in PSO can maintain their steady movement throughout the search space even when they modify their mode of movement in response to environmental changes. The velocity is expressed by [12]:

$$V_i(t)=wV_i(t\text{-}1)+C_1r_1\left(P_{best\,i}\text{-}x_i(t\text{-}1)\right)+C_2r_2\left(g_{best}\text{-}x_i(t\text{-}1)\right)$$

$wV_i(t\text{-}1)$ This term is used to prevent the particles from a radical change and forces them to stay in the old field of movement.

$C_1r_1\left(P_{best\,i}\text{-}x_i(t\text{-}1)\right)$ This part of the expression is to use the personal experience of the particles or to follow the best personal solution

$C_2r_2\left(g_{best}\text{-}x_i(t\text{-}1)\right)$ The last term is to make the particles follow the total solution or the best solution of the swarm.

w is a variable or fixed number as needed to keep the particles in the searching interval and prevent radical changes in the solutions; it depends on the improved speed of the solution.

C_1 *and* C_2 represent the individual and social learning rates respectively.

r_1 *and* r_2 random variables in between 0 and 1.

The position of each particle is as defined in the equation [13]:

$$x_i(t)=x_i(t\text{-}1)+V_i(t)$$

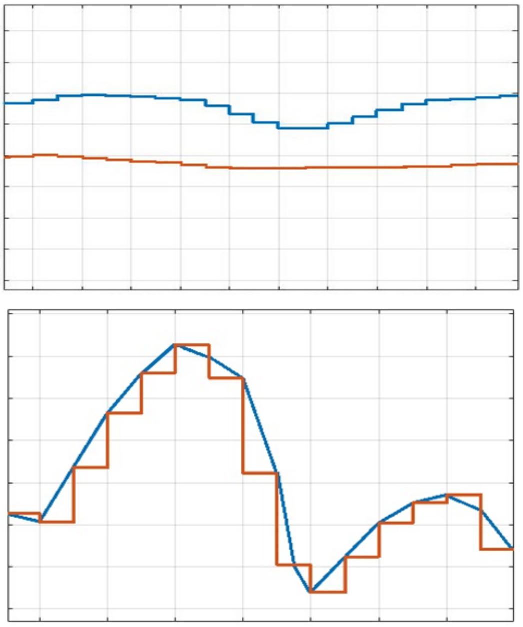

Fig. 1. On the left Without PSO (Only ANN) in the right with PSO algorithm

Each particle determines its own position based on its own experience (Pbest) and the experience of other particles (Gbest) by adjusting their velocity and position based on a motion function [7], we have to update the two best solutions each cycle by using the fitness function or the objective function F to maintain the results in the solution space by a simple condition:

$$\begin{cases} P_{best\,i}=x_i \text{ if } F(x_i) \text{ is better than } F(P_{best\,i}) \\ g_{best}=P_{best\,i} \text{ if } F(P_{best\,i}) \text{ is better than } F(g_{best}) \end{cases}$$

The PSO algorithm keeps repeating until all the population is used or the solution starts to converge to a set of values.

B. The Artificial Neural Network (ANN)

An Artificial Neural Network is a procedure that maps inputs and outputs patterns that illustrate a problem. During the training process, the ANN learn information after several iterations. When the learning process finishes, it is ready to [14]:

- Classify the new information.
- Predict new behaviours.
- Solve nonlinear problems.

The structure is represented by functions (series of neurons) connected and organised in layers, the actual problem codification patterns are transmitted through layers, and the information is transformed using a corresponding synaptic weight [15]. Then, depending on whether or not there is a connection between the neurons in the following layers, they summate the information.

A threshold representing the minimum needs for activating a neuron, is considered as another input called bias.

Afterwards, the summation function is presented, and the outcome is evaluated using transfer functions activated by neuron input. The output neuron receives the result and transmits it to the other linked neurons till they reach the upper layer.

Eventually, the ANN's output is established to evaluated the performance, and the synaptic weights are required to be changed or adjusted during the process of learning until they produce the desired behaviour.

To determine if the ANN has learned, we have two methods:

1. Computes the amount of similarity between input patterns and previously known information (non-supervised learning).
2. The output is compared with the desire patterns (supervised learning).

The classic back propagation (BP) algorithm, for example, adjusts the weights to achieve the minimum error [12], but it cannot solve noncontinuous problems.

Thus, to improve the performance and solve complex problems, it is a necessary to used additional methods that can deal with noncontinuous and nonlinear problems.

C. PSO Algorithm and ANN Hybridisation

In order to obtain the database to train the ANN controller, we developed a program that generates the maximum voltage, current and power at various atmospheric conditions; the program gives their exact values based on the given STC parameters of the photovoltaic module. With the program, we can obtain as many points as possible to boost the performance of the controller, which depends on the database's size and the chosen training functions for the hidden layers.

The PSO algorithm is used as the additional method to optimises the ANN controller by capturing the generated weights and reduce the calculation error.

Without the PSO, we can see in Fig. 1 (on the left) that the controller is not trucking all the MPPs, and there are some losses. Thus, with its utilisation, we clearly can see that in the interval of 20 MPP, there are only (2 or 3) lost points.

The figure is for the output power of a PV generator between 1.5 and 1.62 seconds, the maximum power 1028.72W and the minimum is 1028.66W with the PSO; with only the ANN controller and in the same time interval we can remark that the actual power is following the reference but with a difference of about 1.12W and no intersections. Hybridization of PSO and ANN involves combining the strengths of both techniques to improve the overall performance of an optimization task. To do this we used the PSO to optimize the weights and biases parameters of the ANN, in order to improve its accuracy in classification or prediction tasks.

The main advantage of PSO-ANN hybridization is that it can improve the efficiency and accuracy of the ANN learning process, especially for large and complex datasets.

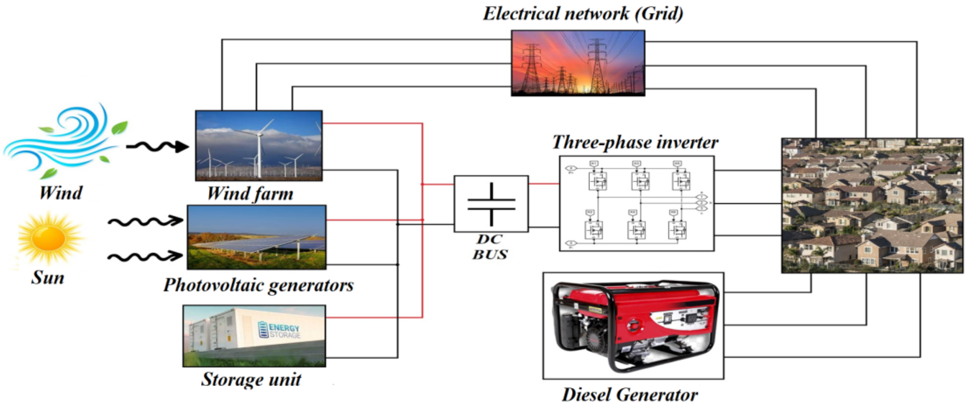

Fig. 2. The new energy system

PSO helps to avoid getting trapped in local minima and can quickly converge to the global minimum, while ANN provides the ability to model complex relationships between variables.

In this study, the PSO-ANN hybrid algorithm is used to predict the power output of a photovoltaic (PV) system based on random atmospheric conditions. The PSO algorithm is used to optimize the weights and biases of an artificial neural network (ANN) to minimize the mean absolute error (MAE) between the predicted and actual power output. The PSO algorithm is initialized with random particles, and each particle represents a set of weights and biases for the ANN. The fitness function for each particle is evaluated by training the ANN with the particle's weights and biases and computing the MAE on the training data. The PSO algorithm iteratively updates the positions and velocities of the particles to search for the set of weights and biases that minimizes the fitness function. And it terminates when either the maximum number of iterations is reached or the fitness function has converged [16]. Finally, the best set of weights and biases found by the PSO algorithm is used to predict the power output on the test data, and the performance of the model is evaluated using the root-mean-square error (RMSE) between the predicted and actual power output

The PSO helped increase the amount of extracted energy from the PVG, and the ANN controller gave a dynamic and adaptive response. However, with the optimisation, the results were more accurate and efficient.

The New Energy system

Hybrid power systems are the future of renewable energy systems; the load will be supplied 24h, 7/7, with no interruptions and blackouts. In the daylight, the load is supplied with the wind and (or) the PV generators; at night, the storage unit is responsible for supplying the charge; in worst cases, the conventional generator will always be in line, ready to be triggered.

Our system is constructed by connecting a backstepping controlled Doubly-Fed Induction Generator (DFIG) as a wind generator, a Particle Swarm Optimization-Artificial Neural Network (PSO-ANN) controlled Photovoltaic (PV) system, a diesel generator, and a storage system.

The advantages of a hybrid energy management system include:

- Reliability: By combining multiple energy sources, the system is less reliant on any single source of energy and can provide a more stable and reliable power supply.
- Sustainability: Integrating renewable energy sources into the system reduces reliance on fossil fuels and helps to reduce greenhouse gas emissions.
- Efficiency: The system can be designed to operate at a higher efficiency by balancing the power output of each component to meet the demand.
- Cost-effectiveness: The use of renewable energy sources can help to reduce operating costs and lower the overall cost of energy generation.

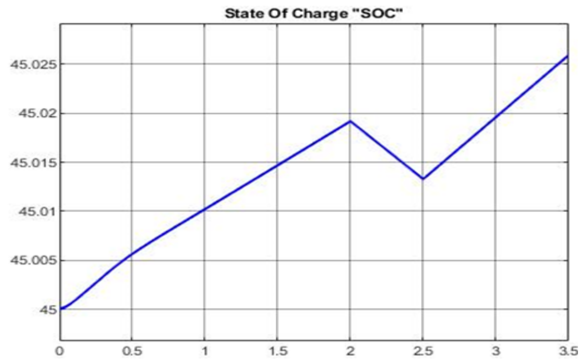

Fig. 3. The State of Charge of the battery

In order to simulate a real-life situation (in the case where the grid is off), we planned the simulation as follows: from zero to one in the morning (with good wind speed), the load
is supplied by the wind turbine, and the PV power is stored in the battery, afternoon from one to two (when the wind speed slows down with a good insolation), the PV generators are feeding the load.

At night from 2 to 2.5 the battery is triggered, at this point we assume that the battery is low in charge so that the diesel generator will start from 2.5.

Simulation Results

In a study by S. Krishnan and K. Sathiyasekar (2019) [17], the PSO-ANN hybrid algorithm was compared with the ANN and SVR methods for predicting the power output of a PV system. The authors used a dataset of temperature, irradiance, wind speed, and humidity for a PV system and divided the dataset into training and testing sets. They trained the PSO-ANN hybrid algorithm, ANN method, and SVR method on the training set and evaluated their performance on the testing set using the RMSE and MAE metrics.

The results of the study showed that the PSO-ANN hybrid algorithm outperformed the ANN and SVR methods in terms of the RMSE and MAE metrics. The RMSE values for the PSO-ANN hybrid algorithm, ANN method, and SVR method were 25.21 W, 36.81 W, and 36.59 W, respectively. The MAE values for the PSO-ANN hybrid algorithm, ANN method, and SVR method on the training set and evaluated their performance on the testing set using the RMSE and MAE metrics.

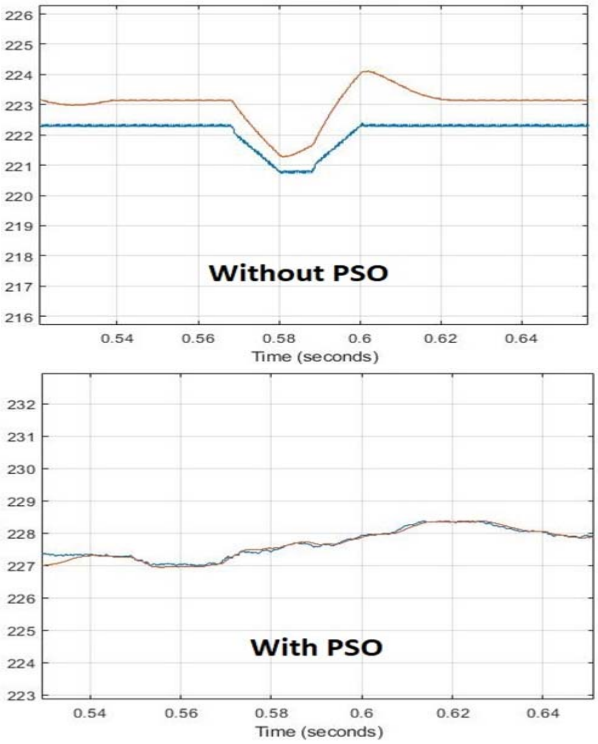

Fig. 4. The Efficiency of the PSO algorithm

The results of the study showed that the PSO-ANN hybrid algorithm outperformed the ANN and SVR methods in terms of the RMSE and MAE metrics. The RMSE values for the PSO-ANN hybrid algorithm, ANN method, and SVR method were 25.21 W, 36.81 W, and 36.59 W, respectively. The MAE values for the PSO-ANN hybrid algorithm, ANN method, and SVR method were 17.43 W, 25.19 W, and 24.71 W, respectively.

Due to the large data set that we produced with the developed program we were able to achieve the following results in terms of MAE and RMSE:
MAE: With PSO = 0.8002W and without PSO = 2.0644W
RMSE: Without PSO = 4.1325W and with PSO = 3.2349W

As we can see in Fig.5, the load is always supplied at all times, Whatever the atmospheric Conditions.

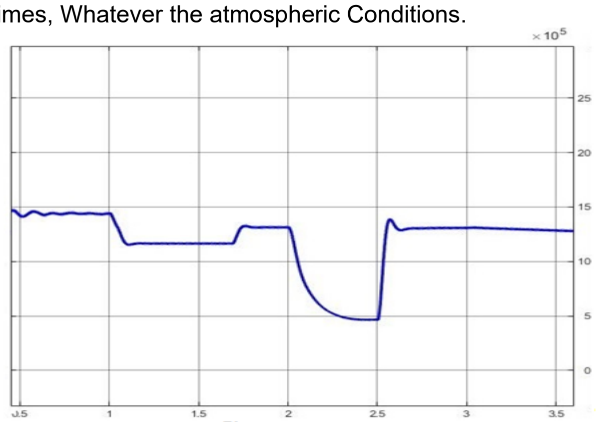

Fig. 5. The load Power

The weak side of this system is at daylight, when it’s not gaining the maximum amount of power from either the wind or the PV generators; and this is the role of the advanced hybrid control system we suggested in this study.

As planned the system is extracting the maximum power from the wind as shown in Fig 5. In the Fig 6 we can remark the roll of the PSO in boosting the performance of the ANN regulator in extraction the maximum power of the PVG.

In Fig. 4 with the red is the power of the PV generator and in blue the extracted power by the load and the battery. On the left the ANN controller has followed the PV power but with an error of about 1W, with contrary, on the right, with the PSO algorithm the error is reduced to it minimum values.

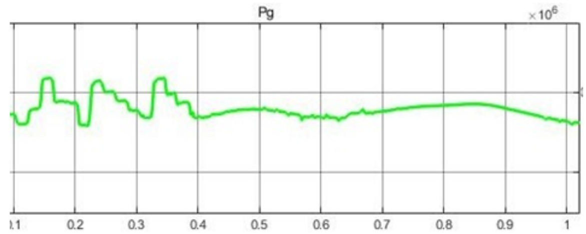

Fig. 6. The Power of the wind turbine.

Conclusion

The new energy can be summed up in three significant revolutions: Cleaner, Closer, Smarter. That some have a tendency to cut into an environmental movement, a societal trend and advances in the automation of energy systems (smart grids). The reality is more complex, and it is in fact a whole that must be taken into account with.

On one hand, increasingly diffuse energy production systems that require much finer control. And on the other, citizens who want to reclaim energy through an engaged and collaborative approach.

These two trends imply increasingly local interconnected and unpredictable energy systems. They will have to equip themselves with real-time intelligence adapted to this increasing complexity and capable of self-learning the behaviours of the industry and consumers that make up this expanded energy system.

In conclusion, the PSO-ANN hybrid algorithm is a powerful technique that combines the strengths of Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) to improve the accuracy and efficiency of predictive models. The PSO algorithm is used to optimize the weights and biases of the ANN model, which is trained on input-output pairs of the system being modelled. The PSO-ANN hybrid algorithm has been successfully applied to various fields, including power systems, control systems, and image processing, to name a few.

In the context of a PV system, the PSO-ANN hybrid algorithm can be used to predict the output power of the system based on its input features such as solar irradiance, temperature, and wind speed. The performance of the PSO-ANN hybrid algorithm can be evaluated using metrics such as RMSE and MAE, which provide a measure of the difference between the predicted and actual output power values. To improve the performance of the PSO-ANN hybrid algorithm, various approaches can be applied, such as using a larger and more diverse dataset, optimizing the hyperparameters, and using cross-validation

***Authors**:*
Mr. Ghalem Abdelhak. Department of Electrotechnics, Faculty of Electrical Engineering, Interaction Networks-Converters-Machines Laboratory, E-mail: abdelhak.ghalem@univ-sba.dz
Prof. Naceri Abdellatif. Department of Electrotechnics, Faculty of Electrical Engineering, Interaction Networks-Converters-Machines Laboratory, E-mail: abdnaceri@yahoo.fr
Dr. Djeriri Youcef. Department of Electrotechnics, Faculty of Electrical Engineering, Intelligent Control and Electrical Power Systems Laboratory, E-mail: ydjeriri@yahoo.fr.
All: Djillali Liabes University of Sidi Bel Abbes 22000, Algeria.

REFERENCES

[1] Pr. Abdellatif NACERI, Energie Nouvelle & Intelligence Artificielle ‘ENIA’, Laboratoire de Recherche IRECOM (UDL – SBA).

[2] Ujjwal Datta, Akhtar Kalam, Juan Shi, Hybrid PV–wind renewable energy sources for microgrid application: an overview, Hybrid-Renewable Energy Systems in Microgrids 2018 Elsevier Ltd

[3] Ahmad Taher Azar and Nashwa Ahmad Kamal, Renewable Energy Systems: Modelling, Optimization and Control (Advances in Nonlinear Dynamics and Chaos (ANDC)), ISBN: 978-0-12-820004-9, 2021 Elsevier Inc.

[4] Salas, Vicente & Olías, Emilio & Barrado, A. & Lazaro, A.. (2006). Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems. Solar Energy Materials and Solar Cells. 90. 1555-1578. 10.1016/j.solmat.2005.10.023.

[5] Dongshu Wang, Dapei Tan, Lei Liu, Particle swarm optimization algorithm: an overview, Springer-Verlag Berlin Heidelberg 2017.

[6] Lina Mahgoub, Yahya Mohamed, Novel Sampling Techniques for Reservoir History Matching Optimisation and Uncertainty Quantification in Flow Prediction, Heriot-Watt University January 2011.

[7] Muhammad Djalal, Makmur Saini, A.M. Shiddiq Yunus, Ikhlas Kitta, Optimal Power System Stabilizer Design Using Craziness Particle Swarm Optimization In Sulselrabar System, 10/2021 P. 76 Przeglad Elektrotechniczny. doi:10.15199/48.2021.10.15

[8] Fawaz S. Abdulla1, Ali N. Hamoodi1, Abdulaziz M. Kheder, Particle Swarm Optimization Algorithm for Solar PV System under Partial Shading, 10/2021 Str. 87 Przeglad Elektrotechniczny. doi:10.15199/48.2021.10.17.

[9] Millonas MM, et al (1993) Swarms, phase transitions, and collective intelligence (paper 1); and a nonequilibrium statistical field theory of swarms and other spatially extended complex systems (paper 2). Technical rep.

[10] Ankush Shrivastava, Vipin Verma, Multi-clustered Energy Level based Efficient Routing Protocol in Wireless Sensor Network, International Journal of Computer Applications (0975 - 8887) Volume 181 - No.32, December 2018.

[11] Mrs.S.Gandhimathi, S.Vasuki, P. Jega Suguna, V.Janaki, S.Jaya Priya, Unsupervised Change Detection of Multispectral Images using Genetic based Particle Swarm Optimization, International Journal of Engineering Research & Technology (IJERT) NCIECC-2017 Conference Proceedings.

[12] Aleksandar Lazinica, Particle Swarm Optimization, ISBN 978-953-7619-48-0.

[13] Sharifi MR, Akbarifard S, Qaderi K, Madadi MR. Comparative analysis of some evolutionary-based models in optimization of dam reservoirs operation. Sci Rep. 2021 Aug 2;11(1):15611. doi: 10.1038/s41598-021-95159-4. PMID: 34341441; PMCID: PMC8329043.

[14] Garro BA, Vázquez RA. Designing Artificial Neural Networks Using Particle Swarm Optimization Algorithms. Comput Intell Neurosci. 2015;2015:369298. doi: 10.1155/2015/369298. Epub 2015 Jun 29. PMID: 26221132; PMCID: PMC4499655.

[15] Maria Puig-Arnavat, Joan Carles Bruno, Recent Advances in Thermo-Chemical Conversion of Biomass, Chapter 5 - Artificial Neural Networks for Thermochemical Conversion of Biomass, ISBN 9780444632890, Elsevier 2015

[16] Krishnan, S. & Sathiyasekar, K.. (2019). A Novel Salp Swarm Optimization MPP Tracking Algorithm for the Solar Photovoltaic Systems under Partial Shading Conditions. Journal of Circuits, Systems and Computers. 29. 10.1142/S0218126620500176

[17] Liu X, Gan H, Luo Y, Chen Y, Gao L. Digital-Twin-Based Real-Time Optimization for a Fractional Order Controller for Industrial Robots. Fractal and Fractional. 2023; 7(2):167. https://doi.org/10.3390/fractalfract7020167