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Soft computing approaches for photovoltaic water pumping systems: A review

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ABSTRACT

Water pumping systems are crucial for extracting water from deep wells. However, electricity shortages and high fuel prices significantly impact the efficiency and reliability of these systems. Therefore, renewable energy sources have gained more attention as alternatives to fossil fuels. Photovoltaic (PV) energy-based pumping systems, in particular, are becoming popular, especially in rural areas where grid connections are often unavailable. Several factors influence the performance of photovoltaic water pumping systems (PVWPS), including solar irradiance, temperature, system design, maintenance, and pumping load. To ensure optimal performance under these varying conditions, two controllers are crucial. The first controller is the Maximum Power Point Tracking (MPPT) controller, designed to maximize power extraction from the PV panels under varying environmental conditions (in particular, solar radiation and temperature). The second controller regulates the speed and torque of the induction motor (IM) which drives the pump responsible for water extraction. Therefore, to improve the performance of these controllers under different conditions. This review paper first examines widely used soft computing methods, providing a detailed description of each. These methods are then applied to both the MPPT and the IM controllers, offering valuable insights for researchers looking to develop advanced PVWPS control configurations for future applications.

1. Introduction

Water is one of life's most indispensable requisites for drinking, daily household chores, and extensive applications such as irrigation, the building industry, and hydropower generation (Imjai et al., 2020). However, the unequal distribution of water resources on a global scale has given rise to water scarcity in numerous regions, posing a substantial threat to the well-being of communities (Yokomatsu et al., 2020). Among the world's countries, Morocco faces a critical problem with water scarcity, particularly in rural areas(Kaczmarek et al., 2023). This issue arises due to limited water resources, uneven distribution, daily irrigation demands, the impact of climate change, and inefficient water management practices. To address the scarcity of surface water, groundwater from aquifers is often utilized, particularly in regions where surface water is unavailable. However, bringing this groundwater to the surface manually or with the aid of animals proves to be challenging. Therefore, mechanized water pumping has emerged as a solution for extracting water from significant depths, necessitating readily available power sources such as diesel-generated electricity (Kusakana, 2018). However, the absence of electricity and high diesel costs significantly affect the pumping requirements for community water supply and agriculture. As a result, using renewable energy sources such as wind, solar, or biogas to power water pumping systems presents an appealing alternative to conventional electricity and diesel-based systems, showcasing great potential as a viable substitute. The demand for renewable energy has significantly increased due to its environmental benefits, such as reducing greenhouse gas emissions, mitigating climate change, and minimizing the carbon footprint in energy production (Zakariazadeh et al., 2024). Therefore, among the advancements seen worldwide in sustainable energy adoption, Morocco has also made

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significant strides in adopting renewable energy projects to capitalize on its abundant natural resources and minimize reliance on fossil fuels (Boulakhbar et al., 2020). According to the latest report from the Project Manager at Global Data, shown in Fig. 1, Morocco's current goal is to expand the percentage of renewable energy in total power capacity to 52% by 2030, 70% by 2040, and 80% by 2050 (Moudene et al., 2023). Among various types of renewable energies, Morocco has successfully implemented large-scale solar projects(Hanger et al., 2016). The country boasts an installed solar PV capacity of approximately 860 MW, encompassing Concentrated Solar Power (CSP) and Solar PV power (Pitz-Paal and Letcher, 2020). The water pumping system based on solar energy has seen a significant increase in usage in recent years. As a result, Morocco has become uniquely positioned to harness photovoltaic (PV) panels for sustainable water-pumping applications(Senthil Kumar et al., 2020). The Photovoltaic Water Pumping System (PVWPS) typically consists of a PV array (connected in series and parallel), a power conditioning unit (which can be either a DC/DC converter, a DC/AC inverter, or both), an electric motor, and a pump. The system functions by converting the electrical energy generated by the PV array into mechanical energy via the electric motor, which is then further transformed into hydraulic energy by the pump. PVWPS fall into three main categories: standalone, hybrid, or grid-connected, as shown in Fig. 2. Each type offers distinct advantages and is selected based on various factors, including location, energy requirements, cost considerations, and grid availability (Akhila et al., 2018). Standalone PV water pumping systems (PVWPS) are primarily used for irrigation, livestock watering, and water supply in rural areas where grid access is unavailable or unreliable (Muralidhar et al., 2021). Consequently, most researchers have focused on studying standalone PVWPS, which can operate either with a battery, known as a battery PVWPS, where surplus energy generated by solar panels is stored when not immediately used by the water pump, or without a battery, known as a tank PVWPS. The tank PVWPS uses a tank to store water pumped during sunny periods for use during non-sunny hours.

Researchers have studied the comparison between these two types. In Ref(Soenen et al., 2021), a comparison between battery PVWPS and tank PVWPS for rural water access is conducted. According to the findings of this research, PVWPS with batteries has a reduced impact on groundwater and is better equipped to adjust to fluctuations in water demand. However, its financial viability depends on proper battery maintenance and recycling facilities. The optimized design and analysis of two types of PVWPS were studied In Ref (Orts-Grau et al., 2021), which proved that PVWPS with tanks is more cost-effective than battery PVWPS. A comparative study between PVWPS with batteries and PVWPS with tanks for urban water supply is presented In Ref (Pardo et al., 2020). The study concluded that battery storage was less expensive in their case study, but the optimal choice depends on specific network and location factors. In Ref(Allouhi et al., 2019), the comparison between the two PVWPS types for rural water supply is proposed. The PVWPS battery offers cost savings, reduced groundwater impact, and greater adaptability. However, local sustainable battery maintenance and recycling are vital for long-term affordability. A hybrid storage system for solar water pumping that combines batteries and water tanks is proposed In Ref (Medghalchi et al., 2023). This approach optimizes system size and cost-effectiveness using the Imperialist Competitive Algorithm (ICA). The results showed that the hybrid configuration is more feasible and economical than other options. As a result, the choice between these two types depends on sunlight availability, water demand, and system reliability. Therefore, this review paper will examine solar water pumping systems without batteries. Considering the potential complexities and costs associated with battery maintenance and recycling, this review paper will examine solar water pumping systems that use water tanks, to provide a more sustainable and cost-effective solution. In Photovoltaic Water Pumping Systems (PVWPS), an electric motor is essential to drive the pump. This motor can be either a DC motor, which directly utilizes the power from the PV array or an AC motor that requires a DC-AC inverter. The inverter converts the output voltage from an intermediate converter or the direct PV voltage into a variable voltage/variable frequency power source to drive the AC motor, ultimately operating the pump. The selection of a motor for photovoltaic water pumping systems is critical and considers factors like efficiency, availability, price, and reliability. DC motors have been explored by many researchers for PVWPS applications(Ene et al., 2021). Their advantages include ease of control and direct connection to the PV system using a DC-DC converter. However, limitations like brush and commutator wear necessitate increased maintenance and restrict operation to a single voltage level(Muhsen et al., 2017). These drawbacks have driven research toward implementing AC motors in PVWPS due to their potential for higher efficiency and improved durability. Among AC motors, induction motors (IM) stand out for their simple design and operation, leading to ease of maintenance and repair (Errouha et al., 2020). Therefore, this review paper will focus on PVWPS utilizing induction motors (IM). To achieve optimal pump performance, efficient water delivery, component longevity, and minimal energy waste, PVWPS requires two crucial controllers. The first controller is for the solar panels, which have a specific point known as the maximum

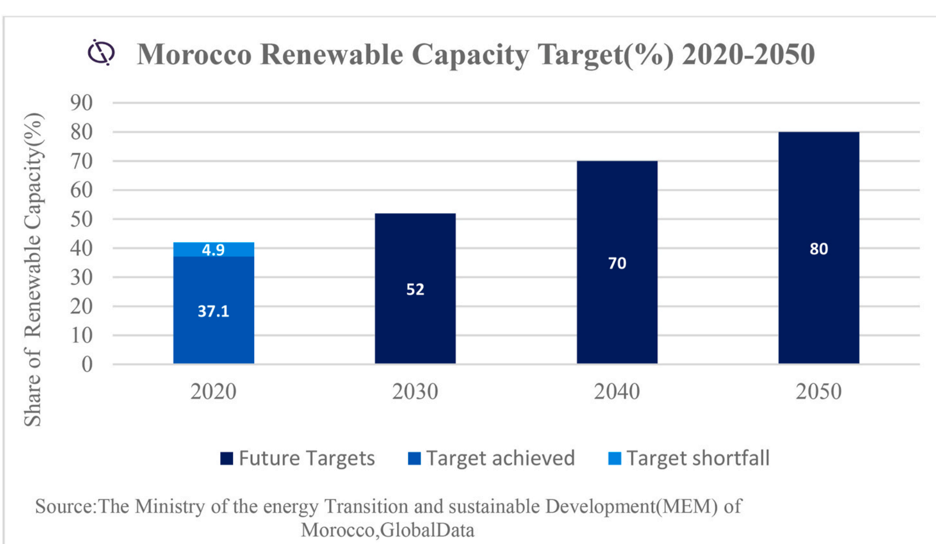

Fig. 1. Renewable energy capacity targets as a percentage of total power generation in Morocco from 2020 to 2050 (Morocco, 2024).

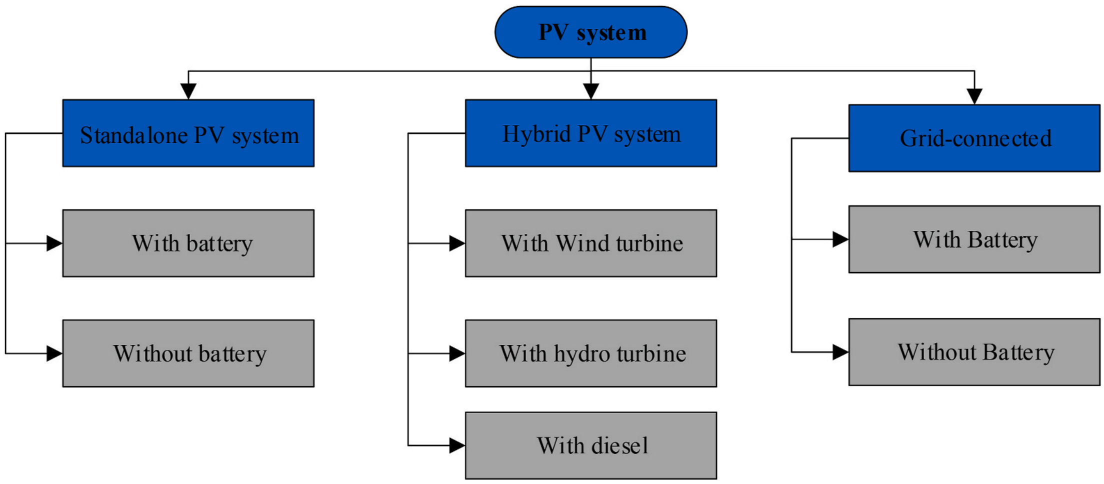

Fig. 2. PV water pumping system classification(Muralidhar et al., 2021).

power point (MPP), where they can deliver the maximum amount of power under given environmental conditions, such as sunlight intensity and temperature(Powell et al., 2021). However, this MPP can vary with changing environmental conditions. Therefore, to find and maintain the MPPT from the solar panels at all times, MPPT techniques are used, which optimize the output from the PV array by continuously adjusting the operating voltage and current to ensure that the solar panels work at their maximum efficiency. As a result, the system can extract the most power from the available sunlight, enhancing the overall efficiency of the PVWPS and maximizing the water pumping output. Many MPPT techniques have been proposed in the literature (Logeswaran et A., 2014). These techniques are generally divided into two categories: (1) conventional methods (CMs) and (2) soft computing methods (SCMs). They differ in efficiency, tracking speed, steady-state oscillations, implementation complexity, hardware requirements, global MPP tracking capability, and cost(Mao et al., 2020). CMs, such as Perturb and Observe (P&O) (Ramesh, 2018), Hill Climbing (HC) (Rawat, 2023), and Incremental Conductance (INC) (Chellakhi et al., 2022), have been around for a long time. Their simplicity and ease of implementation are two important advantages(Bendib et al., 2015). Additionally, these methods perform well under uniform radiation and temperature conditions. SCMs include Artificial Neural Networks (ANNs) (Fousseyni Toure et al., 2021), Fuzzy Logic Controllers (FLCs) (Ozdemir et al., 2017), Particle Swarm Optimization (PSO) (Alshareef et al., 2019), Ant Colony Optimization (ACO) (Phanden et al., 2021), Artificial Bee Colony (ABC) (soufyane Benyoucef et al., 2015), and Bat Algorithm (BA) (Kaced et al., 2017). These methods offer robustness and high efficiency in extracting the maximum power point(Yang et al., 2020). The second controller is designed for the induction motor, which, despite its advantages, faces challenges due to unmeasurable state variables, such as flux(Altimania et al., 2023). These limitations necessitate advanced control algorithms to effectively regulate the torque and flux of these machines in real time, which can protect the PVWPS from overloads and failures and provide flexibility in adjusting water output as needed (Poompavai et al., 2019). Numerous control techniques have been studied, including the Scalar Control (SC) technique(Yahyaoui et al., 2018), initially adopted for its simplicity and affordability. However, SC is less efficient than other methods because it does not directly regulate the motor's flux and torque. Subsequently, the Field Oriented Control (FOC) proposed to separate the motor's flux and torque (Saady et al., 2021), resulting in precise speed control and swift torque response accuracy across the entire speed spectrum. However, FOC can be affected by external load disturbances and parameter fluctuations, and it is not as robust in nonlinear systems as in linear systems. Studying the Sliding Mode Control (SMC) system ensured meticulous control applicable to precision-oriented scenarios(Nassiri and Labbadi et Mohamed., 2022). However, SMC can experience chattering, which can cause vibrations and noise in the system. To surmount these challenges and regulate the torque of the induction motor. Direct torque control (DTC), an approach introduced by Takashi and Noguchi(Saady et al., 2023), presents several advantages over alternative control methods. These advantages include straightforward implementation, robustness to motor parameter variations, and stable operation in response to changing motor characteristics. However, employing hysteresis controllers may result in noticeable oscillations in electromagnetic torque and stator flux, particularly at lower speeds. These oscillations can lead to mechanical vibrations and increased noise levels. Integrating soft computing methods into Direct Torque Control has garnered significant attention from researchers in recent years. Techniques such as Genetic Algorithms (Elgbaily et al., 2022), Ant Colony Optimization (Mahfoud et al., 2022a), and Artificial Neural Networks (Gdaim et al., 2023) have been incorporated into DTC, leading to notable improvements in machine performance. These enhancements include more accurate tracking of speed and torque references, faster response times, and reduced overshoot. Additionally, a significant reduction in torque ripples, exceeding 50%, has been successfully achieved. Therefore, the main objective of this literature review is to provide an overview of integrating soft computing methods to enhance the performance of photovoltaic water pumping system controllers, offering valuable insights to researchers in this field. This review article is structured into the subsequent sections: Section 2 presents the structure of the PVWPS; Section 3 discusses various types of soft computing methods; Section 4 provides an overview of soft computing-based MPPT for PV systems and PVWPS, as well as an overview of soft computing-based DTC control methods for the PVWPS. Section 5 presents a recapitulation and provides suggestions for authors working on new methods to enhance the PVWPS. Finally, Section 6 Concludes the review paper by summarizing its key findings.

2. Structure of PV water pumping system

With the increasing electricity crises in rural and remote areas, photovoltaic water pumping systems have gained popularity due to their self-reliance and independence from other energy sources such as diesel and grid power(Verma et al., 2021). Therefore, to further illustrate the performance benefits of PV water pumping systems compared to other systems, a comparative analysis is presented in Table 1. This table outlines various criteria, emphasizing the potential advantages of PVWPS over traditional systems and alternative renewable energy sources, including efficiency, reliability, cost-effectiveness, and environmental impact, showcasing the superior attributes of the PVWPS model.

Table 1
Comparative analysis of the PVWPS, traditional systems, and other renewable energy sources.

Criteria	Traditional systems	PVWPS	Other Renewable Energy
Energy Source	Fossil fuels	solar energy	wind, hydro, biomass
Cost-Effectiveness	High fuel and operational costs	Low operational and maintenance costs, no fuel required	Varies, can have high maintenance costs
Grid Independence	Dependent on grid or fuel supply	Operates independently from the grid, ideal for remote areas	Varies, some systems may need grid support
Environmental Impact	High greenhouse gas emissions, environmental pollution	No greenhouse gas emissions, environmentally friendly	Generally low emissions, but depends on the specific system
Technological Advancements	Limited to basic control systems	MPPT controllers for maximum efficiency, advanced motor control	Varies, some systems may have advanced control but not universally
The accuracy and efficiency	Low accuracy and efficiency	High accuracy and efficiency due to advanced controllers	Varies, depends on the specific technology and implementation
Scalability and Flexibility	Limited scalability and flexibility	Easily scalable and adaptable to different needs and installation sizes	Varies, some systems are scalable but may have higher costs
Maintenance and Durability	Higher maintenance and durability issues	Durable with minimal maintenance	Varies, maintenance needs can be high depending on technology

Among the various criteria shown in Table 1 for the PVWPS, cost-effectiveness, and accuracy-efficiency are two essential factors for assessing the viability and long-term benefits of PVWPS in rural and remote areas.

2.1. Cost-effectiveness

Various designs are used to develop PV water pumping systems. However, many of the systems examined in the literature employ a multi-stage configuration(Saady et al., 2023). This configuration typically includes a PV array, a DC/DC boost converter, a DC/AC inverter, and an AC motor connected to a centrifugal pump, as illustrated in Fig. 3. The modeling details for each component are provided in Appendix A.

To accurately evaluate the feasibility and economic benefits of PVWPS, it is essential to understand the cost of each component. These cost details play a critical role in effective planning and informed decision-making. Table 2 provides a comprehensive summary of the system specifications and economic information for each component of the 1.5 kW PVWPS. It highlights the parameters such as initial cost, maintenance cost, operational cost, and expected lifespan. By detailing these aspects, the table emphasizes the system's cost-effectiveness, durability, and overall economic advantages, demonstrating its potential as a highly efficient and financially beneficial solution for water pumping needs.

System Overview.

– Total Initial Cost Range: \$3350 - \$6200
– Annual Maintenance Cost Range: \$70 - \$170

Table 2
Costs, maintenance, and lifespan of PVWPS components.

Component	Specification	Initial Cost (\$)	Maintenance Cost (\$/year)	Expected Lifespan (years)
PV Array	Power: 1.5 kW	\$2250 - \$4500	\$20 - \$50	25–30
DC-DC Boost Converter	Efficiency: 95%	\$100 -\$300	\$10 - \$30	10–15
DC-AC Inverter	Efficiency: 94%	\$200 -\$600	\$20 - \$50	10–15
Induction Motor & Pump	Flow Rate: 50 L/min	\$300 -\$800	\$30 - \$70	10–15
Other Components & Installation	Miscellaneous components and installation	\$500 -\$1000	\$10 - \$20	10–15

– Overall System Lifespan: Typically, 10–30 years, depending on component and system maintenance.

2.2. The accuracy and efficiency

To ensure the accuracy and optimum performance of the PV water pumping system, researchers have proposed various control strategies, including load matching, MPPT algorithms, sun tracking control, and charge control (with batteries) (El Hammoumi et al., 2022). However, the majority of research has focused on two primary control methods. The first method involves an MPPT controller, which maximizes power extraction from the PV source by adjusting the duty cycle of a DC-DC

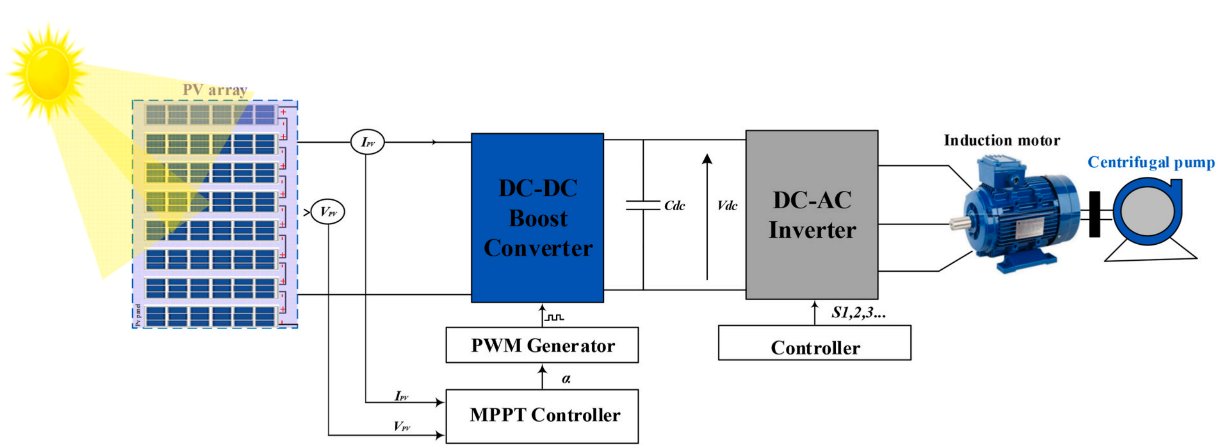

Fig. 3. Schematic diagram of Photovoltaic Water Pumping Systems.

converter and regulating the DC bus voltage. The second method is the motor controller, which governs motor operation through a Voltage Source Inverter. Therefore, many researchers have proposed various controllers to enhance these aspects. In Ref (Singh et al., 2018) an efficient PVWPS with an induction motor drive (IMD) is proposed. It employs advanced control techniques, including INC-based MPPT for the PV array and a scalar-controlled VSI for the IMD. These controls optimize power extraction, reduce losses, eliminate sensor requirements, and adapt to pump performance variations. A low-cost PVWPS with a three-phase induction motor is introduced In Ref(Talbi et al., 2018). It utilized innovative control techniques, including an improved P&O algorithm for stable PV power, PTC for precise IM control, and FLC for voltage regulation. Simulations and hardware testing demonstrate superior performance compared to conventional methods. In Ref(Achour et al., 2016), the suggested control scheme for the PVWPS includes sliding-mode control to optimize power from the PV array and direct torque control to regulate the induction motor. The system's effectiveness is confirmed through MATLAB/Simulink simulations, even under parameter variations. The PVWPS control system proposed In Ref(Saady et al., 2021), utilizes INC-based MPPT for the PV array and employs IFOC for regulating the induction motor. The results favored INC over P&O, showing reduced oscillations and improved performance during sudden irradiation changes. In Ref(Design, 2023), an efficient off-grid PVWPS for rural areas is studied. It combines an improved Fractional Open-Circuit Voltage-based MPPT method with closed-loop control, reducing the need for additional sensors for the IM. Testing with a 1KVA prototype demonstrates fast response, minimal oscillations, 99% efficiency, and high flow rates. This system is a reliable solution for off-grid water extraction. To enhance the efficiency of a stand-alone PVG system for water pumping, two validated MPPT methods are proposed In Ref (Implementation, 2023), constant voltage (CV) and incremental conductance. Both methods feed a DC/DC boost converter, which supplies power to motor pumps through a DC/AC inverter. The experimental results confirm the success of CV control and INC in achieving the intended Maximum Power Point, although they differ in approach and stability of MPP attainment.

As previously discussed, photovoltaic arrays and induction motors (IM) are core components of PV water pumping systems. The PV array provides the necessary power to operate the motor, which drives the pump. However, the performance of PV arrays can be affected by frequently occurring partial shading conditions (PSC).

PSC leads to a reduced output power and increased power mismatch due to the creation of multiple local peaks in the power-voltage curve. This phenomenon occurs because bypass diodes activate to protect the shaded cells, causing the power output to fluctuate and complicating the power management(Li et al., 2018). Traditional Maximum Power Point Tracking algorithms often falter under these circumstances, becoming trapped at local maxima rather than achieving the global optimum. Consequently, substantial power losses occur, significantly diminishing overall system efficiency. Furthermore, precise regulation of the speed and torque of the induction motor is essential for achieving optimal performance and ensuring the system operates at its highest efficiency (El Ouanjli et al., 2019).

To address these challenges, this review paper will discuss the definition of soft computing methods, their advantages and disadvantages, and provide an overview of their application in PV systems, with a particular focus on enhancing the MPPT controller and the IM controller for PV water-pumping systems. The application of soft computing techniques promises to improve the efficiency and accuracy of these systems by effectively managing partial shading conditions and optimizing motor performance.

3. Some soft computing methods

Conventional methods applied to complex systems such as Induction Motor control and Maximum Power Point Tracking in photovoltaic (PV) systems face significant challenges. These methods rely on fixed algorithms that often struggle with adapting to non-linearities, dynamic environmental conditions, and uncertainties in system parameters.

Researchers have increasingly adopted soft computing methods to address these challenges(Harirchian et al., 2021). Unlike traditional approaches, SC methods provide dynamic and adaptive solutions. They excel in handling complex, non-linear behaviors and uncertainties through probabilistic modeling, approximate solutions, and flexibility. These methods fall into two main categories: artificial intelligence (AI) and bio-inspired techniques. As illustrated in Fig. 4, the AI category includes Artificial Neural Networks and Fuzzy Logic Control, which focus on mimicking human cognition and reasoning processes. On the other hand, the bio-inspired category encompasses Evolutionary Computing and Swarm Intelligence. Evolutionary Computing involves techniques such as Genetic Algorithms and Evolutionary Algorithms, which simulate the process of natural selection to solve optimization problems. Swarm Intelligence includes methods like Artificial Bee Colony Optimization and Ant Colony Optimization, which draw inspiration from the collective behavior of social insects.

3.1. Fuzzy-logic control

FLC is one of the most powerful methods for developing nonlinear controllers, leveraging heuristic information derived from the designer's expertise and experience. This approach allows the designer to select acceptable inputs and fine-tune the rule-base table effectively. The implementation of the FLC is divided into three primary processes, as depicted in Fig. 5 (Baramadeh et al., 2021). The first procedure is fuzzification, in which input mistakes are turned into linguistic variables using membership functions. These functions can take various forms, such as triangular, trapezoidal, or Gaussian. The triangular membership function is the most commonly used due to its simplicity and computational efficiency. Membership functions are crucial as they transform precise numerical inputs into qualitative descriptions that align with specific fuzzy sets. Fig. 6 shows an example of five memberships with distinct fuzzy levels utilized for inputs and output variables: NB (negative big), NS (negative small), ZE (zero), PS (positive small), and PB (positive big). The second process is called rule inference, which uses linguistic rules to determine the controlling action based on the response provided to a set of input values, thereby defining the fuzzy output for each action. These involve formulating rules in the form of "IF-THEN" statements, where the "IF" part specifies the conditions based on the input variables, and the "THEN" part specifies the corresponding output or control action. This mechanism allows the system to infer the appropriate response based on the given inputs, making the system flexible and adaptive. To illustrate this process more clearly, consider an example of a rule in Table 3. The last process is defuzzification, which involves transforming the linguistic variable output into a precise numeric variable. Defuzzification can be done using several algorithms, each of which has its own accuracy and computational intensity, such as Bisector of Area (BoA), Center of Gravity (COG), and the Max Criterion Method (MCM). FLC has various advantages, such as flexibility, robustness, and transparency. It can effectively handle complex, nonlinear systems that are difficult to model with traditional methods, making it a useful tool for many applications. In Ref (Mishra et al., 2023), a fuzzy logic controller for wind turbines is proposed to limit power, enhance quality, and reduce loads by adjusting the pitch angle. The results demonstrate that the optimized and auto-adjusted FLC significantly outperforms traditional controllers in terms of stability, response speed, and energy efficiency. In Ref (El-Barbary, 2012), The fuzzy logic-based controller is applied to the indirect rotor field-oriented control technique for five-phase induction motor drives. The proposed controller was experimentally implemented and rigorously tested, demonstrating robust performance across operating conditions. This versatility and reliability highlight its suitability for high-performance applications in five-phase induction motor drives. However, fuzzy

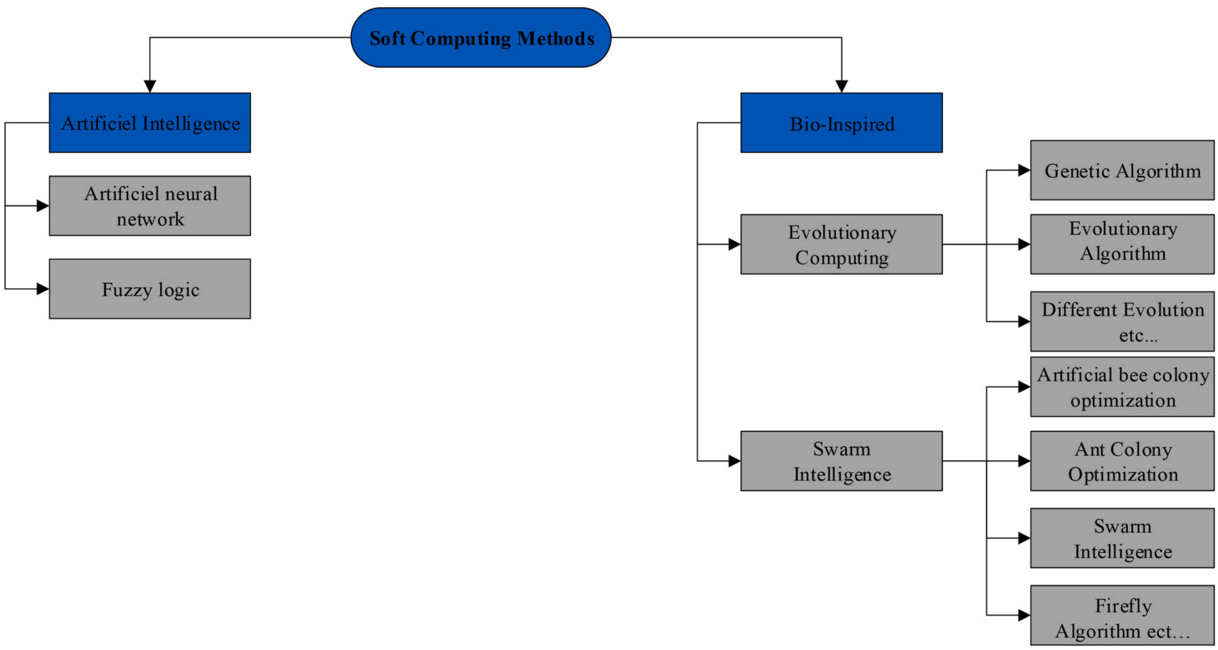

Fig. 4. An overview of some common soft computing methods(Balamurugan et al., 2017).

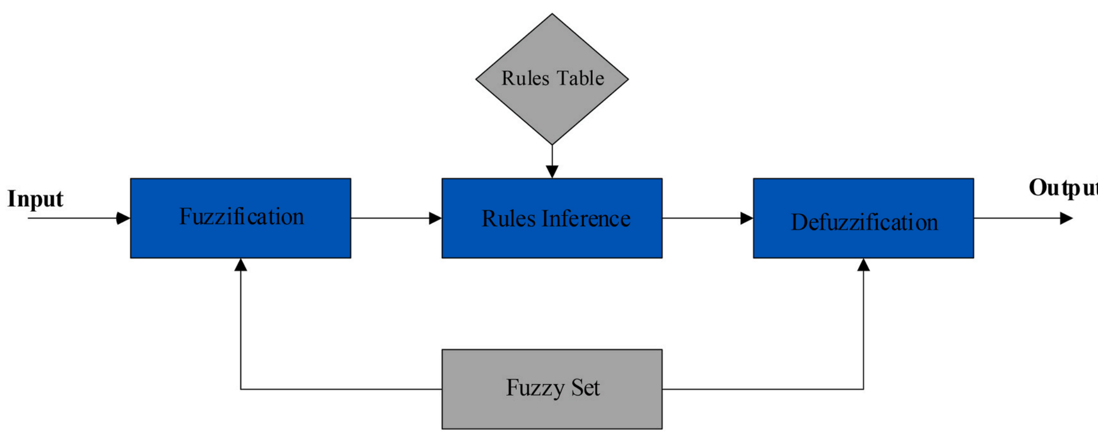

Fig. 5. Schematic diagram of fuzzy logic control (FLC) (Ozdemir et al., 2017).

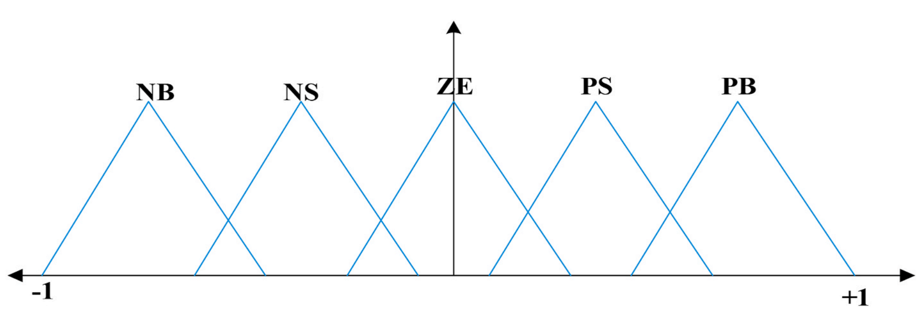

Fig. 6. Fuzzy membership functions used in the fuzzification process.

logic control can be complex to design and require a lot of expertise and experience to create a good model. Additionally, the fuzzy logic approach involves making subjective decisions about how to model and represent data, which can lead to different interpretations and results.

3.2. Artificial neural network

ANNs are computational models inspired by the structure and function of the human brain(Hussain et al., 2021). ANNs learn by processing information through interconnected layers of artificial neurons. These neurons are trained using datasets to recognize patterns in the input data. Once trained, the ANN can identify similar patterns in new

Table 3
The fuzzy control rules.

Input 1	Input 2				
	PB	PS	ZE	NS	NB
NB	ZE	NS	NB	NB	NB
NS	PS	ZE	NS	NB	NB
ZE	PB	PS	ZE	NS	NB
PS	PB	PB	PS	ZE	NS
PB	PB	PB	PB	PS	ZE

data during the validation phase. As illustrated in Fig. 7, the ANN typically consists of three layers: an input layer, one or more hidden layers, and an output layer. Each layer comprises numerous neurons that receive input signals from other neurons in the network. The received signals are then weighted and added together. The resulting value is passed through an activation function to produce an output signal, which can be used to learn complex patterns and relationships in the data. Finally, the output signal is transmitted to other neurons in the network for further processing. The ability of ANNs to learn and adapt to new data patterns over time makes them suitable for various applications. ANN is proposed to forecast the performance of single slope single basin solar stills in air-dry environments In Ref(Immanual et al., 2023). The study uses data from previous research to develop a model that predicts solar still productivity with high accuracy (0.99459) using the LM algorithm. The results show that the developed model effectively forecasts productivity, demonstrating a high level of precision. In Ref (Taghinezhad et al., 2022) the ANNs is used to simulate the performance of a ducted wind turbine under different operating conditions. The suggested ANN is shown to be effective in predicting turbine power curves. In Ref (Yang et al., 2022)ANNs is also used to predict power, emissions, and combustion phasing indicators of internal combustion engines (ICEs). However, the lack of transparency of ANNs can be a disadvantage, impeding the comprehension of decision-making and predictive processes. Furthermore, ANNs can be computationally intensive, requiring substantial resources for training and deployment, which can be a drawback in certain applications.

The generic output equation is expressed as:

$$Z = b_k + \sum_{j=1}^{h} H_j * w_{jk} \tag{1}$$

$$H_j = f(v_j) = \frac{1}{1 + e^{v_j}} \tag{2}$$

$$v_j = b_j + \sum_{i=1}^{n} x_i * w_{ij} \tag{3}$$

where H_j is the output of the neuron in the hidden layer, $x_i(1, \ldots n)$ is the input variable, w_{ij} is the connection weight between the input variable i and neuron j in the hidden layer, w_{jk} is the connection weight between neuron j in the hidden layer and the output neuron, b_j is the bias of neuron j in the hidden layer, b_k is the bias of the output neuron, and v_j is the output of the neuron in the output layer. f is a nonlinear activation function for neuron j in the hidden layer, which can be either a sigmoid function or a hyperbolic tangent (tanh) function. Meanwhile, the output Z has a linear activation function for the output neuron.

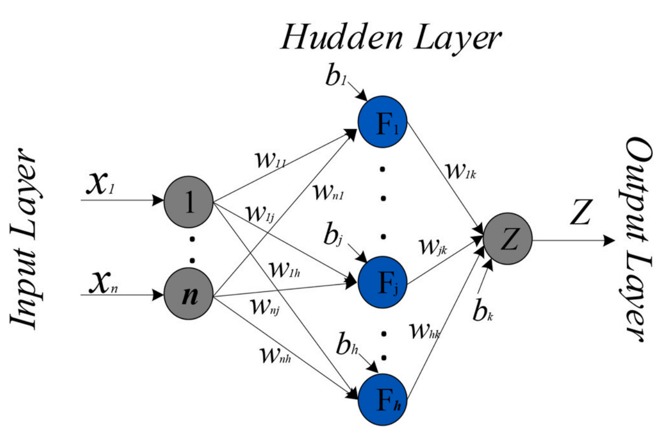

Fig. 7. The artificial neural network's architecture(Hussain et al., 2023).

3.3. Partial swarm optimization

The PSO is an example of an evolutionary algorithm inspired by the social behavior of birds foraging or schooling fish. The primary concept behind the PSO method is to find the optimal solution through particle cooperation and competition(Wang et al., 2018). The PSO starts its algorithm with a population of random solutions known as particles. These particles are traversed around a multidimensional search space in search of the optimal solution. Each particle within this search space adjusts its behavior based on its own experiences and the experiences of neighboring particles. Thus, the position of the particles is influenced by the best particle in a neighborhood P_{best} and the best solution obtained by all particles in the population G_{best}. During each iteration, the particle determines where to move by comparing P_{best} and G_{best} and updating the velocity (V) and position (T) based on the following equations:

$$V_i^{k+1} = wV_i^k + c_1 r_1 \left(P_{best\ i} - T_i^k\right) + c_2 r_2 \left(G_{best} - T_i^k\right) \tag{4}$$

$$T_i^{k+1} = T_i^k + V_i^{k+1} \tag{5}$$

Where i represents the number of the particles, k is the number of iterations, w is the inertia weight variable c_1, c_2 are the acceleration factor r_1, r_1 are two random numbers chosen in the range [0, 1].

The PSO algorithm is effective for generating the global optimum because it is theoretically simple, has high tracking accuracy, and offers quick convergence. These strengths make it suitable for a wide range of applications, such as, In Ref(Fan et al., 2022), a PSO-MPC approach for load frequency control (LFC) in power grids with wind turbines introduced. This method integrates PSO into the MPC model, improving frequency regulation and reducing computational burden. Simulations confirm its effectiveness and superior performance.In Ref(Energies, 2023), a comparative study is proposed to compare a six-phase squirrel cage induction motor optimized using PSO with traditional three-phase motors for electric propulsion systems. The optimized six-phase motor shows improved efficiency and performance, with reduced weight and power loss, increased efficiency, and a higher power factor, making it a more reliable and cost-effective option for electric propulsion. However, PSO suffers from several drawbacks, including premature convergence to local optima and difficulties in selecting appropriate control parameters, often leading to suboptimal solutions(Particle, 2024).

3.4. Ant Colony Optimization

The ACO is a swarm intelligence technique employed for solving discrete optimization problems and generating near-optimal solutions based on ants' behavior in searching for food, where the ants move randomly in different paths, to search for the food source area, as soon as ants find a food source, they evaluate it and carry some food back to the nest, during their return they leave an indication for other ants around the place of food through a chemical signal called pheromone, then the other ants follow in its movement the shortest path between the nest and food, depending on the probability that the amount of pheromone is high in this path (Rezvanian et al., 2023).Other-wise, the pheromone that moves in the longest path evaporated and disappears by itself. The following Fig. 8 helps to understand the ACO method.

Ant uses the roulette wheel algorithm to determine the next point to be reached at each phase of the path construction, based on equation (6)

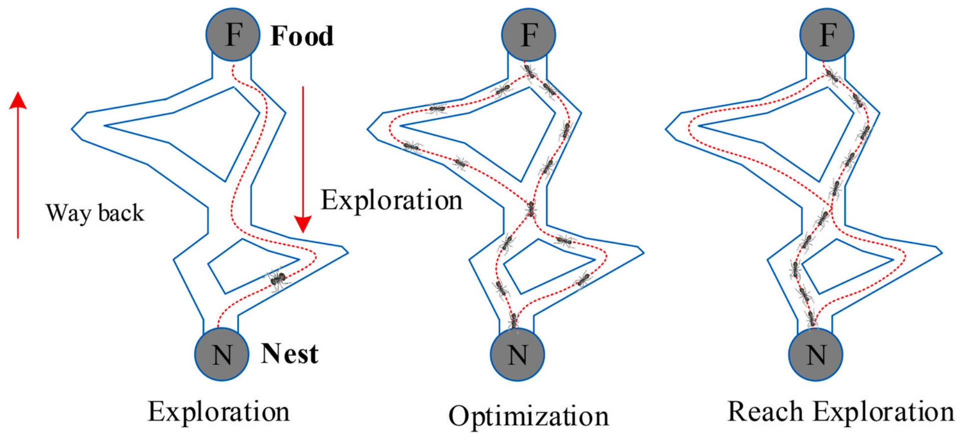

Fig. 8. Functional operation of the ant colony algorithm(Rezvanian et al., 2023).

shown below.

$$\begin{cases} P_{ij}^k = \dfrac{[\tau_{ij}]^{\gamma}[\eta_{ij}]^{\delta}}{\sum\limits_{l=T_i^k}[\tau_{ij}]^{\gamma}[\eta_{ij}]^{\delta}}\, j \in T_i^K \\ \qquad 0 \end{cases} \tag{6}$$

where i and j denote the start point and end point respectively, γ is the pheromone factor, δ is the heuristic factor, τ_{ij} is the pheromone concentration from i to j, η_{ij} is the inverse of the distance from point i to j, P_{ij}^k represents the probability of ant k from point i to j. The formula indicates that as the pheromone concentration increases, the probability also rises, leading to a shorter path.

At the end of each iteration, the pheromone quantity left by ants is required to be updated. (Each ant reaches the next nodes or passes to all nodes), the pheromone is updated according to the formula shown in equation (7).

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t-1) + \sum_{k=1}^{m}\Delta\tau_{ij}^{(k)} \tag{7}$$

Where τ_{ij} Total Pheromone deposit by ant on the path ij, ρ is Pheromone Evaporation, $\Delta\tau_{ij}^{(k)}$ is Total Pheromone deposit by kth ant on the path ij, m is Number of Ants.

$$\Delta\tau_{ij}^k = \begin{Bmatrix} \dfrac{\zeta f_{best}}{fworst}\ if\ i,j \in Global\ best\ path \\ 0\ Otherwise \end{Bmatrix} \tag{8}$$

Where f_{best} is the best objective function, f_{worst} is the worst objective function, ζ is the scaling parameter.

In ACO, ants use pheromone trails and heuristics to efficiently traverse the search space, enabling them to reach a near-optimal solution more quickly, which makes it suitable for a wide range of optimization problems. In Ref(IJGI)the ACO is used to determine the optimal route for public transportation. The algorithm successfully determines the shortest route for the Trans Banyumas Corridor 3 and identifies new routes for Corridor 4 and Corridor 5. In Ref(Chen et al., 2008)the ACO is used to identify the parameters of the induction motor for the vector control ACO showed more precision and required less computing time compared to Genetic Algorithm and Adaptive Genetic Algorithm in digital simulations. In Ref (Liu et al., 2023)a refined model for adaptive tutoring systems that incorporates ACO is introduced. The model generates an adaptive optimal learning path based on learning and problem-solving styles. The architecture of the algorithm enables the recording and analysis of collective learner behavior, creating a feedback loop toward learning goals. The study shows improved performance compared to previous adaptive tutoring systems. Despite ACO's advantages, it also has two major disadvantages, including sensitivity to parameter settings and computational complexity (Dorigo and Stützle, 2019).

3.5. Artificial bee colony optimization

The ABC algorithm draws inspiration from the intelligent foraging behavior exhibited by honey bee colonies, which is applied to search for the optimal solution. The honey bees are categorized into three groups: employed bees (forager bees), onlooker bees (observer bees), and scouts. Employed bees search for food or exploit a food source, and then transmit this knowledge (the location of the food) through a vibration dance in the bee colony to the onlooker bees. The onlooker bees decide which food sources are the best among those found by the employed bees. Each food source is associated with only one employed bee. This means that the count of employed bees matches both the count of food sources and the count of onlooker bees. Employed bees that cannot improve their food sources after a predefined number of attempts are transformed into scouts, and they abandon their current food sources. Subsequently, the scout bee initiates random searches for new food sources(Abu-Mouti et al., 2012). The steps of the ABC algorithm are summarized as follow.

- **Step 1**: the determination of the initial population of the solution (food source) then analyzes the quality of a food source is called its "fitness value" of the population solution and memorize the best.

$$y_j^k = y_{min}^k + rand[0,1](y_{max}^k - y_{min}^k) \tag{9}$$

J = 1, 2, 3 … … …., SN k = 1, 2, 3 … … …, M

Where SN and M are the total number of optimization parameters and y_{min}^k and y_{max}^k are the parameter minimal and maximum values, respectively.

Following initialization, each population of the solutions is exposed to repeated cycles of the search operations of the employed bees, the observer bees and the scout bees until maximum cycle number (MCN) is reached.

- **Step 2**: Employed bee phase: each employed bee produces a new solution y_new_{jk} by adjusting the associated old solution $\left(y_{jk}\right)$ by the following equation Eq. (10) and then evaluates the fitness (fiti) values for each new population solution.

$$y\_new_{jk} = y_{jk} + \varnothing_{jk}\left(y_{jk} + y_{lk}\right) \tag{10}$$

Where l∈ {1, 2 … SN} and k ∈ {1, 2, M} are randomly chosen indexes. And $\varnothing_{jk}$ is a random number between [−1, 1] which is used to adjust the old food source to become the new food source in the next iteration.

The greedy selection process is employed in the selection operation by doing the comparison between the nectar amount (fitness) of the old solution and the new solution if the fitness of the new solution is higher than the old solution then the bees memorize the new solution and forget the old. Otherwise, the old keep unchanged.

- **Step 3**: A specific food source is picked by onlooker bees according to its probability (P_i) of acquiring better nectar, which is determined by the following expression:

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{11}$$

To determine the fitness values of the solutions, the following equation (12) is used:

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & if\ f_i \geq 0 \\ 1 + abc\, f(i) \quad if & f_i \leq 0 \end{cases} \tag{12}$$

- Step **4**: At the completion of each search cycle, if the fitness of a solution cannot be improved and exceeds the threshold number of trials, which is termed "limit", is exhausted, At the same time, the corresponding employed bee will change into a scout bee and go back to step 1 to seek new source food again.

ABC has been studied by many researchers due to its fast convergence, high flexibility, and ease of implementation. In Ref (Unlersen et al., 2021) the ABC algorithm is proposed to develop a mathematical expression to predict the temperature rise in power electronic circuits. The approach provides an effective way to ensure proper cooling and thermal management. In Ref(Oliva et al., 2014) For improving the performance of solar energy systems, the ABC algorithm is used to identify the parameters of solar cells. The suggested method is compared to other well-known optimization methods, and the experimental findings reveal that the ABC algorithm surpasses other methods in terms of robustness and accuracy, particularly in facing multi-modal objective functions. Despite ABC's ability to search for robust equations, its development capability is limited, leading to poor solution quality, local optimum, and slow global convergence (Durgut et al., 2021).

3.6. Genetic algorithms

GA is an optimization method based on natural selection and genetics to find solutions to the optimization problem. The primary concept of this algorithm is to apply genetic changes (Selection, crossover, mutation, and insertion) on a population of individuals with the goal of eventually achieving an optimum individual according to the maximum of a function (fitness function) (Lambora et al., 2019). The process of a GA starts with generating a random population of n-bit chromosomes (candidate solutions). Each chromosome is composed of "genes," where each gene is an instance of a particular "allele" (such as 0 or 1). Fitness values are calculated for each chromosome to reflect their goodness, and chromosomes with higher fitness values are selected for inclusion in the next generation's population. After that, the crossover operator is applied. This operator swaps a subsequence of two chosen chromosomes to produce two offspring. Following the crossover, some genes in the new chromosomes that have a low random probability can be subjected to the mutation operator. In this operator, the bits are flipped, meaning that a 0 can become a 1 and vice versa. The end of the GA involves the insertion operator, where the new population is integrated into the old population to replace the chromosome with the minimum fitness function. The whole process of a GA is repeated until the fitness value of the chromosome is stabilized and remains unchanged for many generations(Katoch et al., 2021).

The GA advantage lies in its ability to perform multi-objective optimization, which makes it a particularly powerful tool for solving multi-objective problems. In Ref (Zou et al., 2019)to address the problem of energy losses in hydraulic drive systems due to pumps on discharge and low-efficiency motors, GA is used to quickly and accurately select motor pumps from combinations with a greater range of types and the number of elements, which resulted in a 26.97% reduction in energy consumption. In Ref(Masoum et al., 2010), GAs are used to optimize the placement and power ratio of a hybrid PV-wind system (HPWS). The algorithm determines the best location and configuration for a 1MVA HPWS across 265 candidate sites in the U.S optimizing the number of 40 kW PV and 68.46 kW wind units based on cost functions and environmental conditions. Despite the advantages of GA, this algorithm takes a significant amount of time to converge and fine-tune all parameters, including the mutation rate, elitism percentage, crossover parameters, and fitness normalization(Mahmoodabadi et al., 2016).

3.7. Bat Algorithm

The BA is a metaheuristic algorithm inspired by the biological behavior of microbats. These microbats use a type of sonar called echolocation to locate prey, navigate around obstacles, and find their roosting crevices in the dark. These bats emit a high-intensity sound pulse and then listen for the echo that rebounds from objects in their vicinity. This process enables them to identify the object's characteristics, such as its type, size, movement, and distance from them (Shehab et al., 2023).BA works using N bats searching for food, each flying randomly with a speed $v(i)$ from position $y(i)$, with varying wavelengths (λ) and loudness A_0 as the bats get closer to food, they can automatically adjust the frequency or wavelength of their emitted pulses and their rate of transmitting sound pulses r between 0 and 1. While the loudness of the transmitted sound pulse should fluctuate from a large positive value of A_0 to a minimum constant value A_{min}.

In the optimization task, each bat has its own randomly assigned frequency of $[f_{min}, f_{max}]$, where then in the time step (t + 1) the new position $y(i+1)$ and the new velocity $v(i+1)$ for each bat can be determined and updated by the following equations:

$$f_i = f_{min} + (f_{max} - f_{min})\gamma \tag{13}$$

$$v_i^{t+1} = v_i^t + (y_i^t - y_{best}^t) f_i \tag{14}$$

$$y_i^{t+1} = y_i^t + v_i^{t+1} \tag{15}$$

Where $\gamma \epsilon [0,1]$ a vector is randomly selected from a uniform distribution. y_{best}^t is the current global best position (solution) which is acquired by comparing all the solutions among all the N bats at each iteration t. f_{min}, f_{max} are respectively the minimal and the maximal frequency which are chosen depending on the size of the searching area.

Once the bat positions have been updated, a random number is generated. If this random number exceeds the pulse emission rate, a new center is generated around the current best solution, which can be determined using equation (16).

$$x_{new} = x_{old} + \varepsilon A^t \tag{16}$$

Where, $\varepsilon \epsilon [-1,1]$, represents a random number, whereas A^t is the average loudness of all the bats at the latest state.

As the iterations progress, the loudness of A_i and the pulse rate of emission change as the global optimum position approaches the prey/food where the loudness decreases and the pulse rate increases according to equations (17) and (18)

$$A_i^{t+1} = \delta A_i^t \tag{17}$$

$$r_i^{t+1} = r_i^0\left(1 - e^{-\beta t}\right) \tag{18}$$

δ and β are two constants.

The best position is determined based on the frequency values, where the position of the high-frequency bat is chosen as the global best solution.

The BA offers numerous benefits, with a significant advantage being its ability to achieve extremely fast convergence during a critical phase by transitioning from exploration to exploitation. This feature makes it applicable to many optimization problems. In Ref(Zebari et al., 2020) the BA is used to improve the energy efficiency of smart homes. This approach outperforms other algorithms and ensures better comfort at minimal energy consumption, making it valuable for smart home systems. In Ref(Tholath Jose, 2014)the BA-based economic load dispatch solution addressing wind energy integration and stochastic wind power output is proposed. The study demonstrated the algorithm's feasibility in scenarios with and without wind power. In addition to the advantages of the BA, this algorithm has encountered some drawbacks, such as early convergence, sensitivity to parameters, and a lack of theoretical analysis that require further attention to enhance its performance (Guo et al., 2019).

4. The application of the soft computing methods

4.1. An overview of soft computing based MPPT controller for PV system

Due to the non-linear I-V characteristics of the PV source, tracking the maximum power point under various environmental conditions can sometimes be a challenging task. Therefore, several MPPT algorithms have been proposed, classified into two types: conventional methods and soft computing methods(Basha et al., 2020). Furthermore, conventional methods offer superior performance under stable irradiance, but when there are rapid changes in irradiance and shading conditions, the results can be unsatisfactory. Consequently, many researchers have shown increasing interest in using soft computing methods to improve the efficiency of PV systems, as shown in Fig. 9.

This section discusses some of the previous works on SC-based MPPT methods, such as FOC, ANN, ABC, ACO, and hybrid methods that combine two or more SC techniques. In Ref(Hussain et al., 2023)an Artificial Neural Network based MPPT algorithm for PV systems is introduced. The algorithm generates a reference voltage by training temperature and irradiance data, which is then compared to the voltage produced by the PV panel for MPPT. Simulation studies show that the proposed algorithm performs better under various temperature and irradiance conditions. The Fuzzy Logic Control algorithm is proposed In Ref(Baramadeh et al., 2021) for modeling a Maximum Power Point Tracker in a 60-kW photovoltaic (PV) system with a battery load. The study investigates the behavior of the system under various environmental conditions using MATLAB/Simulink. The results demonstrate that FLC provides high performance, reducing settling time and limiting oscillation around the steady-state value, leading to increased battery life. In Ref(Nour Ali, 2018)an intelligent MPPT method for a standalone PV system using ANN modeling and an FLC is proposed. The ANN is trained to estimate the MPP voltage under various conditions of solar irradiance and temperature, and the FLC generates an appropriate control signal for the DC-DC converter. Simulation results show good performance especially under the variable conditions.

In Ref (Kermadi et al., 2015), an MPPT algorithm based on PSO is examined for the purpose of optimizing power extraction from PV systems that include lithium-ion batteries, even when operating under partial shading conditions. The proposed algorithm introduces a variable sampling time to reduce the time spent during the exploration phase and integrates a comparator to compare the reference voltage generated by the PSO algorithm with the PV array's output voltage. Once the PV array voltage aligns with the reference voltage, the corresponding power is recorded, and the next agent is considered as the new reference voltage for the converter. The system is modeled and simulated in Matlab/Simulink, and the simulation results demonstrate that the proposed approach can track the global peak in less than 500 ms under any conditions. In Ref(Technologies, 2023)a simple Genetic Algorithm based MPPT method for PV systems is introduced. The suggested technique tracks the global maximum power point effectively, reduces oscillations around the maximum power point, enhances stability, and boosts output power efficiency. Results show its superiority over other techniques, and it is experimentally validated using real PV panels. The algorithm also allows for easy calculation of current and voltage factors. In Ref (Nour Ali, 2018)an improved Artificial Neural Network based MPPT system for photovoltaic systems is proposed. The proposed system uses alternative inputs and a genetic algorithm optimization to design the ANN topology. Simulation results demonstrate the superiority of the improved ANN design for MPPT, resulting in increased efficiency for PV systems. In Ref (Titri et al., 2017)a novel bio-inspired Maximum Power Point Tracking controller based on the ACO algorithm with a New Pheromone Updating strategy (ACO-NPU MPPT) is proposed. The suggested controller is intended to have a high tracking capacity with high precision, low oscillations, and high resilience while consuming minimal calculation time. Tests are conducted to determine the suitable ACO-NPU parameters, and assessments are

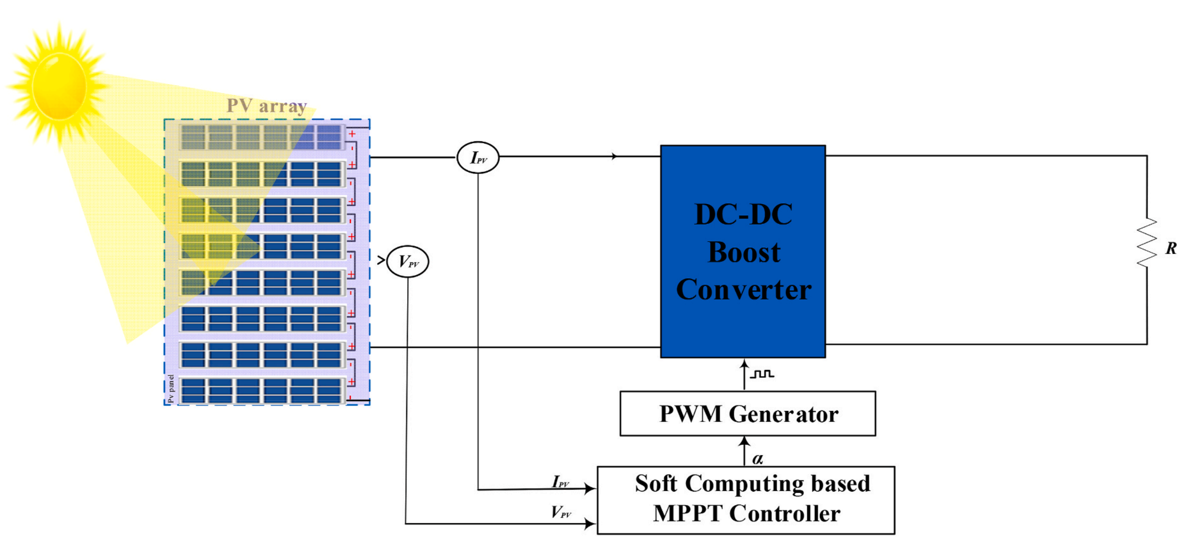

Fig. 9. Schematic diagram of PV system.

carried out under varying weather conditions, including both slow and rapid variations, as well as different partial shading patterns. The results illustrate the superiority and robustness of the proposed controller, which can effectively track the global maximum power point, even when dealing with partial shading conditions. In Ref (Technologies, 2023), a hybrid GA-ACO algorithm is proposed for tracking the maximum power point of photovoltaic module arrays (PVMA) under partially shaded conditions. The GA-ACO algorithm dynamically adjusts the iteration parameters of ACO using the slope of the P-V characteristic curve at the PVMA work point. Simulation results show that the GA-ACO algorithm is able to quickly track the global maximum power point when multiple peaks are produced in the output P-V characteristic curve of the PVMA. In Ref(soufyane Benyoucef et al., 2015), the optimization of photovoltaic (PV) system performance for maximum power extraction is proposed using an ABC algorithm. The ABC-based MPPT algorithm utilizes data values from the PV module to determine the optimal voltage for maximizing power extraction. Subsequently, the MPPT strategy is applied to derive the voltage reference for the outer PI control loop, which, in turn, furnishes the current reference for the predictive digital current programmed control. The performance of the proposed ABC-based MPPT algorithm is assessed in comparison to the PSO-based MPPT algorithm. Furthermore, the proposed algorithm undergoes experimental validation in a laboratory setup. Both simulation and experimental results demonstrate that it performs satisfactorily. In Ref (Kaced et al., 2017) a new Maximum Power Point Tracking algorithm based on the Bat Algorithm for solar panels is proposed. Simulations demonstrate its accuracy even under shading conditions, outperforming the Perturb and Observe and Particle Swarm Optimization methods. A hardware implementation on an FPGA confirms its efficiency in real-time applications.

The previous discussion is summarized in Table 4, considering aspects such as tracking, tracking speed, oscillations, accuracy, complexity, cost, etc. Based on this Table, it is clear that each MPPT control approach has its unique set of advantages and disadvantages. It is important to note that these MPPT control methods are not flawless and offer significant research and development opportunities, particularly in the context of PSCs (Photovoltaic Solar Cells).

4.2. An overview of some soft computing based MPPT controller for PVWPS

Soft computing methods have enabled the MPPT controller for the PV system to be significantly enhanced in terms of performance, especially under shading conditions. Since PV arrays play a key role in the PV water pumping system, this section of the review discusses the previous studies focusing on soft computing techniques based MPPT controller for the PVWPS as presented in Fig. 10.

In Ref (Bouchakour et al., 2021), a comparative study of four MPPT controllers is proposed for a PV water-pumping system with an induction motor and a centrifugal pump. It assesses their efficiency and daily water output, aiming to optimize motor efficiency and PV generator power. The FL-PI controller, especially when optimized with PSO or GA, outperformed the conventional ‘P&O′ algorithm. The FL-PI-PSO controller is recommended because of its superior efficiency and productivity during steady-state. In Ref(Bouchakour et al., 2018), an MPPT system based on an adaptive Fuzzy Logic Controller is introduced to enhance the performance of a photovoltaic water pumping system with an induction motor. Simulation results indicate that the FLC-controlled system outperforms direct coupling in terms of robustness, fast response, and no overshoot in power and water pumping. In Ref(Chouiekh et al., 2022), a solar pumping system is proposed for El Jadida, Morocco, using the Artificial Bee Colony method for Maximum Power Point Tracking to ensure efficient operation under varying weather conditions. The ABC method enhances system stability, reduces response time (3.5 h), and improves water flow (82.35% better than P&O and 50% better than FLC) even under low insolation conditions (25.55 W/m2).

In Ref (Mathematics, 2023), a Salp Swarm Algorithm (SSA) based MPPT method is proposed to enhance solar water pumping systems employing induction motors in remote areas. Simulations conducted in MATLAB demonstrate SSA’s remarkable effectiveness in shaded conditions, leading to increased pump flow rates. However, it’s worth noting that SSA exhibits slower performance in comparison. Nonetheless, SSA outperforms particle swarm optimization and genetic algorithms in locating the optimal power point. In Ref (Shetty et al., 2023) to improve the power extraction from the PV array under partial shading conditions in PV photovoltaic water pumping systems in rural India, a hybrid PSO-INC algorithm is proposed. The results indicate that this approach outperforms the other methods, offering faster convergence, reduced oscillations, lower torque variation, and improved accuracy in power capture. Overall, the hybrid PSO-INC approach proved to be the most effective choice for the IM-based SWPS. In Ref(Solar, 2023), a novel MPSO algorithm is introduced for maximum power extraction from a photovoltaic array, designed to drive an induction motor in irrigation systems. The algorithm demonstrates remarkable accuracy in simulations, achieving up to 99.5% efficiency under partial shading, and yields favorable experimental results with an efficiency range of 98.2% without partial shading and 88.89%–90.84% efficiency under partial shading conditions. System efficiency varies between 73.4% and 81.2% depending on sunlight conditions.

In Ref(Belhachat et al., 2017) to optimize PVWPS, an Adaptive Neuro-Fuzzy Inference System (ANFIS) based MPPT algorithm is studied to track the maximum power point effectively from the PV array. A sensorless control approach using sliding mode and neural networks with fuzzy logic is also studied to regulate motor speed and improve system performance. By using these two improved controls, the reliance on electric batteries is reduced by prioritizing water storage, enhancing overall efficiency.

4.3. An overview of the soft computing-based motor controller for the PVWPS

In the previous section, this review paper did not emphasize the

Table 4
Comparison of soft computing methods based MPPT.

Ref	MPPT Algorithm	Type	Tracking Speed	Efficiency	Cost	Tracking Global MPP	Accuracy	Hardware Implementation	Sensors	Oscillation around MPP
Baramadeh et al. (2021)	FLC	AI	medium	good	high	no	high	complex	V, I	no
Hussain et al. (2023)	ANN	AI	medium	good	high	yes	high	complex	G, T, V, I	no
Kermadi et al. (2015)	PSO	BI	fast	very good	high	yes	high	complex	V, I	no
Technologies , (2023)	ACO	BI	fast	very good	high	yes	high	complex	V, I	no
soufyane Benyoucef et al. (2015)	ABC	BI	fast	very good	high	yes	high	complex	V, I	no
Hadji et al. (2018)	GA	BI	fast	very good	high	yes	high	complex	V, I	no
Kaced et al. (2017)	BA	BI	fast	very good	high	yes	high	complex	V, I	no

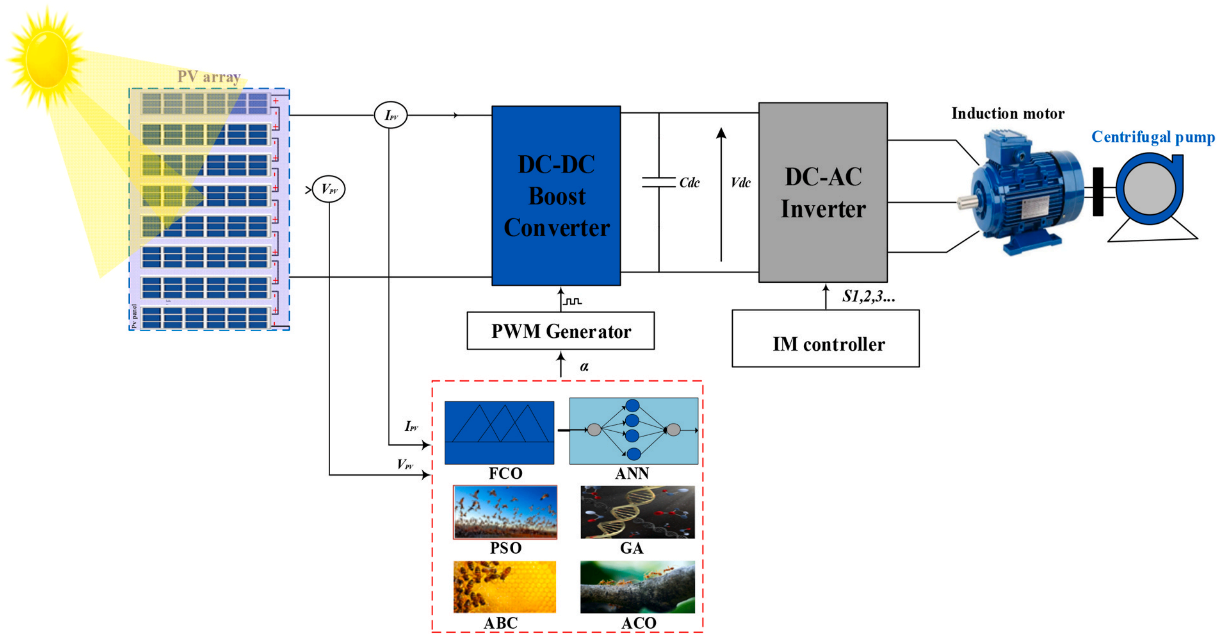

Fig. 10. PV water pumping system schematic with some popular soft computing MPPT control methods.

importance of motor control in PVWPS, which is essential for enhancing the motor's starting performance even under lower solar irradiation levels and for regulating the switching pulses of the Voltage Source Inverter. Hence, various control methods, including Scalar (V/f control), Direct Torque Control, and Vector control, have been examined, each with its own set of advantages, disadvantages, and limitations. However, Direct Torque Control is the most sensorless type of control in relation to parameter variations when compared to other control methods and can provide good dynamic control without the need for mechanical transducers on the machine shaft. Nonetheless, DTC has several drawbacks, including high torque and flux ripples, especially at low speeds. These can lead to unwanted mechanical vibrations and noise, and the absence of direct current can increase harmonic losses. Additionally, the practical implementation of DTC requires a low sampling period, necessitating a high calculation frequency, which can impose constraints on the control architecture (Abdelouhab et al., 2023). Most of the problems in DTC arise from its hysteresis comparators, switching tables, and PID speed controller, which regulate the reference torque. Therefore, the majority of research projects have concentrated on integrating advanced control strategies to address the challenges associated with Direct Torque Control, as depicted in Fig. 11. Among these innovative methods, Artificial Intelligence (AI)-based DTC has garnered significant attention and extensive discussion. AI-based DTC is divided into two categories: AI and BI methods. Particular focus has been placed on AI methods such as Fuzzy Logic Control and Artificial Neural Networks, which have been extensively discussed and researched by many experts in the field(El Ouanjli et al., 2019). Replacing these components with AI techniques, such as fuzzy logic and artificial neural networks, can be an excellent solution to enhance the dynamic performance of DTC control, thus improving the performance of the PVWPS, as depicted in Fig. 12. Therefore, this section explains some of the previous works on AI-based DTC. In Ref(Belgacem et al., 2022), fuzzy logic is proposed to replace the

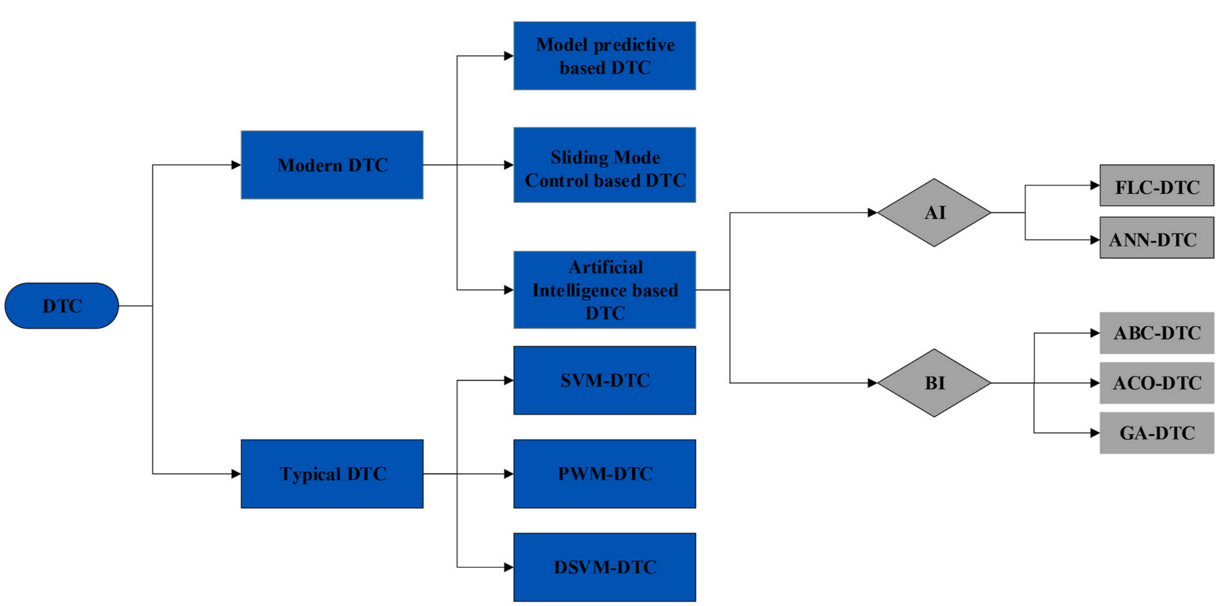

Fig. 11. An overview of direct torque control improvement techniques(El Ouanjli et al., 2019).

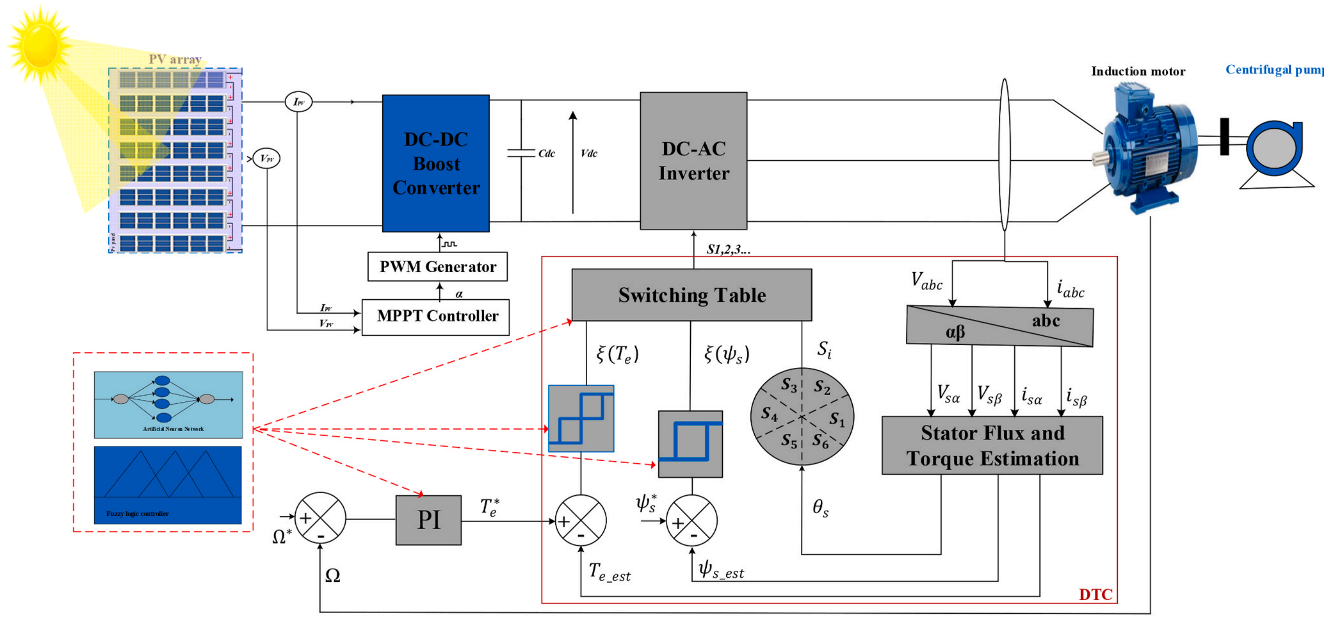

Fig. 12. Diagram of AI-based on DTC control of the induction machine for PV water pumping system.

switching table and hysteresis comparators in the conventional DTC-based induction motor for photovoltaic water pumping systems. The simulation results show a reduction in torque and flux ripple, an improvement in the stator current waveform, and enhanced system performance and robustness compared to traditional systems. In addition to the replacement of the switching table and hysteresis comparators, the authors In Ref (Shankar et al., 2017)replaced the speed controller with a controller based on fuzzy logic which enhanced the speed response, decreased the dependency on parameter change of the induction machine, and provided high robustness of the PVWPS.In Ref (Mahfoud et al., 2021)An Adaptive Neuro-Fuzzy Inference System (ANFIS) based DTC is proposed for driving centrifugal pumps with Induction Motors. It surpasses conventional DTC and DTC with fuzzy logic control in terms of torque, flux, speed, and pump pressure, eliminating overshoot and ripples. ANFIS-DTC offers enhanced control capabilities, simplified design, reduced complexity, and smoother pump pressure output. In Ref(Saady et al., 2023) Artificial Neural Networks-based PVWPS controls are proposed. One ANN-based controller maximizes power extraction from the PV array, optimizing performance under varying sunlight levels. Another ANN-based controller improves Direct Torque Control for the induction motor, addressing issues like ripples, high switching frequency, and low-speed challenges. Simulation and experiments show significant improvements in system performance, including reduced ripples and increased water output.

4.4. Recapitulation and suggestions

The analysis of numerous articles on PV water pumping systems has primarily focused on the integration of two types of soft computing methods: artificial intelligence and bio-inspired methods into the MPPT controller. In contrast, artificial intelligence has been primarily explored to address the disadvantages of DTC in an induction motor within the PV water pumping system, as discussed in the third part. The integration of the artificial intelligence methods has demonstrated their potential to improve the performance of conventional DTC by reducing torque and flux ripple, speed estimation accuracy, and improving inverter switching frequency, However, the ANN and FLC face the challenges when applied to DTC relate to the difficulty of training the network and the possibility of overfitting or unfitting for the ANN and tuning the FLC's parameters can be time-consuming and require specialized knowledge. Therefore, bio-inspired control techniques such as GA, PSO, ABC, and ACO have been employed to find optimal gain values for the speed controller-based DTC of induction motors, as shown in Fig. 13. This results in reduced overshoot in the steady-state response and shorter settling times. To date, there have been no articles in PVWPS that employ bio-inspired methods to regulate motor speed. To provide insight to authors interested in working on these methods in the context of PVWPS, here is some of the previous work on DTC with bio-inspired methods for induction motors and Doubly Fed Induction Motors (DFIM). In Ref (Mahfoud et al., 2021) DTC-based GA is proposed to select PI parameters for a Doubly Fed Induction Motor. This process involves optimizing the PI parameters offline, where several values are tested and the best PI gains are applied online. The validation study in MATLAB/Simulink showed significant improvements in performance, with torque ripples reduced by 64.44% and flux ripples by 50%. In addition, overshoot speed and torque have been reduced by approximately 90% and 86%, respectively. For the same purpose, which enhances Proportional-Integral-Derivative (PID) controllers in the DTC of IM. In Ref(Elgbaily et al., 2022) a comparison is made between genetic algorithms and particle swarm optimization for optimizing the PID controller for Direct Torque Control of a three-phase induction motor. The results showed that PSO-DTC control provided the best results in terms of accuracy and stability, with low fluctuations in output torque. In Ref (Boukhalfa et al., 2019), three hybrid methods (PID-PSO, Fuzzy-PSO, and GA-PSO) were analyzed and compared for improving the speed control loop behavior of dual star induction motor (DSIM) drives. The algorithms are implemented in MATLAB, and the results show that Fuzzy-PSO is the most appropriate approach, reducing torque ripples, improving rise time, and avoiding disturbances that affect drive performance. In Ref (Mahfoud et al., 2022b) Ant Colony Optimization is also proposed for the optimization of PID controller gains in the context of Direct Torque Control for a doubly fed induction motor (DFIM). The proposed ACO-DTC strategy is investigated both theoretically and experimentally using the dSPACE Board DS1104 and MATLAB/Simulink, demonstrating improved system performance in both simulation and experimental results. In Ref (Hannan et al., 2018), an examination of the Artificial Bee Colony Algorithm is conducted to minimize torque and flux ripple in a conventional direct torque control induction motor drive by adjusting the values of K_p and K_i in the speed controller. The use of the ABC-based PI controller maintains a constant speed of the motor despite load torque fluctuations, improving system

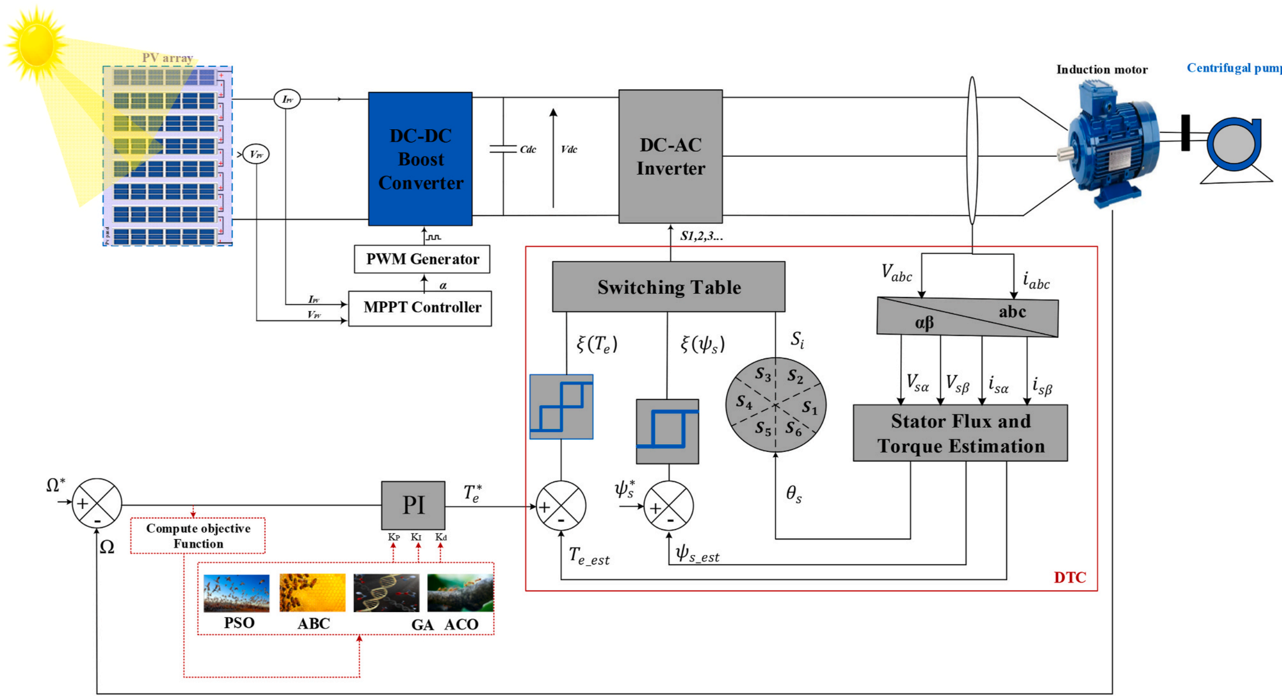

Fig. 13. Diagram of BI-based on DTC control of the induction machine for PV water pumping system.

performance at low speeds.

Table 5 summarizes the control strategies discussed to improve the performance of DTC in terms of torque and flux response, speed response, current THD (Total Harmonic Distortion), complexity, regulation, and improvement.

The results presented in the table show that ANN-DTC and FLC-DTC have made significant improvements in terms of fast torque and flux response, low ripple, and good speed response. However, these methods also come with a higher level of complexity. On the other hand, advanced algorithms such as ACO-DTC, ABC-DTC, GA-DTC, and BA-DTC have demonstrated even greater enhancements over traditional DTC, providing faster torque and flux response, lower ripple, better speed response, lower current distortion, and higher overall performance. This makes them well-suited for high-performance applications, despite their increased complexity.

Building on this comparison, the integration of Bio-Inspired Direct Torque Control (BI-DTC) into photovoltaic water pumping systems offers several notable advantages. BI-DTC merges the robustness and fast dynamic response of traditional DTC with the adaptive and optimization capabilities of bio-inspired algorithms. This fusion enhances system performance, improves efficiency, and allows for better adaptability to varying environmental conditions. Moreover, BI-DTC facilitates real-time optimization of control parameters, leading to more precise and efficient motor control, which is particularly beneficial for the fluctuating power outputs common in PV systems. However, it is important to note that the complexity and computational demands of BI algorithms represent potential drawbacks. Implementing these advanced algorithms requires sophisticated hardware and computational resources, potentially increasing system costs and complexity. Additionally, the extensive tuning and validation needed for BI algorithms can be time-consuming and may necessitate specialized expertise.

5. Conclusion

In conclusion, this comprehensive review highlights the critical role of photovoltaic water pumping systems in addressing water scarcity, particularly in rural areas, by providing a sustainable and cost-effective alternative to traditional methods. The review emphasizes the application of various soft computing methods to enhance two essential controllers within PVWPS: the Maximum Power Point Tracking controller

Table 5
Analysis of soft computing methods for Direct torque control.

Ref	Optimization algorithm	Torque and Flux response	Torque and Flux ripple	Speed response	Current THD	Improvement	Complexity	Regulation
El Ouanjli et al. (2019)	DTC	medium	high	poor	More distortion	low	simple	hysteresis
Saoudi et al. (2021)	FLC-DTC	fast	low	good	Less distortion	medium	very complex	FLC
Saady et al. (2023)	ANN-DTC	fast	low	good	Less distortion	medium	very complex	ANN
Mahfoud et al. (2022b)	ACO-DTC	very fast	very low	very good	Less distortion	high	complex	ACO-PI
Hannan et al. (2018)	ABC-DTC	very fast	very low	very good	Less distortion	high	complex	ABC-PI
Mahfoud et al. (2021)	GA-DTC	very fast	very low	very good	Less distortion	high	complex	GA-PI
Rubio (2023)	BA-DTC	very fast	very low	very good	Less distortion	high	complex	BA-PI

and the induction motor controller.

Soft computing methods for MPPT significantly improve tracking efficiency and convergence, facilitating superior power extraction from photovoltaic panels and enhancing system adaptability to changing environmental conditions. These methods, despite their higher computational demands, offer better tracking speed, efficiency, and accuracy.

For the IM controller, integrating soft computing techniques into direct torque control (DTC) effectively reduces torque and flux ripples and decreases inverter switching frequency. These enhancements improve motor performance and reliability, though the optimal method selection depends on specific application requirements, cost, and hardware availability.

Overall, incorporating soft computing methods into PVWPS controllers results in more efficient, reliable, and adaptable water pumping systems, reinforcing the cost-effectiveness and sustainability of PVWPS. This review serves as a valuable resource for researchers and practitioners interested in applying soft computing methods specifically within PVWPS. Future research should focus on optimizing these methods to manage computational demands and further refine their application in PVWPS to maximize their impact.

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CRediT authorship contribution statement

Ikram Saady: Writing – original draft, Validation, Methodology, Investigation, Data curation. **Btissam Majout:** Writing – review & editing, Validation. **Mohamed Said Adouairi:** Writing – review & editing. **Mohammed Karim:** Validation, Supervision. **Badre Bossoufi:** Writing – review & editing, Validation, Supervision. **Mishari Metab Almalki:** Supervision. **Thamer A.H. Alghamdi:** Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this review paper.

Data availability

No data was used for the research described in the article.

Appendix A

- PV panel Modeling

Fig. 14 presents the equivalent circuit of the photovoltaic (PV) model employed in this paper. This model consists of four primary components: a photocurrent source (I_{ph}), a diode (D), a shunt resistor (R_{sh}), and a series resistor (R_s) (Muhsen et al., 2017).

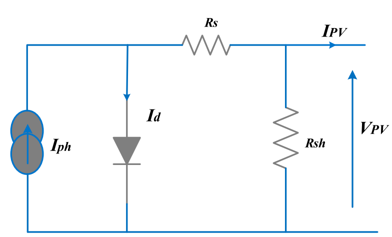

Fig. 14. The equivalent circuits of the PV panel.

The mathematical expressions for the current (I_{PV}) and voltage (V_{PV}) generated by the PV panel are as follows:

$$I_{PV} = I_{ph} - I_s\left(e^{\frac{q(V+R_sI_{PV})}{aKTN_s}} - 1\right) - \frac{(V_{PV}+I_{PV}R_s)}{R_{sh}} \tag{19}$$

$$I_{ph} = \Big(I_{sc} + K_i(T-298.15)\frac{G}{1000} \tag{20}$$

$$I_s = \frac{I_{sc}+K_i(T-298.15)}{e^{\frac{q(V_{oc}+K_v(T-298.15))}{aKTN_s}} - 1} \tag{21}$$

The power output of the PV array is calculated using the following equation:

$$P_{mpp} = n_p \times I_{mpp} \times n_s \times V_{mpp} \tag{22}$$

- **DC-DC Boost converter Modeling**

A DC-DC boost converter, situated between the PV array and the inverter, elevates the input DC voltage (Vpv) to a higher DC voltage (Vdc) based on its duty cycle (α), controlled by the MPPT system(Ramesh, 2018). Fig. 15 illustrates the equivalent circuit of the DC-DC boost converter.

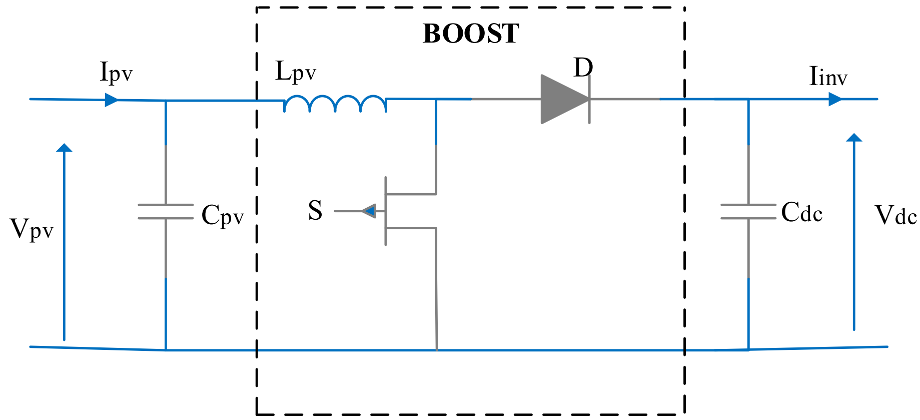

Fig. 15. The boost Converter design.

The parameters of the boost converter, including duty cycle (α), inductor (L_{PV}), and capacitor (C_{dc}), should be determined based on Continuous Conduction Mode (CCM) (Kaced et al., 2017). The equations for these parameters are as follows:

- Duty cycle:

$$\alpha = \frac{V_{dc} - V_{PV}}{V_{dc}} \tag{23}$$

- Inductor (Lpv):

$$L_{PV} = \frac{V_{PV}\,\alpha}{\Delta I f_s} \tag{24}$$

Where: f_s is the switching frequency and $\Delta\ I$ is the current ripple.

- DC Link voltage of the VSI

$$V_{dc} = \frac{2\sqrt{2} \times V_{LL}}{\sqrt{3}} \tag{25}$$

Where V_{LL} is the RMS line voltage of the induction motor.

- DC Link Capacitor of the VSI

The DC bus capacitor is calculated by:

$$C_{dc} = \frac{6\alpha V_{LL} I_L t}{\sqrt{3}\left(V_{dc}^{*2} - V_{dc}^2\right)} \tag{26}$$

Where V_{dc}^* is the reference DC bus voltage, V_{dc} is the measured DC bus voltage, t is the time duration for modifying the DC link voltage, α is the duty cycle, and I_L is the line current of the induction motor.

- **Induction motor Modeling**

The (α-β) frame mathematical model of the induction motor can be denoted by the following equations (Errouha et al., 2020):
The stator and rotor voltages in the α-β reference frame can be expressed as follows:
For the stator:

$$\begin{cases} V_{s\alpha} = R_s I_s + \dfrac{d\varnothing_{s\alpha}}{dt} \\ V_{s\beta} = R_s I_s + \dfrac{d\varnothing_{s\beta}}{dt} \end{cases} \tag{27}$$

For the rotor:

$$\begin{cases} 0 = R_r I_{r\alpha} + \dfrac{d\varnothing_{r\alpha}}{dt} + \omega_m \varnothing_{r\beta} \\ 0 = R_r I_{r\beta} + \dfrac{d\varnothing_{r\beta}}{dt} + \omega_m \varnothing_{r\alpha} \end{cases} \tag{28}$$

The stator and rotor fluxes in the α-β reference frame can be expressed as follows:
For stator

$$\begin{cases} \varnothing_{s\alpha} = L_s I_{s\alpha} + M I_{r\alpha} \\ \varnothing_{s\beta} = L_s I_{s\beta} + M I_{r\beta} \end{cases} \tag{29}$$

For Rotor

$$\begin{cases} \varnothing_{r\alpha} = L_r I_{r\alpha} + M I_{s\alpha} \\ \varnothing_{r\beta} = L_r I_{r\beta} + M I_{s\beta} \end{cases} \tag{30}$$

Where: $I_{s\alpha}$, $I_{s\beta}$, $I_{r\alpha}$,and $I_{r\beta}$ denote the stator and rotor currents in the (α-β) frame respectively. M stands for the mutual inductance, L_s and L_r are the inductances of the stator and rotor, and R_s and R_r are the resistances of the stator and rotor.

The electromagnetic torque in the (α-β) reference frame is expressed as follows:

$$T_e = \frac{3}{2} \times p\left(I_{s\beta}\varnothing_{s\alpha} - I_{s\alpha}\varnothing_{s\beta}\right) \tag{31}$$

- **Centrifugal Pump Modeling**

The centrifugal pump load torque $\left(T_{pump}\right)$ is considered to be proportional to the square of the induction motor rotor speed (Ω) ,as described by Equation (32) (Saady et al., 2023).

$$T_{pump} = K_{pump}\Omega^2 \tag{32}$$

Where K_{pump} represents the constant of the centrifugal pump.

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