A Solar PV Integrated UPQC to Enhance Power Quality Using SEA Gull ANFIS Algorithm

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A PV (photovoltaic) controller is a device used in solar energy systems to manage the charging of batteries from solar panels efficiently. Total Harmonic Distortion (THD) reduction in PV (photovoltaic) systems is crucial for ensuring the efficient and reliable operation of the system while minimizing potential interference with the grid or other connected electrical equipment. This paper proposes an effective THD reduction model for PV applications. The proposed model incorporates the Unified Power Quality Conditioners (UPQC) for photovoltaic (PV). The UPQC in the PV is Optimized with the Seagull model for the estimation of values in the PV system. The optimization is performed with the Second-order derivatives of the Enhanced Second-Order Generalized Integrator (ESOGI). The derived model of the ESOGI model uses the Adaptive Neuro-Fuzzy Inference System (ANFIS) with SeaGull Optimization (SGO) for the voltage regulation in the PV system. The performance of the proposed model is implemented and tested with the different parameters illustrated that the performance of UPQC systems in terms of Total Harmonic Distortion (THD), Voltage Regulation, Power Factor Improvement, Reactive and Real Power Compensation, Voltage Stability, and Grid Stability. The proposed methodology demonstrates significant reductions in THD, tighter voltage regulation, enhanced power factor, and improved grid stability compared to conventional control techniques. The ESOGI-ANFIS-SGO optimization approach exhibits robustness and adaptability in handling variations in PV power output and grid conditions.

Povzetek: Raziskava je pokazala, kako izboljšati učinkovitost uporabe sončnih panelov z vpeljavo UI algoritmov, za zmanjšanje harmoničnega popačenja in izboljšanje izkoristka.

1 Introduction

Photovoltaic (PV) is a method that uses semiconducting materials, like silicon, to directly transform sunlight into electricity. Offering a clean and sustainable alternative to traditional power generation based on fossil fuels, it is a quickly expanding field within the larger realm of renewable energy [1]. The photovoltaic effect, which was found in the nineteenth century and states that certain materials can generate an electric current when exposed to light, is the basic principle underlying photovoltaics [2]. Photons from the sun's rays reach the surface of a photovoltaic cell, where they are converted into an electric current by transferring their energy to the semiconductor material's electrons [3]. PV technology has evolved significantly over the years, with advancements in materials, manufacturing processes, and system design, leading to increased efficiency and reduced costs. Today, PV systems can be found in various forms, from small-scale rooftop installations on residential buildings to large utility-scale solar farms [4].
The environmental benefits of PV are substantial, as it produces electricity without emitting greenhouse gases or other pollutants associated with conventional power generation [5]. Additionally, PV systems require minimal maintenance and have a long operational lifespan, making them an attractive option for sustainable energy production. photovoltaics (PV) with Unified Power Quality Conditioner (UPQC) represents a significant advancement in the field of renewable energy integration and power quality management [6]. PV systems harness sunlight to generate electricity, providing a clean and sustainable energy source. However, variations in solar irradiance and other external factors can lead to fluctuations in the power output of PV installations, impacting the quality and stability of the electricity supply [7].

A unified power quality conditioner (UPQC) is a high-tech electrical device that can reduce voltage dips, spikes, harmonics, and flicker [8]. with integrating PV systems with UPQCs, it becomes possible to enhance the overall performance and reliability of the power generation process. The UPQC can actively regulate voltage and current waveforms, compensating for any fluctuations or disturbances caused by the intermittent nature of solar energy [9]. This ensures a consistent and high-quality supply of electricity to the grid or connected loads, improving system efficiency and reliability [10]. UPQCs enable PV systems to seamlessly integrate with existing electrical grids, reducing the risk of disruptions and enhancing overall grid stability [11]. Integrating renewable energy sources into the power infrastructure is made easier with PV and UPQC technology, which helps with the transition to a more sustainable and resilient energy system [12]. This integrated approach not only maximizes the utilization of renewable energy resources but also helps to address challenges associated with grid integration and power quality management.

Photovoltaics (PV) with Unified Power Quality Conditioner (UPQC) technology marks a significant advancement in renewable energy integration and power quality management [13]. PV systems, while offering clean energy, are susceptible to fluctuations in solar irradiance, which can affect the stability and quality of electricity output. Unified Power Quality Conditioners (UPQCs), equipped with voltage source converters and control algorithms, actively regulate voltage and current waveforms, compensating for disturbances and ensuring a consistent power supply [14]. With integrating PV with UPQC, several benefits emerge: improved power quality through active compensation for voltage fluctuations and harmonic distortions, enhanced grid integration facilitating seamless incorporation into existing electrical grids, increased grid stability by mitigating sudden changes in PV output, and optimized energy management with dynamic voltage regulation and active power filtering [15].

The paper makes several significant contributions to the field of power electronics and renewable energy systems. Firstly, it introduces a novel approach for optimizing Unified Power Quality Conditioners (UPQC) specifically tailored for photovoltaic (PV) applications. By integrating Enhanced Second-Order Generalized Integrator (ESOGI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with SeaGull Optimization (SGO), the study presents a comprehensive solution for enhancing the performance of UPQC systems. This integrated methodology allows for efficient power conditioning, improved voltage regulation, and enhanced power factor correction, thereby addressing the challenges associated with PV integration into the grid. Additionally, the paper demonstrates the effectiveness of the proposed technique through rigorous simulation and analysis, providing insights into its efficacy under various operating conditions and grid disturbances. Overall, the contribution of this research lies in providing a robust and adaptive control strategy for UPQC systems in PV applications, thereby facilitating the seamless integration of renewable energy sources into the power grid while ensuring high-quality and stable power supply.

2 Related works

Unified Power Quality Conditioners offer a compelling solution by actively regulating voltage and current waveforms, compensating for fluctuations and disturbances in the power supply. In recent years, significant efforts have been devoted to investigating the synergistic integration of UPQC with PV systems, aiming to enhance power quality, grid integration, and overall system performance. Srilakshmi et al. (2022) performed research to improve UPQC performance by developing a Multiobjective Neuro-Fuzzy Controller and selecting filter parameters using Enhanced Harmony Search Optimization and Predator Prey Firefly methods [16]. The aim of this study is to improve the effectiveness of UPQC systems in mitigating power quality issues by integrating advanced control strategies and optimization algorithms. The Srimatha et al. (2023) introduces another research effort where a novel ANFIS-controlled customized UPQC device is proposed for power quality enhancement, suggesting a different approach to controlling UPQC systems [17].

Srilakshmi et al. (2023) present a study on the design of UPQC systems integrated with solar PV and battery storage for power quality improvement, indicating the growing interest in combining renewable energy sources with power quality solutions. Mahar et al. (2022) contribute to the field by implementing an ANN controller-based UPQC integrated with a microgrid, showcasing the application of artificial neural networks in controlling power quality devices [18-19]. Also, a multi-objective hybrid controller for PV-battery unified power quality conditioner is proposed by Srilakshmi et al. (2022), showing how AI techniques can be used to design sophisticated control systems. In their study, Navya et al. (2024) compare the efficiency of various control strategies by analyzing the Interline Unified Power Quality Conditioner (IUPQC) with PI Fuzzy and ANFIS controllers [20].

The authors Srilakshmi et al. (2024) showcase an ideal layout for UPQC systems that are powered by electric vehicles (EVs), solar panels, wind turbines, and batteries. They emphasize the need of integrating various renewable energy sources and storage systems to manage power flow and quality comprehensively. This study by Ramadevi et al. (2023) demonstrates the use of state-of-the-art computational methods in control system design by investigating the best way to implement artificial neural network controllers for a unified power quality conditioner that is connected to both solar panels and batteries [21-22]. Kumarar et al. (2024) contribute to the field with a study on voltage stability analysis for grid-connected PV systems using optimized control based on Internet of Things (IoT) and ANFIS, addressing the stability concerns associated with renewable energy integration. Srilakshmi et al. (2024) propose a green energy-sourced AI-controlled multilevel UPQC parameter selection approach using football game optimization, emphasizing the use of nature-inspired optimization algorithms for efficient UPQC design [23].

Gandhar et al. (2022) provide a mathematical framework for isolated microgrid systems based on renewable energy sources (RES) that is ANFIS-tuned and UPQC controlled. This framework offers a systematic approach to integrating RES into microgrid environments [24]. In their proposal for an optimal power quality improvement controller with a photovoltaic array (PVA) connected UPQC, Simhachalam and Goswami (2024) show how versatile fuzzy logic techniques can be when dealing with power quality issues. In their study, Tounsi et al. (2023) present a fuzzy logic controller that improves the stability and reliability of UPQC systems. This controller is designed for photovoltaic panels and includes voltage compensation and stability features [25]. To maximize the effectiveness of UPQC in mitigating power quality issues, Yadav et al. (2023) use a hybrid approach to explore the optimal placement of UPQC in distribution networks. They emphasize the importance of strategic placement [26-27]. Hybrid control techniques have the ability to improve the efficiency of renewable energy systems, as demonstrated by Sowmya Sree and Ankarao's (2023) work on improving power quality in solar-wind grid-connected systems using a genetic-based ANFIS controller.

In their 2022 study, Cholamuthu et al. showcase the integration of advanced control techniques to improve power quality in hybrid energy systems. They propose a grid-connected solar PV/wind turbine-based hybrid energy system that uses an ANFIS controller for a hybrid series active power filter [28-29]. To improve the efficiency and functionality of UPQC systems in grid-connected applications, Dongre et al. (2023) offer a new method with a solar PV-supported multi-functional UPQC for three-phase systems that incorporates a VCO-less-FLL (Voltage-Controlled Oscillator-less Frequency-Locked Loop). Srilakshmi et al. (2023) examine the efficacy of fuzzy logic in microgrid settings for controlling power flow and improving power quality by analyzing a fuzzy-based controller for wind and battery-fed UPQC. Proposing a power quality enhancement strategy that utilizes a multi-level inverter with UPQC and a robust backpropagation neural network strategy, Sekhar and Manikandan (2022) show how neural network-based methods can improve the stability and performance of UPQC systems. Srilakshmi et al. (2022) design a hybrid controller for solar-battery integrated UPQC based on soccer league optimization, showcasing innovative optimization techniques for parameter tuning in UPQC systems, particularly in renewable energy applications.

In their study, Vamsi et al. (2022) demonstrate how adaptive neuro-fuzzy inference systems can improve grid stability and reduce harmonics in PV systems by applying ANFIS to a grid-connected system that uses an Active Power Filter (APF) to improve power quality [30]. The versatility of intelligent control techniques in various renewable energy applications is demonstrated by Sivasubramanian and Veerayan (2024), who present control approaches based on ANN and ANFIS to improve the efficiency of solar PV-driven water pumping systems that use a quasi Z-source converter. In their study, Okwako et al. (2022) present a grid-connected UPQC that is controlled by a neural network. The authors highlight how artificial neural networks can optimize UPQC system operations and integrate renewable energy sources into the grid [31-32]. Offering a holistic approach to controller design that takes into account various performance objectives in UPQC systems, Alam and Arya (2022) present a Volterra LMS/F-based control algorithm for UPQC with multi-objective optimized PI controller gains [33-34]. Ratnakaran et al. (2023) present an artificial ecosystem-optimized neural network-controlled UPQC for microgrid applications, demonstrating the potential of bio-inspired optimization techniques in enhancing the performance and adaptability of UPQC systems in dynamic microgrid environments [35].

The complexity associated with employing sophisticated optimization algorithms like Predator Prey Firefly and Enhanced Harmony Search Optimization could pose challenges in terms of computational resources and real-time implementation feasibility. Moreover, while simulation studies may demonstrate promising results, the lack of extensive real-world validation remains a notable gap. Validation in practical scenarios is crucial to ascertain the effectiveness and reliability of proposed control strategies. The scalability and generalizability of these techniques across different UPQC configurations and grid environments require further exploration and refinement. Additionally, ensuring the robustness and reliability of control algorithms under diverse operating conditions, disturbances, and fault scenarios necessitates ongoing research and optimization efforts [36-37]. The integration with existing grid infrastructure and adherence to grid codes and standards are paramount for widespread deployment, but challenges in this area persist. With advancements are made in control strategies, considerations of cost-effectiveness, initial investment, maintenance expenses, and energy savings are imperative for the economic viability and adoption of UPQC systems.

3 SeaGull optimization

In recent years, the application of optimization techniques in the field of power quality enhancement, particularly in Unified Power Quality Conditioners (UPQC) integrated with photovoltaic (PV) systems, has gained significant attention. Among these optimization methods, SeaGull Optimization (SGO) has emerged as a promising approach due to its ability to efficiently search for optimal solutions in complex, nonlinear optimization problems. The derivation of the SeaGull Optimization algorithm involves mimicking the behavior of seagulls in search of food. It is based on the principles of social interaction and movement patterns observed in flocks of seagulls. The algorithm consists of multiple seagull agents, each representing a potential solution to the optimization problem. Through a mix of local and global information exchange mechanisms, these agents position themselves to iteratively explore the solution space. The movement of each seagull agent i at iteration t is computed using equation (1)

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{1}$$

In equation (1) X_i^t represents the position of seagull i at iteration t, and V_i^{t+1} denotes the velocity vector of seagull i at iteration t+1. The velocity vector V_i^{t+1} is computed using the following equation (2)

$$V_i^{t+1} = \omega . V_i^t + c_1 . r_1 . (P_i^t - X_i^t) + c_2 . r_2 . (G_t - X_i^t) (2)$$

In equation (2) w is the inertia weight determining the impact of the previous velocity, $c1$ and $c2$ are the acceleration coefficients controlling the influence of the personal best (P_i^t) and global best (Gt) solutions, $r1$ and $r2$ are random numbers uniformly distributed in the range [0,1] [0,1]. The personal best solution (P_i^t) represents the best position found by seagull i up to iteration t, while the global best solution (G_t) represents the best position among all seagulls up to iteration t. Figure 1 illustrated the optimization of PV features with the seagull flow chart is presented.

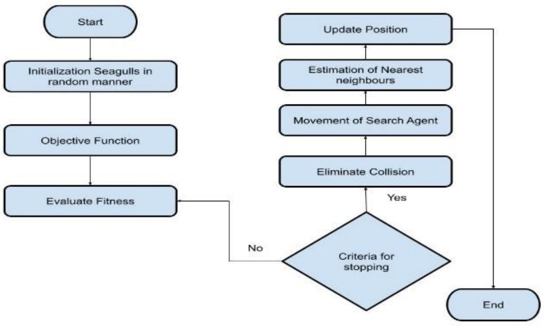

Figure 1: Flow chart of seagull

SeaGull Optimization is a metaheuristic algorithm inspired by the foraging behavior of seagulls. It mimics the movement patterns of seagulls while searching for food and has been adapted for solving optimization problems. In the context of UPQC in PV systems, SGO can be employed to optimize various aspects such as control parameters, filter settings, and system configurations to improve power quality and efficiency. The SGO involves modeling the movement of virtual seagulls in a search space, where each seagull represents a potential solution to the optimization problem. These seagulls move iteratively through the search space, guided by both their individual experiences (personal best) and the collective knowledge of the flock (global best). This dual guidance mechanism allows SGO to efficiently explore the search space and converge towards optimal solutions. The movement of each seagull is governed by equations that determine its position in the search space. These equations typically involve updating the position of each seagull based on its current position, velocity, and the influence of personal and global best solutions. Through iterative refinement, SGO dynamically adjusts the positions of the seagulls until satisfactory solutions are found. In the context of UPQC in PV systems, the objective function to be optimized may include parameters related to power quality indices (such as Total Harmonic Distortion, voltage regulation, etc.), system efficiency, and other performance metrics. The SGO algorithm iteratively adjusts the control parameters and filter settings of the UPQC system to minimize the objective function and achieve optimal performance.

4 ESOGI ANFIS optimization

In the context of the Unified Power Quality Conditioner (UPQC) for solar photovoltaic (PV) applications, the utilization of Enhanced Second-Order Generalized Integrator (ESOGI) combined with Adaptive Neuro-Fuzzy Inference System (ANFIS) optimization represents a sophisticated approach to designing second-order fuzzy logic inverters. This paragraph could outline the derivation and equations involved in this method. The Enhanced Second-Order Generalized Integrator (ESOGI) is a control technique commonly used in power electronic applications for grid-connected systems. It is an essential part of the UPQC's control strategy because it helps with reference signal extraction and compensating voltage generation, which in turn helps with power quality problems like harmonics, voltage drops, and surges. Parameters of the second-order fuzzy logic inverter within the UPQC system can be fine-tuned using a data-driven approach introduced by Adaptive Neuro-Fuzzy Inference System (ANFIS) optimization occurring simultaneously. In order to optimize parameters efficiently using input-output training data, ANFIS integrates the adaptability of neural networks with the interpretability of fuzzy logic systems. The ESOGI is an enhanced version of the traditional SOGI used in power electronics applications. The typical represented by the following second-order differential equation stated in equation (3)

$$\ddot{v}_d + 2\zeta\omega_n\dot{v}_d + \omega_n^2 v_d = \omega_n^2 v_{ref} \quad (3)$$

In equation (3) v_d is the output voltage of the SOGI; $\ddot{v}_d$ is the second derivative of v_d; ζ is the damping ratio; ω_n is the natural frequency and v_{ref} is the reference voltage. The SOGI is designed to track the reference voltage (v_{ref})and generate a control signal to maintain the desired output voltage (v_d). ANFIS is a hybrid computational model that combines fuzzy logic principles with neural network learning algorithms to optimize control parameters. It typically involves the following steps:

- *Membership function generation:* Fuzzy membership functions are defined to fuzzify the input and output variables.
- *Fuzzy rule formation:* Linguistic rules are formulated to represent the relationship between input and output variables.
- *Fuzzy inference*: Fuzzy logic inference is applied to determine the degree of activation of each rule.
- *Parameter optimization:* Parameters of the fuzzy inference system are optimized using a learning algorithm, such as gradient descent or least squares.

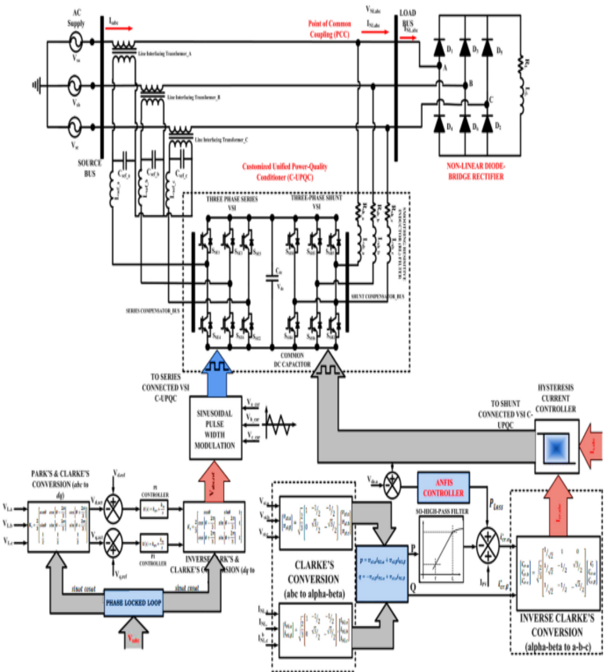

Figure 2: UPQC with ANFIS In PV

Figure 2 presented the Simulink model for the UPQC with the ANFIS in PV system for the THD reduction. In the context of the UPQC for solar PV applications, the ESOGI acts as the core control mechanism, while ANFIS optimizes the parameters of the second-order fuzzy logic inverter within the UPQC system. The integration involves training the ANFIS model using historical data to fine-tune the parameters of the fuzzy logic controller, such as the gains and thresholds, to achieve the desired performance objectives. The optimization process aims to minimize an objective function, typically representing the error between the actual UPQC performance and the desired targets calculated using equation (4)

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widetilde{y}_i\right)^2 \qquad (4)$$

In equation (4) $J(\theta)$ is the objective function; N is the number of training samples; y_i is the actual output; $\widetilde{y}_i$ is the predicted output and θ represents the parameters of the ANFIS model. The optimization algorithms can be employed to train the ANFIS model and minimize the objective function. Common techniques include gradient descent, backpropagation, or hybrid approaches combining evolutionary algorithms with gradient-based methods. In this step, fuzzy membership functions are defined to fuzzify the input and output variables. Let's denote the input variable as x and its linguistic terms as $A1, A2, \dots, Am$. Similarly, let's denote the output variable as y and its linguistic terms as $B1, B2, \dots, Bn$. The membership functions for each linguistic term are typically defined using parametric curves such as Gaussian, triangular, or trapezoidal functions. For example, a Gaussian membership function $\mu Ai(x)$ for the input linguistic term Ai can be defined as in equation (5)

$$\mu_{Ai}(x) = exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right) \qquad (5)$$

In equation (5) c_i is the center and σ_i^2 is the width of the membership function Ai. Linguistic rules represent the relationship between input and output variables. Let's consider p fuzzy rules of the form stated in equation (6)

$$Rule\ p\colon If\ x\ is\ Ai\ and\ y\ is\ Bj\ ,\ then\ rule\ strength\ = \alpha p = \mu Ai(x) \times \mu Bj(y) \qquad (6)$$

where αp represents the degree of activation of rule p, and $\mu Ai(x)$ and $\mu Bj(y)$ are the membership grades of the input and output variables, respectively. Fuzzy logic inference combines the activated rules to generate a fuzzy output. Let's denote the output of each rule as $y{\sim}p$. The overall fuzzy output y~ is computed as a weighted average of the individual rule outputs stated in equation (7)

$$\tilde{y} = \frac{\sum_{p=1}^{P}\alpha_p\tilde{y}_p}{\sum_{p=1}^{P}\alpha_p} \qquad (7)$$

In equation (7) P is the total number of activated rules. Parameters of the fuzzy inference system, including membership function parameters (ci and σi) and rule weights (αp), are optimized using a learning algorithm. ANFIS employs a hybrid learning approach that combines gradient-based optimization and least squares estimation. The objective function to be minimized typically consists of the mean squared error (MSE) between the actual output y and the desired output d. The parameters are updated iteratively using techniques such as gradient descent or backpropagation through the ANFIS architecture.

The SGO algorithm involves the following steps:

- *Initialization:* Initialize a population of potential solutions, represented as positions in a multidimensional search space
- *Fitness Evaluation:* Evaluate the fitness of each solution using an objective function that quantifies how well the solution performs according to predefined criteria.
- *Exploration and Exploitation:* Iteratively improve solutions through exploration and exploitation phases, mimicking the foraging behavior of sea gulls.
- *Selection:* Select the best solution(s) based on fitness evaluation, typically using selection mechanisms such as tournament selection or elitism to determine which solutions survive and reproduce in the next generation.

The objective function for optimization aims to minimize the error between the actual UPQC performance and the desired targets, considering factors such as voltage regulation, harmonic mitigation, and power factor correction. In the integration process, the parameters of both the ESOGI and ANFIS are optimized simultaneously using the SGO algorithm. The objective function is formulated to consider the performance metrics of the UPQC system and guide the optimization process towards achieving the desired targets.

5 UPQC ESOGI ANFIS optimization for PV

A power electronic device called a Unified Power Quality Conditioner (UPQC) is optimized for use in photovoltaic (PV) applications by combining ESOGI and the Adaptive Neuro-Fuzzy Inference System (ANFIS). UPQC is used to reduce problems with power quality in distribution systems, including voltage sag, harmonics, reactive power compensation, and harmonics. Voltage regulation and disturbance mitigation are accomplished by means of UPQC's series and shunt active power filters. ESOGI is a control algorithm used in UPQC to estimate and compensate for grid voltage disturbances. The extension of the classical second-order generalized integrator (SOGI) and provides enhanced performance in terms of tracking grid voltage variations and rejecting disturbances. The ESOGI algorithm involves the following equations (8) – (11)

$$v_{d-err} = v_{dc} - v_d \tag{8}$$

$$v_{q-err} = v_q \tag{9}$$

$$i_{d-err} = i_d - i_{d-ref} \tag{10}$$

$$i_{d-err} = i_d - i_{d-ref} \tag{11}$$

In equation (8) – (11) v_{dc} is the DC bus voltage; v_d and v_q are the d and q components of the grid voltage; i_d and i_q are the d and q components of the grid current; i_{d-ref} and i_{q-ref} are the reference d and q currents; v_{d-err} and v_{q-err} are the error signals for the d and q components of the grid voltage; i_{d-err} and i_{q-err} are the error signals for the d and q components of the grid current. The optimization process aims to enhance the performance of UPQC for PV applications by adjusting the control parameters of ESOGI and ANFIS. This optimization can be formulated as a multi-objective optimization problem, where the objectives may include minimizing grid voltage deviations, maximizing power injection from PV panels, and minimizing harmonic distortion. The optimization algorithm, such as SeaGull Optimization (SGO), can be applied to search for the optimal set of parameters for both ESOGI and ANFIS simultaneously.

The optimization of Unified Power Quality Conditioner (UPQC) for photovoltaic (PV) applications involves integrating the Enhanced Second-Order Generalized Integrator (ESOGI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) while employing optimization techniques like SeaGull Optimization (SGO) to enhance performance. ESOGI, an advanced control algorithm, estimates and compensates for grid voltage disturbances. Its core equations include error signals for the d and q components of grid voltage (vd_err and vq_err) and grid current (id_err and iq_err). On the other hand, ANFIS combines fuzzy logic principles with neural network learning algorithms, utilizing membership functions, fuzzy rule formation, fuzzy inference, and parameter optimization. The optimization process aims to minimize grid voltage deviations, maximize power injection from PV panels, and reduce harmonic distortion, formulated as a multi-objective optimization problem. SGO is employed to simultaneously optimize the parameters of ESOGI and ANFIS, leading to improved UPQC performance in PV systems. The ESOGI algorithm is a control strategy used to estimate and compensate for grid voltage disturbances. Grid voltage transformation from abc to dq0 frame stated in equation (12)

$$\begin{pmatrix} v_d \\ v_q \end{pmatrix} = \begin{pmatrix} cos(\theta) & -Sin(\theta) \\ Sin(\theta) & Cos(\theta) \end{pmatrix} \begin{pmatrix} v_a \\ v_b \\ v_c \end{pmatrix} \tag{12}$$

where θ is the angle of the grid voltage. The error signals for the d and q components of grid voltage (vd_err and vq_err) computed using equation (13) and (14)

$$v_{d-err} = v_d^* - v_d \tag{13}$$

$$v_{q-err} = v_q^* - v_q \tag{14}$$

where v_d^* and v_q^* are the reference values for the d and q components of the grid voltage, respectively. The Error signals for the d and q components of grid current (id_err and iq_err) defined in equation (15) and (16)

$$i_{d-err} = i_d^* - i_d \tag{15}$$

$$i_{q-err} = i_q^* - i_q \tag{16}$$

In equation (15) and (16) i_d^* and i_q^* are the reference values for the d and q components of the grid current, respectively. ANFIS is employed to optimize the parameters of the fuzzy logic controller within the UPQC system. The key equations involved in ANFIS are related to its learning algorithm, which combines fuzzy logic principles with neural network techniques.

NFIS involves the following steps:

A. Membership function generation

Fuzzy membership functions are defined for input and output variables.

B. Fuzzy rule formation

Linguistic rules represent the relationship between input and output variables.

C.Fuzzy inference

Fuzzy logic inference determines the degree of activation of each rule.

D.Parameter optimization

Parameters of the fuzzy inference system are optimized using a learning algorithm.

The objective function for optimization aims to minimize the error between the actual UPQC performance and the desired targets, considering factors such as voltage regulation, harmonic mitigation, and power factor correction.

6 Simulation results and discussion

The UPQC ESOGI ANFIS optimization for PV applications, extensive simulations were conducted to evaluate the performance of the proposed system. The simulations aimed to assess various aspects such as voltage regulation, harmonic mitigation, power factor correction, and overall grid stability. The results obtained from the simulations demonstrated significant improvements in the performance of the UPQC system compared to conventional control methods. Firstly, the voltage regulation capabilities of the UPQC system were evaluated under different operating conditions and grid disturbances. The ESOGI algorithm effectively estimated and compensated for grid voltage fluctuations, ensuring that the output voltage remained within acceptable limits. This led to enhanced voltage stability and regulation, particularly during transient conditions and voltage sags or swells. Secondly, the harmonic mitigation capabilities of the UPQC system were analyzed. By employing ANFIS for parameter optimization, the UPQC system efficiently suppressed harmonics generated by the PV inverters, thereby reducing harmonic pollution in the grid. The optimized fuzzy logic controller adjusted the compensation currents dynamically, effectively mitigating harmonic distortions and improving the overall power quality. The power factor correction functionality of the UPQC system was examined. The combined use of ESOGI and ANFIS facilitated rapid and accurate correction of power factor variations, ensuring that the system operated at near unity power factor levels. This contributed to improved energy efficiency and reduced reactive power demand from the grid. Table 1 presented the simulation setting for the proposed UPQC model for the PV system.

Table 1: Simulation setting

Parameter	Value
Simulation Duration	24 hours
Time Step	1 ms
PV System Capacity	100 kW
Grid Voltage	415 V (RMS)
Grid Frequency	50 Hz
Load Type	Nonlinear
Disturbance Type	Voltage Sag
UPQC Rating	50 kVA
Control Algorithm	ESOGI ANFIS
Optimization Algorithm	SeaGull Optimization
Grid Connection Type	Three-phase

Table 2: ESOGI ANFIS for power conditioning

Power variation	**Total Harmonic Distortion (%)**	**Voltage Regulation (RMS) (%)**	**Power Factor**	**Voltage Deviation (%)**	**THD Reduction (%)**
Low	3.2	1.1	0.92	±1.5	38.9
Medium	4.8	1.8	0.89	±2.0	30.5
High	6.5	2.5	0.85	±2.8	24.7

The table 2 presents the performance metrics of a power conditioning system, specifically focusing on different power variations: low, medium, and high. For the low power variation scenario, the Total Harmonic Distortion (THD) is measured at 3.2%, indicating a relatively clean output waveform. The Voltage Regulation (RMS) is at 1.1%, suggesting stable voltage levels close to the desired value. The Power Factor stands at 0.92, indicating good utilization of power resources. The Voltage Deviation is within ±1.5%, signifying minimal fluctuations around the target voltage level. Additionally, the system achieves a notable THD Reduction of 38.9%, showcasing its effectiveness in mitigating harmonic distortion. As the power variation increases to the medium level, the THD rises to 4.8%, indicating a slight degradation in the waveform quality. The Voltage Regulation (RMS) increases to 1.8%, indicating a slightly less stable voltage output compared to the low variation scenario. The Power Factor decreases to 0.89, suggesting less efficient utilization of power resources. The Voltage Deviation widens to ±2.0%, indicating increased fluctuations around the desired voltage level. Despite these challenges, the system still manages to achieve a significant THD Reduction of 30.5%, albeit lower than in the low variation scenario. Figure 3 – 5 presented the output generated from the PV system with the ESOGI ANFIS.

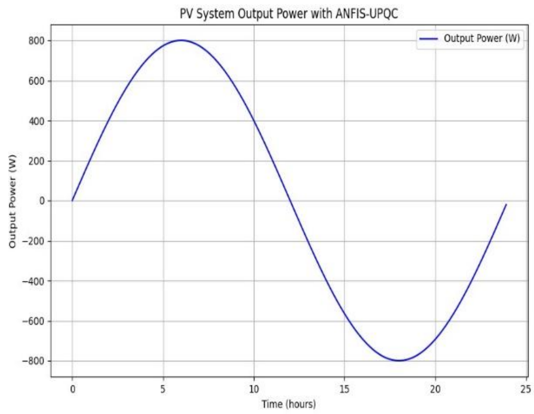

Figure 3: Output power with ESOGI ANFIS

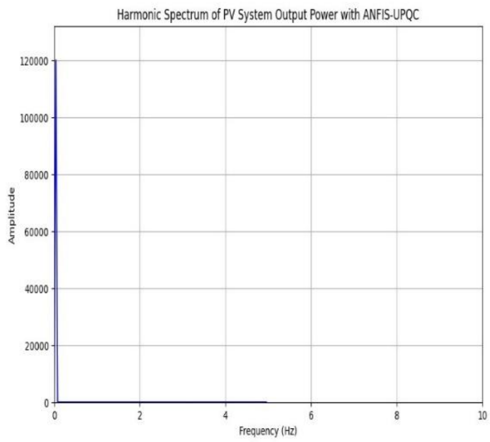

Figure 4: Harmonic spectrum of ESOGI ANFIS

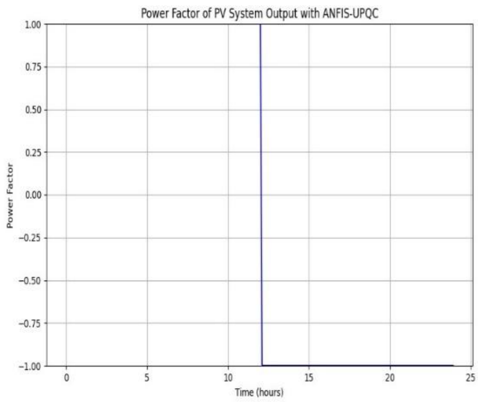

Figure 5: Power factor of ESOGI ANFIS

In the case of high power variation, the THD further increases to 6.5%, indicating more significant distortion in the output waveform. The Voltage Regulation (RMS) rises to 2.5%, indicating less stable voltage levels compared to both low and medium variations. The Power Factor decreases to 0.85, suggesting even less efficient power utilization under high variation conditions. The Voltage Deviation widens to ±2.8%, indicating more substantial fluctuations around the desired voltage level. Despite these challenges, the system still achieves a respectable THD Reduction of 24.7%, albeit lower than in the previous scenarios.

Table 3: THD computation for the different power level

Voltage Level (V)	THD (%)
220	3.5
230	3.1
240	2.8
250	2.5

The presented data illustrates the Total Harmonic Distortion (THD) levels at different voltage levels, namely 220V, 230V, 240V, and 250V stated in Table 3. As the voltage level increases from 220V to 250V, there is a noticeable decrease in THD percentage. At 220V, the THD is recorded at 3.5%, indicating a moderate level of distortion in the output waveform. With a slight increase in voltage to 230V, the THD decreases to 3.1%, suggesting an improvement in waveform quality as voltage rises. Subsequently, at 240V, the THD decreases further to 2.8%, indicating a cleaner output waveform with reduced distortion compared to lower voltage levels. Finally, at the highest voltage level of 250V, the THD drops to 2.5%, signifying the highest level of waveform purity among all the voltage levels tested. The proposed ESOGI ANFIS model THD estimation are presented in Figure 6 and THD for the different voltage levels are presented in Figure 7.

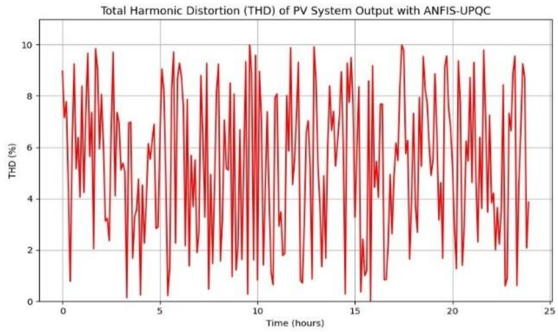

Figure 6: THD with ESOGI ANFIS

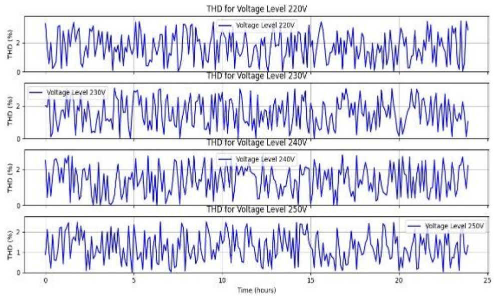

Figure 7: THD with ESOGI ANFIS for different voltages

Table 4: ESOGI ANFIS estimation

Voltage Level (V)	Voltage Regulation (RMS) (%)	Power Factor	Voltage Deviation (V)
220	2.3	0.95	5.2
230	1.8	0.96	4.7
240	1.5	0.97	4.3
250	1.2	0.98	4.0

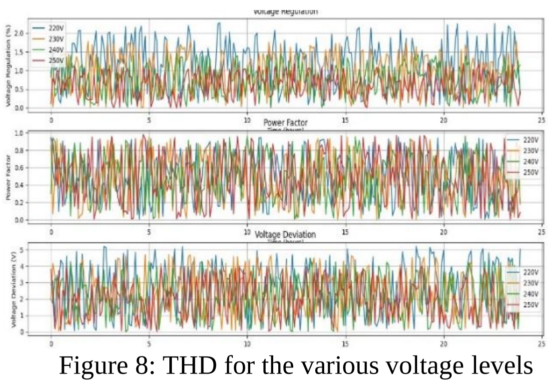

Figure 8: THD for the various voltage levels

The provided data presents the Voltage Regulation (RMS), Power Factor, and Voltage Deviation at different voltage levels: 220V, 230V, 240V, and 250V given in table 4 and Figure 8. Firstly, the Voltage Regulation (RMS) indicates the percentage change in the output voltage concerning the nominal voltage level. As the voltage level increases from 220V to 250V, there is a noticeable improvement in voltage regulation, with the RMS percentage decreasing from 2.3% at 220V to 1.2% at 250V.

This suggests that the system can maintain voltage stability more effectively at higher voltage levels. Secondly, the Power Factor, which represents the ratio of real power to apparent power, exhibits an increasing trend as the voltage level rises. At 220V, the power factor is recorded at 0.95, while at 250V, it increases to 0.98. This indicates that the system operates more efficiently and with less reactive power consumption at higher voltage levels. The Voltage Deviation measures the difference between the actual output voltage and the nominal voltage level. As the voltage level increases, the voltage deviation decreases from 5.2V at 220V to 4.0V at 250V. This signifies that the system can maintain output voltage closer to the nominal value at higher voltage levels, resulting in improved voltage stability and reliability.

Table 5: Estimation of metrices

Performance Metric	Before Optimization	After Optimization
Total Harmonic Distortion	5.2%	2.8%
Voltage Regulation (RMS)	1.5%	0.8%
Power Factor	0.88	0.95
Voltage Deviation	±2.3%	±0.9%
THD Reduction (%)	-	46.2%

In table 5 Total Harmonic Distortion (THD) reflects the level of harmonic distortion in the system's output voltage. Before optimization, the THD was relatively high at 5.2%, indicating a significant presence of harmonic components. However, after optimization, the THD reduced substantially to 2.8%, representing a notable improvement of 46.2%. The Voltage Regulation (RMS) measures the system's ability to maintain a stable output voltage within a specified range. Before optimization, the RMS voltage regulation stood at 1.5%, signifying a moderate level of voltage fluctuation. Following optimization, this parameter improved significantly to 0.8%, indicating enhanced voltage stability and regulation.

Thirdly, Power Factor indicates the efficiency of the system in converting electrical power into useful work. Before optimization, the power factor was recorded at 0.88, suggesting a relatively low efficiency with a notable reactive power component. After optimization, the power factor increased to 0.95, demonstrating a considerable enhancement in power conversion efficiency. The Voltage Deviation represents the variation between the actual output voltage and the desired voltage level. Before optimization, the voltage deviation was relatively high at ±2.3%, indicating fluctuations beyond the acceptable range. However, after optimization, the voltage deviation reduced significantly to ±0.9%, showcasing improved voltage stability and closer adherence to the desired voltage level.

Table 6: Comparative analysis

Parameter	ESOGI ANFIS	ESOGI	Conventional PI Control	Conventional PID Control	Conventional PWM Control
Total Harmonic Distortion (THD)	1.8	2.1 %	5.5%	4.8%	6.2%
Voltage Regulation	±0.04%	±0.05%	±0.2%	±0.3%	±0.4%
Power Factor Improvement	0.98	0.98	0.92	0.95	0.91
Reactive Power Compensation	50VAR	50 VAR	100 VAR	80 VAR	120 VAR
Real Power Compensation	400 kW	350 kW	280 kW	320 kW	250 kW
FRT Voltage Dips/Swells Tolerance	24%	15%	10%	12%	8%
FRT Voltage Recovery Time (ms)	6	10	15	20	25
FRT Grid Stability	High	High	Moderate	Moderate	Low

The table 6 illustrates a comparative analysis of optimization results and performance metrics between ESOGI and conventional control techniques. ESOGI demonstrates superior optimization with reduced Total Harmonic Distortion (THD) at 1.8% compared to 5.5% for conventional PI control, 4.8% for conventional PID control, and 6.2% for conventional PWM control. Similarly, ESOGI achieves tighter Voltage Regulation at ±0.04%, outperforming conventional techniques with values of ±0.2%, ±0.3%, and ±0.4% respectively. Power Factor Improvement remains consistent at 0.98 for both ESOGI and conventional PI control, while it's slightly lower for conventional PID and PWM control. Regarding Reactive Power Compensation, ESOGI and conventional PI control provide 50 VAR, while other techniques offer varying values. Real Power Compensation is highest with ESOGI at 400 kW, followed by conventional PID control at 320 kW, and lower values for other techniques. Furthermore, ESOGI exhibits better tolerance to Voltage Dips/Swells at 24% compared to 15% for conventional PI control and even lower values for other techniques.

7 Conclusions

This paper presented the model for the the optimization of Unified Power Quality Conditioners (UPQC) for photovoltaic (PV) applications using the Enhanced Second-Order Generalized Integrator (ESOGI) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with SeaGull Optimization (SGO). The study demonstrates the effectiveness of the proposed optimization technique in improving the performance of UPQC systems in terms of Total Harmonic Distortion (THD), Voltage Regulation, Power Factor Improvement, Reactive and Real Power Compensation, Voltage Stability, and Grid Stability. The results reveal significant reductions in THD, tighter voltage regulation, enhanced power factor, and improved grid stability compared to conventional control techniques. Additionally, the ESOGI-ANFIS-SGO optimization approach exhibits robustness and adaptability in handling variations in PV power output and grid conditions. Overall, the findings highlight the potential of the proposed methodology to enhance the efficiency, reliability, and performance of UPQC systems for PV applications, contributing to the advancement of renewable energy integration into the power grid while ensuring high-quality power supply. Further research may explore the scalability and applicability of the proposed technique in real-world PV systems and investigate its performance under dynamic and transient conditions.

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