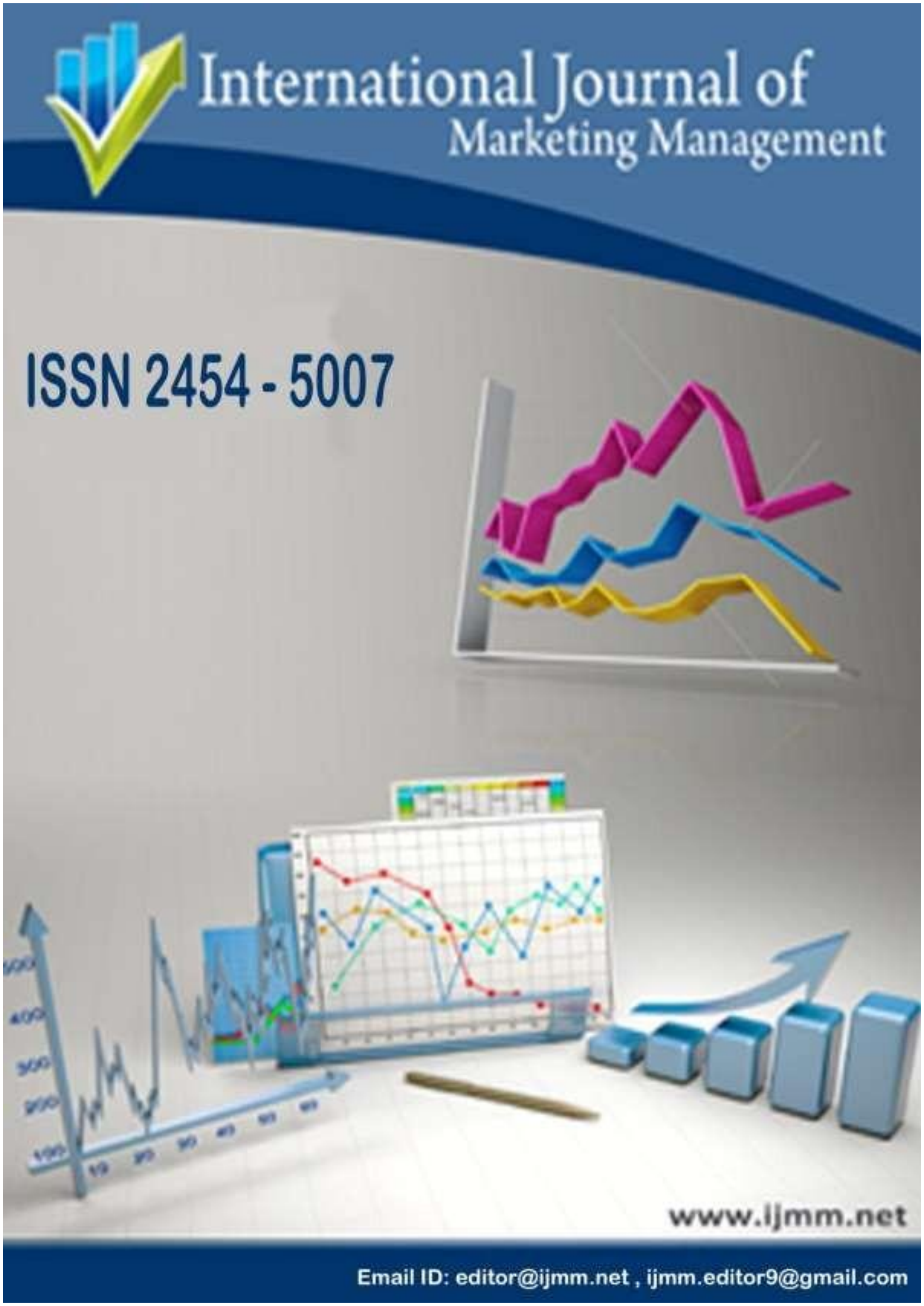
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Machine Learning for Optimizing PV/Wind Smart Grids Using an Improved Spider Wasp Optimizer Algorithm for Learning in Order to Reach SDG7

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Abstract—

In 2015, the Sustainable Development Goals were established by the United Nations to guide nations in their pursuit of a future free of environmental degradation. The seventh Sustainable Development Goal is to provide universal access to affordable, reliable, clean, and sustainable energy. To meet everyday needs in light of changing energy sources, it is important to modernize power systems. The incorporation of smart grids into the power system simplifies complex energy networks. Smart grids and converter autonomy are two additional benefits of integrating Distributed Generation (DG) with RESs like wind and photovoltaic (PV) systems. Nevertheless, smart grids still have difficulties with frequency fluctuations due to generation and load imbalances, as well as fault breakouts. While most studies have focused on steady-state models employing machine learning (ML), this study intends to examine robust performance optimization and talk about future ML applications that might aid with dynamic behavior during fault breakouts. A smart grid power system model is developed in this study to aid in the achievement of SDG7. The main improvement is the way the gains are adjusted using meta-heuristic optimization procedures. This research takes into account the operating system's constraints and uses machine learning based on the enhanced spider wasp optimizer (SWO). We ran the simulations in MATLAB. The system's use of SWO led to good outcomes. Subjects—intelligent grid, optimization, green power, AI, errors

I. INTRODUCTION

Smart grids are a lynchpin in the renewable energy integration puzzle. More efficient integration of renewable energy sources on a large scale is possible; advanced monitoring and consumption systems allow for real-time tracking of energy production and consumption; and demand-based modifications to energy distribution are also possible. Also, smart grids are linked to energy storage technologies like batteries and ESFs to counteract the volatility of renewable power. Energy distribution is optimized and energy use efficiency is advanced by the smart grid, which also makes it possible for consumers to participate and self-manage their energy. Renewable energy may be used in a sustainable way. In addition, it promotes the development of a low-carbon economy and energy transition. Renewable energy sources have the potential to provide 90% of the world's power by 2050, according to IRENA's forecasts [1]. Microgrids may be powered by either direct current (dc) or both. The ability of microgrids to interface with the grid even while operating in an isolated state is one of its most appealing qualities. Having the ability to switch to island mode is really useful in the event that the power grid goes down. Whether a microgrid is ac or dc depends on the specifics of the situation. But dc microgrids are drawing a lot of interest from researchers because they are free from power quality problems, have fewer power conversion steps, and have reduced conversion losses. It is critical to upgrade the power systems in order to meet everyday needs in light of the changing energy sources. When microgrids are integrated into the power system, complicated energy networks become much easier to manage. Furthermore, Distributed Generation (DG) is integrated with Renewable Energy Sources (RESs) such as wind and photovoltaic (PV) systems to provide converter autonomy. Nevertheless, microgrid systems still face challenges like as frequency fluctuations induced by generation and load mismatches and fault breakouts. This study intends to examine future applications of AI to assist with transient behavior during fault breakouts and examine robust performance improvement, whereas most academics focus on employing AI in steady state models. A significant challenge is the microgrid's

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internal controls. Power converters, energy storage devices like batteries and supercapacitors, and voltage regulation are all within the purview of separate control systems in a microgrid system. A hybrid smart grid system's backup mechanism is shown in Fig. 1.

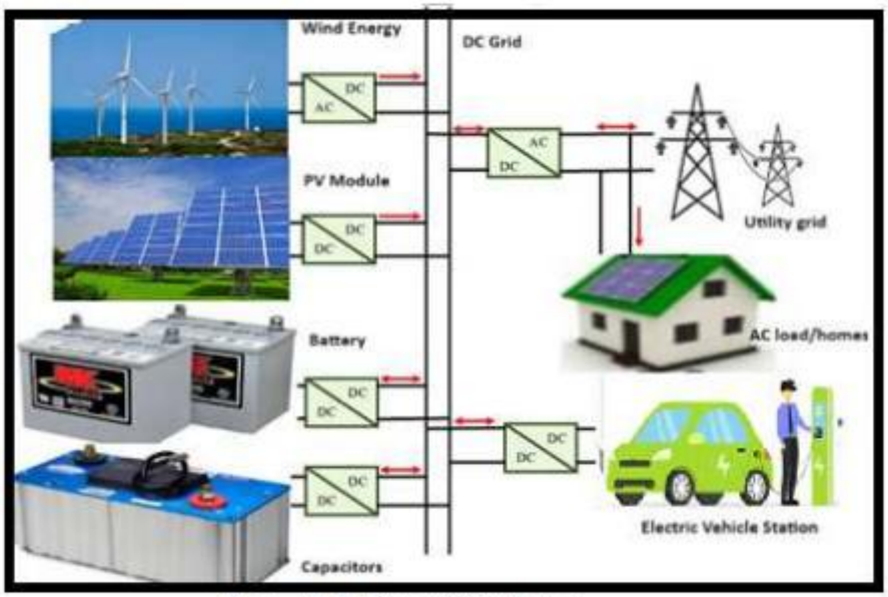

Fig. 1. Hybrid Smart Grid System

Future applications of artificial intelligence metaheuristic optimization algorithms in PV/Wind smart grids during fault outbreaks are discussed in this research, which intends to maximize resilient performance utilizing spider wasp optimizer.

II. METAHEURISTIC OPTIMIZATION IN HYBRID MICROGRID STUDIES: A CRITICAL REVIEW

Numerous taxonomies of metaheuristic algorithms may be found in the literature. One may argue that most of these algorithms draw inspiration from the social behavior and hunting strategies of wild animals, even if they do really belong to different groups. In this part, we will examine metaheuristic algorithms that draw inspiration from nature and fundamental algorithms that have been proposed to address optimization issues. Holland developed the first and most popular method for solving optimization problems in 1992 with the Genetic Algorithm (GA), which was inspired by Darwinian evolutionary concepts. Many improved and recombination variations have described this process, thus it must be one of the successful ones. Most optimization problems involving two mutation and recombination operators have made heavy use of it [2]. In 2001, Geem et al. introduced the Harmony Search (HS) algorithm, which was derived from artists' pursuit of the ideal state of harmony [3]. The initial version of this technique was presented for many optimization problems, and its simplicity was the major reason it was used thereafter. What follows is an explanation of the new metaheuristic algorithms that are based on principles found in nature. The truss structure was examined using a new HS technique for discrete optimization [4]. While the algorithm retains its harmony memory and screw adjustment functions, it uses neighborhood search and the universal best particle swarm search in place of the HS algorithm for the randomization functions. This is the new improvisation method used in the recombined HS algorithm. The HS method was tested on six optimization problems involving truss structures, each with its own unique set of loading conditions. The HS algorithm outperforms competing optimization methods in most cases, both in terms of convergence capability and optimum solution. Quickly converges and provides an optimal mix of exploration and exploitation, the HS algorithm outperforms other methods [5]. With little structural analysis required, it outperforms competing approaches in almost all design samples. In 1995, particle swarm optimization (PSO) [6] was first described, drawing inspiration from the swarming behavior of many creatures. Swarm intelligence, a fascinating field of research, emerged from PSO's subsequent climb to popularity. Computing, design, and planning are just a few of the many optimization domains that have benefited from its use. The ABC algorithm, first developed by Karaboga in 2005 and inspired by beehive behavior, is based on the concept

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of collective intelligence. The ABC algorithm mimics worker, observer, and scout bees using mathematical formulae at each stage. This method, like many metaheuristics, had certain bugs; nevertheless, subsequent versions included fixes and enhanced functionality. In 2008, Yang revealed an algorithm that was influenced by the luminance of fireflies [8]. This algorithm was created to compare the brightness of each firefly to that of other fireflies; fireflies with lower light levels would gravitate toward fireflies with greater light levels. The algorithm was updated since, of course, there are times when fireflies fly randomly.

Animals, insects, birds, aquatic creatures, and plants all exhibit swarm behaviors in nature, which may be used as a model for developing swarm-based metaheuristic algorithms. "Particle swarm optimization," "ant colony optimization," and "artificial bee colony" are all acronyms for the same thing. When designing PSO, scientists looked into how fish and birds travel in schools and how they obtain food. It is the ability of the ant colony to find the quickest route from the food source to the nest that gives ACO its name. A model of the hierarchical behaviors of honeybees in the colony to obtain food sources is ABC [9]. The swarm-based method known as Grey Wolf Optimization (GWO) attempts to simulate the hierarchical hunting techniques used by gray wolves. Four Algorithms for Reproduction: Penicillium (PRA), Dandelion (DA), Pelican (POA), and African Vultures
Other swarm-based algorithms include the AVOA Optimization Algorithm [10].

III. SUGGESTED METAHEURISTIC OPTIMIZATION AGLORITHM

A. Spider Wasp Optimizer:SWO

In this study, we look at a new optimization technique that takes into account the hunting and nesting behaviors and mandatory brood parasitism of certain wasp species—a strategy that involves laying one egg in the abdomen of every spider. Our proposed algorithm, SWO, was initially based on a behavior seen in female spider wasps as they scour their environment for appropriate spiders, paralyze them, and then bring them to nests that were already prepared. Once they find a nest with food and a spider, they pull the spider inside, then place an egg on its abdomen and close the nest. The proposed approach (SWO) randomly distributes a certain number of female wasps over the search space. Their hunting activities, which include both hunting and following, dictate that each spider will continually scan the search area for a mate that is compatible with its own sex. All hymenopterans have a haplodiploid sex-determination machinery that does this. After finding appropriate spiders, feeding them within their web hub, and searching the ground six times for any spiders that have fallen from the web, the female spider wasps will emerge from their nest [11]. As a next step, the female wasps will launch an assault on their victim in an effort to paralyze it and then bring it to their newly built nest. After that, she closes the nest and puts an egg in the spider's belly. Here is a quick rundown of the wasp behaviors that were investigated in this paper: To choose the optimal spider for the larval development, this behavior searches for prey at the beginning of optimization. When they find prey or spiders, they may exhibit following or evasive behavior, such as attempting to escape the hub's orb. The queen wasp paralyzes and drags the best one along as she pursues them. • The goal of nesting behavior is to imitate the process of bringing food to a nest that is large enough to accommodate it and the egg. • Mating behavior: this takes cues from the traits of the offspring produced by hatching eggs by employing the uniform crossover operator between the sexes with a certain probability known as the crossover rate (CR).

B. Generating the initial population

For the proposed approach, each female spider-wasp stands in for a solution from the current generation, which may be represented in the D-dimension vector using the formulas given in (1):

$$\vec{sw} = \left[x_1, x_2, x_3, \ldots, x_D\right] \tag{1}$$

In equation (2), with the lower beginning parameter limit L → and the higher initial parameter bound H →, a set of N vectors may be generated at random.

$$sw_{Pop} = \begin{bmatrix} sw_{1,1} & sw_{1,2} & sw_{1,D} \\ sw_{2,1} & sw_{2,2} & sw_{2,D} \\ sw_{N,1} & sw_{N,2} & sw_{N,D} \end{bmatrix} \tag{2}$$

The initial population of spider wasps is denoted by Pop sw. By using (3), it is possible to produce solutions from the search space at random:

$$\vec{sw}_i^{\,t} = \vec{L} + \vec{r} \times \left(\vec{H} - \vec{L}\right) \tag{3}$$

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In this context, i is the population index (where N = 1, 2,...), t is the generation index, and r → is a D-dimensional vector with beginning values randomly chosen between 0 and 1. The next step is to mathematically mimic the spider wasps' behaviors in order to provide a novel metaheuristic approach to optimization challenges. Here are some examples of the behaviors: • Nesting and hunting habits • Conduct during mating

C. Habits related to hunting and nesting

Looking for a spider or other prey to feed their larvae is the first step for the female wasps on their voyage. Because they wander aimlessly around the search area in pursuit of the optimal prey, this phase is also called the exploring or seeking phase. After that, it would chase its victim by running or flying in a ring around it. The encircling and chasing phase is how we describe this time frame. Last but not least, the spider wasp will drag the paralyzed spider inside the prepared nest to deposit an egg on its abdomen. Stage D: Exploration (Searching) At this point, the process mirrors that of a mother wasp looking for the best spiders to feed her young. The mother wasp, as mentioned before, walks steadily while randomly scanning the search area for the spider that would be the greatest fit for her offspring. The behavior is shown in (4), which updates the current location of each female at each generation t with a constant velocity, to mimic the exploratory activity of the wasps.

$$\vec{sw}_i^{\,t+1} = \vec{sw}_i^{\,t} + \mu_1 * \left(\vec{sw}_b^{\,t} - \vec{sw}_b^{\,t}\right) \quad (4$$

In this scenario, the female wasps are positioned second, and the direction of exploration is defined by two randomly selected indices a and b. Then, 1 µ is used to compute the continuous mobility via the present direction using equation (5):

$$\mu_1 = |rn| * r_1 \quad (5)$$

In this case, rn is a normally distributed random number, and r1 is a 0–1 integer. When a female wasp can't see the spider within the orb, she will search the whole area immediately around it. This action prompted the development of a new equation using unique exploration methods; this new algorithm could then explore the regions around the fallen spider with a step size lower than (30). The location of the fallen spider is represented in equations (6) to (8), and the current female wasp is also updated in this equation with a constant motion at each generation based on the position of a randomly picked female wasp from the population. Here is an explanation of these equivalents:

$$\vec{sw}_i^{\,t+1} = \vec{sw}_c^{\,t} + \mu_2 * \left(\vec{L} + \vec{r}_2 * (\vec{H} - \vec{L})\right) \quad (6)$$

$$\mu_2 = B * \cos(2\pi l) \quad (7)$$

$$B = \frac{1}{1+e^{t}} \quad (8)$$

An index c is selected at random from the population, and l is an integer created at random between 1 and -2. The most promising areas can be discovered and the search space may be explored by combining (4) and (8). Finally, in (9) the choice between in (4) and (8) is decided at random to create the future position of the female wasp:

$$\vec{sw}_i^{\,t+1} = \begin{Bmatrix} Eq.(30) & r_3 < r_4 \\ Eq.(31) & otherwise \end{Bmatrix} \quad (9)$$

When r3 and r3 are two random integers between 0 and 1.

IV. RESULTS AND DISCUSSION

With the use of Buck-Boost technology, all three sources were integrated. These microgrid experiments and models were developed using the MATLAB/Simulink platform. The purpose of this research is to examine how microgrid performance is affected by artificial intelligence. Several challenges must be overcome in order to integrate RESs. As seen in Figure 2, the DC input side of the PV-wind hybrid microgrid system is constructed using MATLAB/Simulink. By integrating PSO and GA in a hybrid model, we may improve the model's operational accuracy, which leads to an integrated system with accurate and successful predictive control.

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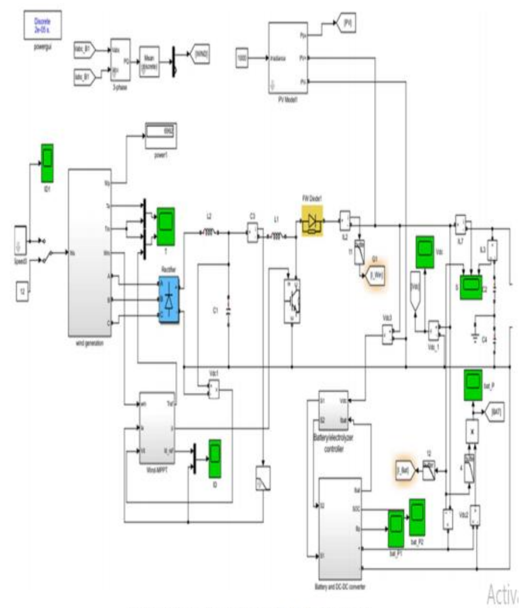

Fig. 2 PV-Wind Hybrid Microgrid System Input DC side in MATLAB/Simulink

Prior to connecting the inverter, the DC side of the hybrid system (Fig. 2), which consists of a PV-wind system, is examined. The model for the high-speed shaft is a damper with inertia. Under typical operating conditions, the DC side of the system examines the output DC voltage Vdc_1, as shown in Fig. 3. In typical settings, the voltage system is enhanced. At t=0.03 seconds, the voltage spikes to

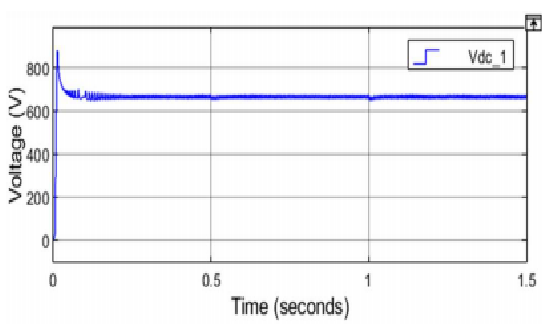

Fig. 3 Output DC voltage Vdc_1 under normal condition

800 V, then decreases to 668 V, but there is overvoltage and no stability. At t=0.1875 seconds, the systems return to normal, and the PV output voltage of 666.6 V becomes steady. The predicted voltage from 22 panels operating at 30.3 V per (30.3 V x 22 panels= 666.6 V) is in agreement with the observed values. The optimization of performance is shown by the combination of high-speed shaft inertia, friction of the high-speed shaft, and the inertia of the generator rotor and gearbox.

In order to stabilize the voltage and allow current to flow into and out of the battery, the charge controller effectively regulated the DC-DC converter. In PQ control mode, when the microgrid is linked to the network, it adjusts the active and reactive output power according on the system's requirements. Figure 4 shows the battery and DC-DC converter. After the first 0.125 seconds, the system becomes more steady, although it remains unstable for the first 0.125 seconds. Once 1.05 seconds have passed, the system stabilizes at 0.5 kW. At its peak, the system delivers 4x10e4 kW of power.

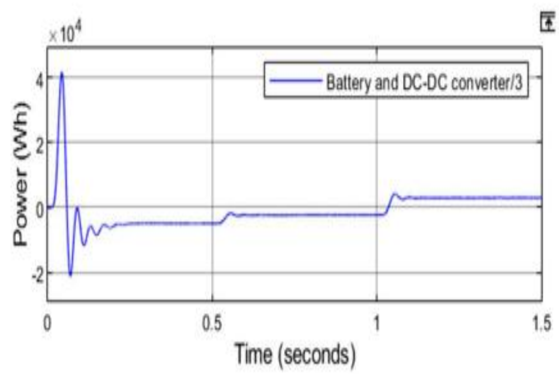

Fig. 4 Equivalent DC phase-to-phase fault circuit

Since integrating a battery is the most cost-effective choice for microgrids, it is essential. This time around, we can see battery scope 4. Pictured in Figure 5 are the system's DC-DC converter and battery P2. For the SOC, you may see percentages. At time zero, the strength of the energy storage system drops from seventy-nine percent to seventy-nine

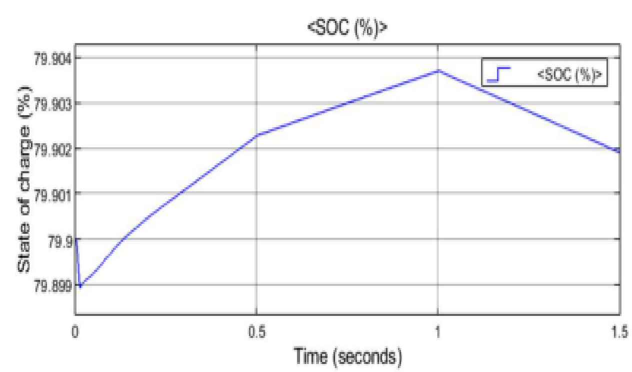

Fig.5 Battery system's DC-DC SOC (%)

point nine percent; at time one, it gradually rises to seventy-nine point four percent. At t=1.5 s, it drops to 79.902%. The power system may be able to run more

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efficiently during peak hours due to the battery's acceptable efficiency and state of charge (%).

From the generation side, Fig. 6 shows the findings of wind-MPPT/1 and wind-generation/Tm during the L-L fault in the simulations. The wind energy production is much different now than it would be

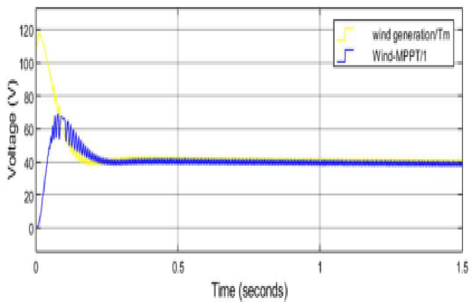

Fig. 6 Wind generation/Tm and wind-MPPT/1

under normal circumstances because of the fault. While the fault was active, the waveform showed a noticeable change in wind MPPT/1 and wind generation. It results in unsteady and imbalanced production. When t=0.625 seconds passes, the wind MPPT/1 reaches 65 kW. There is a precipitous decline from 120 kW, the peak wind generation/Tm, to 40 kW. Both wind-generation/Tm and wind-MPPT/1 are equal at t=0.25 seconds, producing 40 kW of output, and they stay that way.

Figure 7 displays the wind generation achieved by using wind-MPPT/3 and Discrete First Order Filter 1. Connecting a maximum power point tracker (MPPT) to a wind system allows for optimal power harvesting. The wind MPPT/3 determines whether a voltage increase or reduction is necessary to enhance the output power. The boost converter may then

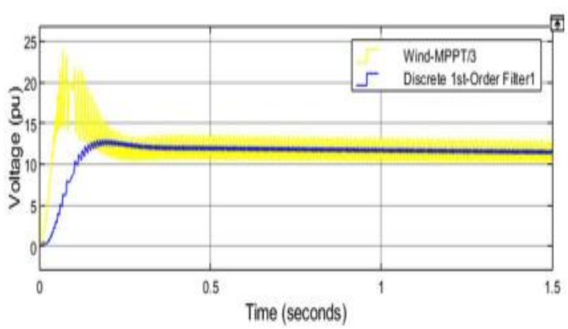

Fig.7 Wind MPPT/3 and Discrete 1st-order Filter1

adjust the voltage based on the duty cycle change it produces, which is a pulse width modulation signal. With its improved and smoother pulse leveling and consistent results leading to direct output, the discrete first-order filter achieves an output of 12 kW. There is a range of 13.5 kW to 10.5 kW for the maximum wind-MPPT/3 power. All of the outputs remain constant beginning at t=0.25 seconds.

As shown in Figure 8, the harmonic analysis of the distorted load current and PCC voltage is shown. The DC/AC MG enters grid-linked mode in the absence of filters in the presence of nonlinear capacitive loading. The load current was discovered to have been significantly distorted due to the influence of the non-linear load in this particular case. With no

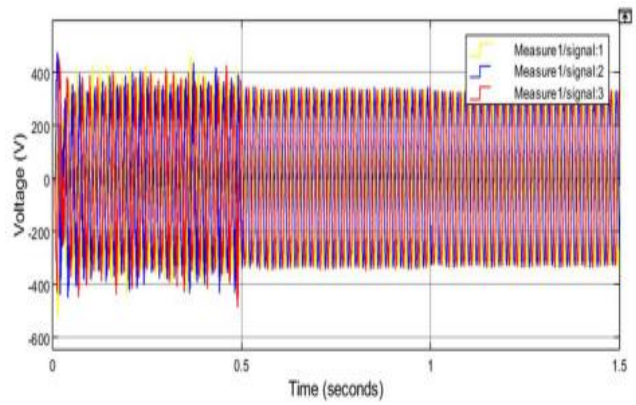

Fig. 8 Harmonic Distortion PCC voltage measure 1

filtering operation, the total harmonic distortion (THD) is 43.39%. ITHD2 has an initial rise of 410 V followed by a dip to about 330 V. The voltage then fluctuates wildly, with several overshoots, between t=0.0135 and t=0.5 seconds, never dropping below 400 V. The system demonstrates stability and improvement between t=0.5 seconds and t=1.5 seconds, since all the measures and signals remain steady and almost identical.

V. CONCLUSION

The suggested SWO-based MPPT controllers' dynamic behavior and whether or not the maximum amount of power is being collected are explored and simulated in the MATLAB/Simulink environment. In terms of power factors and total harmonic distortion (THD), the proposed method greatly enhances the power system. Near t=0.25 seconds, almost all situations in the system are found to be fault-free. It is possible for the system to provide survival and function adequately in the event of a fault breakout. This system regulates power-sharing, frequency, and

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voltage while the device is in island mode and linked to a network. In addition, the controller is supposed to look at both the static and dynamic reactions. The suggested controller has a brief transient working period and can regulate the voltage and frequency of the microgrid with satisfactory performance, according to the simulation findings. So, this controller can govern DG units in a microgrid, considering power-sharing. This result demonstrates that the proposed SWO significantly improved the stability period. Compared to other state-of-the-art algorithms, SWO performed better across a variety of performance metrics. Results from comprehensive statistical analysis and processing of data in real-time have been published. At the 95% confidence interval, the proposed SWO performs much better, as shown by the result statistic.

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