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Optimal Parameter Identification and Extraction of the Solar Module Using Empirical and Quasi-Newton Optimisation Methods.

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Abstract: Parameter identification and extraction of a typical solar module is critical for its effective computation, performance analysis, and optimum power point tracking (OPPT) of the entire photovoltaic (PV) cell working system. The determination or identification of Photovoltaic (PV) model parameters is a tough task mostly when a single or double model is involved. This is due to the nonlinear performance pattern of the current, voltage, and power relationship when in use. Therefore, this paper presents a combination of a laboratory experimental study and an innovative numerical solution approach using the Quasi-Newton method to program and identify the parameters of the single PV model. The peculiar characteristics of the PV cell model panel were studied via the current-voltage (IV) curvatures. For comparative analysis purposes, two more numerical optimization techniques, namely Trust region and Levenberg- Marquardt were also applied to determine the solar cell model parameters in correspondence with three different experimental data acquired in the laboratory. Furthermore, to determine fitting accuracies of the engaged three optimization techniques, three key performance indicators involving the Root Mean Square Error (RMSE), Standard deviation, and Mean Absolute Error (MAE) have been provided. From the results, the proposed Quasi-Newton yields the most preferred fitting performance over the benchmarked Trust region and Levenberg- Marquardt methods by attaining RMSE, MAE, and STD values of 0.00150, 0.00576, and 0.00094 with data 1; 0.00172, 0.00443, and 0.00142 with data 2; 0.00570, 0.00184 and 0.00200 with data 3, respectively. The explored hybrid-based approach can also be extended to identify the double or multi-cell parametric models of the solar cell.

Keywords: Single-diode model, Quasi-Newton optimization method, Parameter identification, Solar PV system

1. Introduction

Energy is an indispensable constituent of the natural environment and thus, without it, there will be no human existence [1]. With the continual rising menace of climate change owing to the frequent and extreme carbonate and gas emissions, several nations of the world are in dear search of clean energy as an alternative to traditional fossil fuels [2]. According to the latest assessment [3], the greenhouse gas emissions effect, plus global warming has pushed renewable energy into a progressively vital component of the ecosphere's energy usage. Though fossil fuels might tentatively possess some capacity to be regenerated over time, still, they face the risk of going into extermination in the nearby future [4]. Today, numerous global issues are directly linked to the frequent use of conventional energy sources. Some of these global issues include insecurity and uncertainties of the recurrent energy supply, unstable energy supply prices, global temperature uprises, and nonrenewable of many carbonates and fossil fuels such as crude oil, coal, and gas. As a result, many countries, and states are now compelled to employ other alternative friendly power resources such as renewable power plants (RPP) [5], than the aforementioned conventional ones [6-8].

One good and sustainable energy source that is gradually serving as a clear alternative to fossil fuels is solar energy due its low environmental impact and cost-competitive factors. While fossil fuels deplete naturally with time, the solar energy source, which is the sun, is most likely to be available and assessable for a couple of decades to come.

RPP can be subdivided into photovoltaic solar (PV), fuel cell, tidal plants, geothermal, wind, and hydropower plants [9]. From the subdivisions, PV solar plants are often regarded as the cleanest electrical power source since they do not lead to greenhouse gases effects [10]. Nevertheless, the poor efficiency of PV system's during electricity generation is one major disadvantage.
Particularly, there exist some vital parameters that regulate and impact the depth of a typical solar cell electrical model. For example, it is important to have a robust understanding of the pattern and performance of current–voltage graph (I-V) connections before the PV cells. The accurate extraction or identification of PV module parameters plays crucial role in precise performance assessment of the solar energy systems.

2. Problem statement

The complications and processes in the parametric extraction of solar PV modules are generally referred to as parameter identification problems. As a result, this key parameter identification problem has been the main focus for several researchers [11-15]. The determination or identification of Photovoltaic (PV) model parameters is particularly a tough task when a single or double model is involved. This is due to nonlinear performance pattern of the current, voltage, and power relationship when in use. Therefore, this paper presents a combination of laboratory experimental studies and innovative numerical solutions using the Quasi-Newton method to identify the model parameters of the single PV cell model. For benchmarking purpose, this paper also provides a thorough analysis of the extracted parameters based on the single solar PV system using other numerical techniques such as the popular Levenberg-Marquardt and Trust region optimization methods solutions

This paper's may contributions are presented as follows:

- The peculiar characteristics of PV cell model panel have been demonstrated experimentally via the current-voltage (I-V) curvatures.
- A robust Quasi-newton algorithm adopted and applied for precise identification of key PV solar cell model parameters
- The capability of the adopted Quasi-Newton model has been established with experimental data in comparison with two standard benchmarking methods, which are Trust Region and Levenberg-Marquardt optimization methods.
- Performance analysis adopted Quasi-Newton model over the two standard benchmarking methods, are demonstrated using at least three indicators.

3. Literature Review

In literature, many metaheuristic methods and algorithms exist that have been engaged by different researchers to identify and determine solar system model parameters, but without achieving the desired success; nevertheless, some of these metaheuristic techniques still yielded nearly local optimal solutions.
In [9, 10], the authors applied deterministic methods involving Interior-point and Lambert W function methods. Though the deterministic method can resolve the parametric identification problem, it however has numerous weaknesses in fronting nonlinear solar cell models that often in turn insensitive initial conditions and poor local optimum convergence solutions [11].
In [12-18], metaheuristics methods involving Simulated Annealing (SA) [12], Artificial Bee Colony (ABC) [13], Genetic Algorithm (GA), [14], Differential Evolution (DE) [15, 16], Particle Swarm Optimization (PSO) [17], and Harmony Search (HS) [18]. nevertheless, some of these metaheuristic techniques still yielded nearly local optimal solutions.
Artificial intelligence tools using fuzzy logic (FL) and neural networks (NN) are presented in [19-22], for solar cell parametric and characteristics analysis, but the main issue with these special tools is their computational complexity and cost of practical implementation. Analytical based method is revealed in [23-25], to cater for similar issues, but generally, analytical method usually lacks computational efficiency since it leads to using more complex equations [26].

4. METHODOLOGY:

The PV Solar Cell Model

There exist multi-cells and single-cell models for determining and identifying the PV solar cell parameters. This paper adopts an extended single diode model (ESDM) with shunt current characteristics. The ESDM is represented by an equivalent circuit with specified operating conditions. Figs 1depicts the prototype structure of the solar cells, with its typical *I-V* characteristic curves

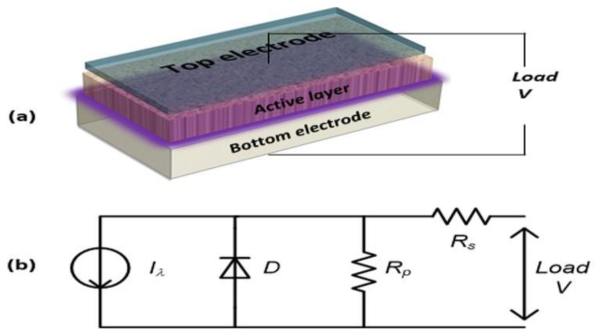

Fig1: depicts the prototype structure of solar cells, with its typical *I-V* characteristic curves

Therefore, the net current of the equivalent circuit so called the output generated current of solar cells can be represented by

$$I = I_\lambda - I_0\left[exp\left(\frac{V+IR_S}{nV_t}\right) - 1\right] - \frac{(V+IR_S)}{R_p} \quad (1)$$

$$I = I_\lambda - I_0\left[exp\left(\frac{V+IR_S}{nV_t}\right) - 1\right] - I_{sh} \quad (2)$$

where,

$$I_{sh} = \frac{(V+IR_S)}{R_p} \quad (3)$$

where n is the ideality factor of the solar cell signifying the charge transport efficiency of the device, I_o is the saturation (generation) current of the diode under dark conditions, V_t is the thermal voltage represented by k_BT/q; K_B is the Boltzmann's constant, T is the temperature in Kelvin, q is the elementary charge and Rs and Rp are the respective series and parallel resistance.

$$I = b_1 - b_2\left[exp\left(\frac{V+I*b_3}{b_4*V_t}\right) - 1\right] - b_5 \quad (4)$$

The foremost goal at this point is how to determine the $\boldsymbol{b} = (b_1, ab_2, b_3, b_4, b_5)$ parameters with optimal accuracy. Thus, this is a core parameter identification problem, and it can be resolved by engaging robust numerical optimization technique.

Parametric Identification of Solar PV cell Model with Quassi-Newton Method

Quasi-Newton Method is a distinctive optimization method that possesses high reliability in solving non-linear programming problem in the least square sense, especially when the standard Newton's method is either too grim to use or rather consumes much time [27, 28].

Given the experimental I-V data points(y_i) of the PV solar cell, the equivalent model parameters of the PV cell model in equation (4) be identified by defining the function, f(x):

$$f(x) = \frac{1}{2}\sum_{i=1}^{n}[y_i - f(x_i, \boldsymbol{b})]^2 \quad (5)$$

$$f(x) = \frac{1}{2}\sum_{i=1}^{n}\boldsymbol{q}(\mathbf{x})^2 \quad (6)$$

where.

$$\boldsymbol{q}(\mathbf{x}) = y_i - f(x_i, \boldsymbol{b}) \quad (7)$$

and

$$\boldsymbol{b} = (b_1, b_2, b_3, b_4, b_5) \quad (8)$$

The gradient of f and the Jacobian of **q** can be expressed as:

$$\nabla \mathrm{f} = J_q^T\boldsymbol{q} \quad (9)$$

$J_q = \frac{\partial f(q_i)}{\partial x_i}$ (10)

By differentiating equation (9) with respect to x, we obtain the Hessian, H of f:

$\nabla^2 f = H = J_q^T J_q + P$ (11)

where,

$P = \sum_{i=1}^{n} q_i \nabla^2 q_i$ (12)

By neglecting the P term and taking the inverse of the equation (11), the Quasi-Newton method is obtained as:

$\nabla^2 f = H \approx (J_q^T J_q)^{-1}$

(13)

Thus, the Quasi-Newton iteration is given by

$\boldsymbol{b}_{t+1} = b_t - \alpha_t H_t \nabla f(b_t)$ (14)

The expression in (13) replaces the direct Hessian constituent in the Newton or Gauss Newton method which could be computationally expensive during application.

The Quasi-Newton update is iteratively generated sequentially until a convergence termination condition is satisfied and improved approximate solutions for $\boldsymbol{b}$ is reached. At every iteration *t* as defined in equation (14), the Quasi-Newton approaches the function $f(b_i)$ and computes the H_i at the point b_i and α_t indicate the learning rate (or step length), that regulates each iteration step size. The Quasi-Newton implementation step is given as:

1. **Input:** b_o guess values, input function, f
2. **Output:** Identified b parametric values, approximate minimizer of input function, f
3. Start by introducing the b_o guess values
   For t=1, 2, …, until convergence **do**
4. Compute $\alpha_t H_t \nabla f(b_t)$,which defines the search direction
5. Determine the appropriate step size α_t
6. Update the current point $\boldsymbol{b}_{t+1} = b_t - \alpha_t H_t \nabla f(b_t)$
7. Examine if convergence criteria are met.
8. Repeat step 2 to 6 if process not optimum

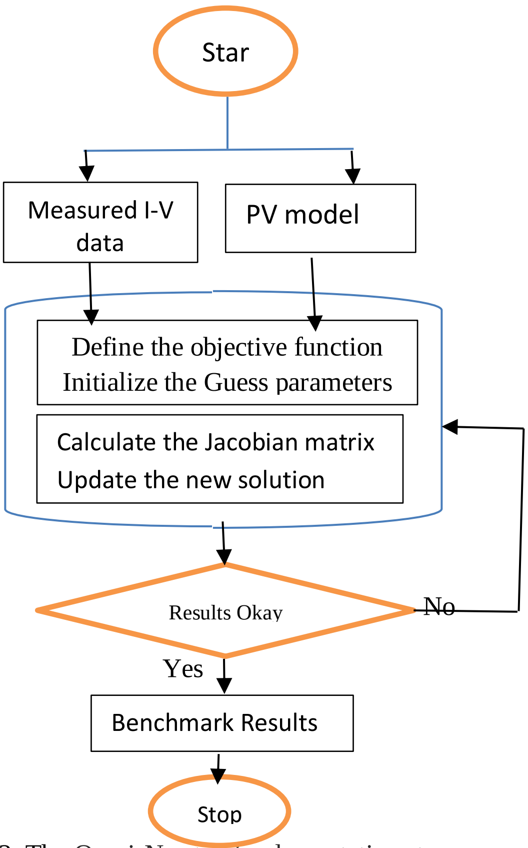

Fig. 2: The Quasi-Newton implementation step

4. Results and Analysis

In this section, the results attained by engaging the Trust region, Levenberg-Mardguardt and Quasi-Newton optimization techniques to solar cell model parameters identification in correspondence with three different experimental data acquired in the laboratory are presented. The codded optimization techniques, their implementation and the resultant graphical presentations were achieved in MATLAB R2018a software platform. To determine fitting accuracies of the engaged three optimization techniques, three key performance indicators involving the Root Mean Square Error (RMSE), Standard deviation and Mean Absolute Error (MAE) [29, 30], are also reported in section.

Shown in Fig.2 – 4 are the current versus voltage plots and the fitting accuracy attained with Quasi-newton in comparison with other techniques after solar cell model parameters. From the results, the Quasi-Newton yields the most preferred fitting performance with RMSE, MAE and STD values of 0.00150, 0.00576, and 0.00094 with data 1; 0.00172, 0.00443, and 0.00142 with data 2; 0.00570, 0.00184 and 0.00200 with data 3. The detailed performance summary of other two methods are presented in table 1 for comparative analysis.

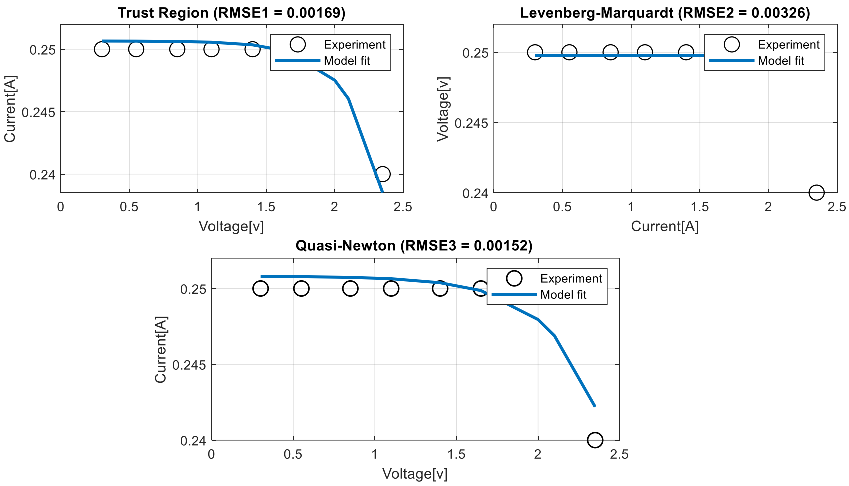

Fig. 3: Fitting accuracy attained with Quasi-newton in comparison with other techniques using Experimental data 1

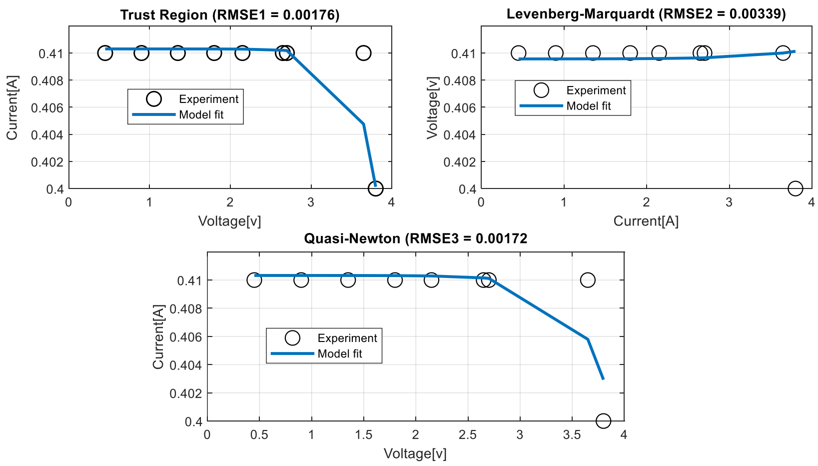

Fig. 4: Fitting accuracy attained with Quasi-newton in comparison with other techniques using Experimental data 2

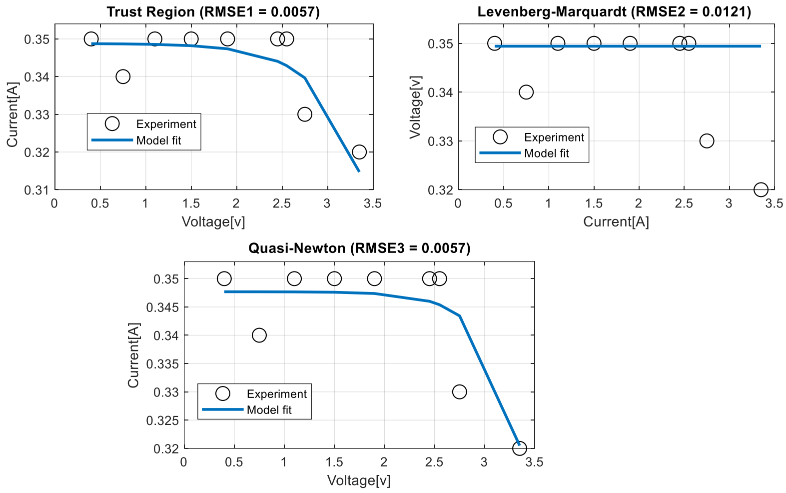

Fig. 5: Fitting accuracy attained with Quasi-newton in comparison with other techniques using Experimental data 1

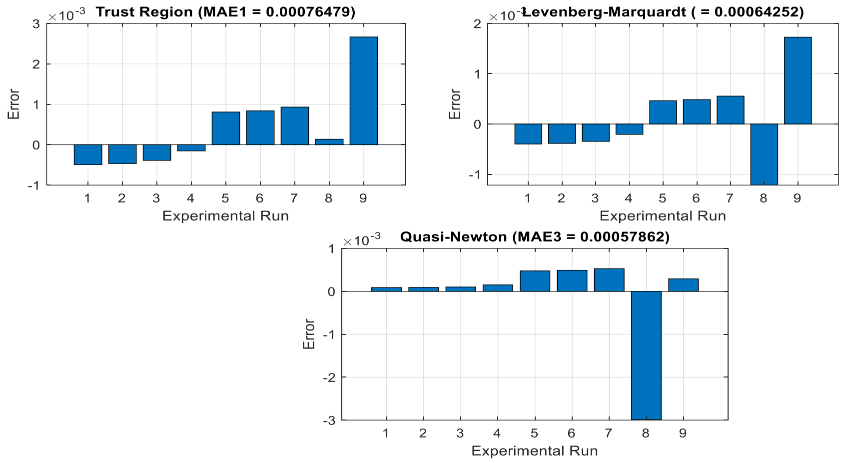

Fig. 6: Residual error spread attained with Quasi-newton in comparison with other techniques during parametric solar cell identification using experimental data 1

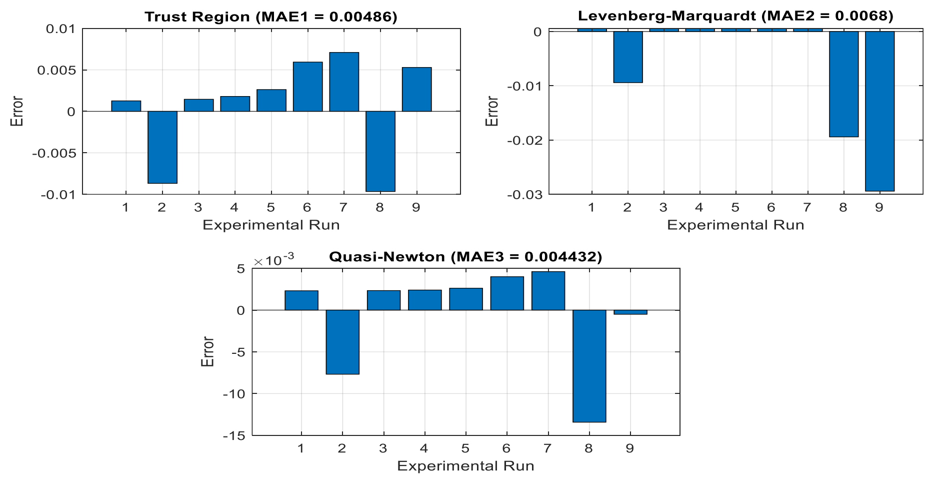

Fig. 8: Residual error spread attained with Quasi-newton in comparison with other techniques during parametric solar cell identification using experimental data 2

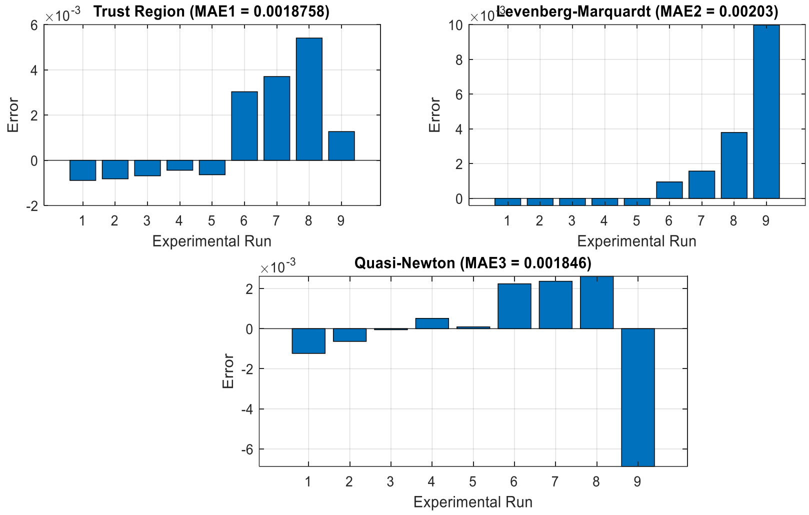

Fig. 8: Residual error spread attained with Quasi-newton in comparison with other techniques during parametric solar cell identification using experimental data 3

Table 1: Summary of Fitting accuracy attained with Quasi-newton in comparison with other techniques

	Indicator	Trust Region	Levenberg-Mardguardt	Quasi-Newton
Experiment data 1	RMSE	0.00169	0.00326	0.00150
	MAE	0.00076	0.00064	0.00057
	STD	0.00117	0.00299	0.00094
Experiment data 2	RMSE	0.00176	0.00339	0.00172
	MAE	0.00486	0.00680	0.00443
	STD	0.00156	0.00307	0.00142
Experiment data 3	RMSE	0.00570	0.00121	0.00570
	MAE	0.00189	0.00203	0.00184
	STD	0.00654	0.00299	0.00200

6. Conclusion

Generally, the electrical solar cell model possesses a number relevant parameters whose values needs precise identification for its PV model systems design and enhancement. The precise application of metaheuristic techniques in identifying the key parameters of solar cell systems remained a better means of contributing hugely to its performance development and upgrading.

Therefore, this paper presents a combination of laboratory experimental study and innovative numerical solutions using the Quasi-Newton to identify the model parameters of the single PV model. The peculiar characteristics of PV cell model panel are studied via the current-voltage (IV) curvatures. For comparative analysis purposes two more numerical optimization techniques, namely Trust region and Levenberg- Marquardt were also applied to determine the solar cell model parameters in correspondence with three different experimental data acquired in the laboratory. Furthermore, to determine fitting accuracies of the engaged three optimization techniques, three key performance indicators involving the Root Mean Square Error (RMSE), Standard deviation and Mean Absolute Error (MAE) have been provided. From the results, the proposed Quasi-Newton yields the most preferred fitting performance with RMSE, MAE, and STD values of 0.00150, 0.00576, and 0.00094 with data 1; 0.00172, 0.00443, and 0.00142 with data 2; 0.00570, 0.00184 and 0.00200 with data 3. The explored hybrid-based approach can also be extended to identify the double or multi-cell parametric models

References

[1]. Isabona, j., Srivastava, V. M. Downlink Massive MIMO Systems: Achievable Sum Rates and Energy Efficiency Perspective for Future 5G Systems. Wireless Pers. Commun. 96(2): 2779-2796 (2017), https://doi.org/10.1007/s11277-017-4324-y

[2]. Joseph Isabona, Viranjay M. Srivastava, "Energy-Efficient Communication in Large Scale Antenna Systems: Impact of Variable User Capacity and Number of Transmission Antennas," *Progress In Electromagnetics Research M*, Vol. 58, 205-213, 2017. doi:10.2528/PIERM17052306

[3]. Rehman, A.; Radulescu, M.; Cismaș, L.M.; Cismaș, C.-M.; Chandio, A.A.; Simoni, S. Renewable Energy, Urbanization, Fossil Fuel Consumption, and Economic Growth Dilemma in Romania: Examining the Short- and Long-Term Impact. *Energies* 2022, *15*, 7180. https://doi.org/10.3390/en15197180

[4]. Guri¸s, B.; Tiftikçigil, B.Y. The Renewable Energy Consumption-Economic Growth Nexus in Turkey. Sos. Bilim. Ara¸stırma Derg.2020, 9, 105–111.

[5]. Breyer C, Khalili S, Rantanen E, Bogdanov D. Solar photovoltaic capacity demand for a fully sustainable transport sector – how to fulfil the Paris agreement by 2050. 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC), 10-15 June 2018, pp. 1632- 1637.

[6]. Tvaronaviˇcien ˙ e, M.; Prakapien˙ e, D.; Garškait˙e-Milvydien˙ e, K.; Prakapas, R.; Nawrot, Ł. Energy Efficiency in the Long Run in the, Selected European Countries. Econ. Sociol. 2018, 11, 245–254.

[7] Joseph Isabona, Wireless Transmission Reliability Study for Large Scale MIMO Systems Under Minimum Mean Square and Zero Forcing Equalization Schemes, Abacus (Mathematics Science Series), Vol. 44, No 1, pp.316-322, Aug. 2019.

[8]. Isabona, J. & Obahiagbon, K., Impact of Linear and Nonlinear Channel Equalization Algorithms on User Achievable Rates and Energy Efficiency on Uplink Large Scale MIMO Techniques for Next Generation Networks, Journal of Scientific and Engineering Research, 2018, 5(6), 97-107, 2018.

[9]. AlRashidi, M.R.; AlHajri, M.F.; El-Naggar, K.M.; Al-Othman, A.K. A new estimation approach for determining the I–V characteristics of solar cells. Sol. Energy 2011, 85, 1543–1550.

[10]. Lun, S.X.; Wang, S.; Yang, G.H.; Guo, T.T. A new explicit double-diode modeling method based on Lambert W-function for photovoltaic arrays. Sol. Energy 2015, 116, 69–82.

[11]. Malki, A.; Mohamed, A.A.; Rashwan, Y.I.; El-Sehiemy, R.A.; Elhosseini, M.A. Parameter Identification of Photovoltaic Cell Model Using Modified Elephant Herding Optimization-Based Algorithms. Appl. Sci. 2021, 11, 11929. https://doi.org/10.3390/app 112411929

[12]. El-Naggar, K.M.; AlRashidi, M.R.; AlHajri, M.F.; Al-Othman, A.K. Simulated annealing algorithm for photovoltaic parameters identification. Sol. Energy 2012, 86, 266–274.

[13]. Oliva, D.; Cuevas, E.; Pajares, G. Parameter identification of solar cells using artificial bee colony optimization. Energy 2014, 72, 93–102.

[14]. Khalik, M.A.; Sherif, M.; Saraya, S.; Areed, F. Parameter identification problem: Real-coded GA approach. Appl. Math. Comput. 2007, 187, 1495–1501.

[15]. Chellaswamy, C.; Ramesh, R. Parameter extraction of solar cell models based on adaptive differential evolution algorithm. Renew. Energy 2016, 97, 823–837.

[16]. Ishaque, K.; Salam, Z.; Mekhilef, S.; Shamsudin, A. Parameter extraction of solar photovoltaic modules using penalty-based differential evolution. Appl. Energy 2012, 99, 297–308.

[17]. A. Dali, A. Bouharchouche and S. Diaf, "Parameter identification of photovoltaic cell/module using genetic algorithm (GA) and particle swarm optimization (PSO)," *2015 3rd International Conference on Control, Engineering & Information Technology (CEIT)*, 2015, pp. 1-6, doi: 10.1109/CEIT.2015.7233137.

[18]. Askarzadeh, A.; Rezazadeh, A. Parameter identification for solar cell models using harmony search-based algorithms. Sol. Energy 2012, 86, 3241–3249.

[19]. Elshatter, T.F., Elhagree, M.E. et al., 1997. Fuzzy Modeling and Simulation of Photovoltaic.

[20]. Almonacid, F., Rus, C., et al., 2009. Characterization of Si-crystalline PV modules by artificial neural networks. Renewable Energy 34, 941–949

[21]. Valerio Lo Brano**,** Giuseppina Ciulla, and Mariavittoria Di Falco, Artificial Neural Networks to Predict the Power Output of a PV Panel, International Journal of Photoenergy, vol. 2014, Article ID 193083, 12 pages, 2014. https://doi.org/10.1155/2014/193083

[22]. Abdulrahman Th. Mohammad et al 2021, Prediction of PV Solar Panel Output Characteristics Using a Multilayer Artificial Neural Network (MLANN) IOP Conf. Ser.: Mater. Sci. Eng. 1105 012013. doi:10.1088/1757-899X/1105/1/012013.

[23]. Bendib B, Belmili H, Krim F. A survey of the most used MPPT methods: conventional and advanced algorithms applied for photovoltaic systems. *Renew Sustain Energy Rev*. 2015; 45: 637- 648.

[24]. Haider Ibrahim, Nader Anani, Evaluation of Analytical Methods for Parameter Extraction of PV modules, Energy Procedia,Vol.1342017, pp. 69-78, https://doi.org/10.1016/j.egypro.2017.09.601.

[25]. U. Jadli, P. Thakur and R. D. Shukla, "A New Parameter Estimation Method of Solar Photovoltaic," in *IEEE Journal of Photovoltaics*, vol. 8, no. 1, pp. 239-247, Jan. 2018, doi: 10.1109/JPHOTOV.2017.2767602.
[26]. Ahmed A. Zaki Diab, Hussien I. Abdul-Ghaffar, Abdelsalam A. Ahmed, Husam A. Ramadan, An effective model parameter estimation of PEMFCs using GWO algorithm and its variants, IET Renewable Power Generation, 10.1049/rpg2.12359, 16, 7, (1380-1400), (2021).
[27]. Haelterman, Rob (2009). "Analytical study of the Least Squares Quasi-Newton method for interaction problems". *PhD Thesis, Ghent University*. Retrieved 2014-08-14.
[28]. Isabona Joseph and D.O. Ojuh. Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains, I.J. Intelligent Systems and Applications, 2021, 3, 35-42, 2021.
[29]. I. Odesanya Joseph Isabona, Jangfa T. zhimwang, and Ikechi Risi, Cascade Forward Neural Networks-based Adaptive Model for Real-time Adaptive Learning of Stochastic Signal Power Datasets, *I. J. Computer Network and Information Security*, 2022, 3, 63-74 (http://www.mecs-press.org/) DOI: 10.5815/ijcnis.2022.03.05.
[30] J. Isabona, (2019), Maximum likelihood Parameter based Estimation for In-depth Prognosis Investigation of Stochastic Electric Field Strength Data, BIU Journal of Basic and Applied Sciences, vol. 4(1): 127 – 136, 2019.