13 Building integrated system to generation DC-power based on renewable energy

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Abstract

This paper builds an integrated system based on different types of hardware (i.e., CPU, GPU, and FPGA) to increase the production of electrical power (DC-power) in less time based on solar plants; That system collects data in real-time and pre-processing it. Then create two embedded intelligence models (i.e., linear and nonlinear); after that implementation, both based on CPU, GPU, and FPGA). The main point of that paper compares the performance of two types of smart micro-grid systems the first is based on linear embedded intelligence (LEI) while the other is based on nonlinear embedded intelligence (NEI) to determine which one is more efficient in a generation the max DC-power in less time. As a result, in both models, the FPGA gives a time of implementation less than CPU and GPU. Also; there is a high correlation between (DC power and AC power), (DC power and irradiation), (DC power, AC power, module temperature, and ambient temperature). NEI model requires preparing multi parameters but their results are best than LEI. Finally, the features more effective in generating max DC-power are AC-power, irradiance, and temperature.

Keywords: FPGA, linear embedded intelligence model, max Dc power, non-linear embedded intelligence model, renewable energy.

Introduction

Renewable energy is a scientific term given to energy that is generated without polluting the environment. It is a type of inexhaustible energy, and it is called renewable energy because it comes from natural sources (wind, sun, water), its advantages renewable energy is available in most countries of the world. Do not pollute the environment, Maintains the general health of living organisms. Economical in many uses, ensuring continued availability and existence. Uncomplicated techniques are used. And it is constantly renewed. In addition to generating electrical energy from nature or sources that are not harmful to the environment, in some countries, such as Iraq the amount of energy they produce is insufficient, which makes them need to import energy from other countries.

On the other hand, some countries produce energy in a greater quantity than they need at certain times and do not use all the produced energy, but at other times energy is not produced with a need for it so in this paper, we will store the excess energy from some times and use it when needed there are several types of renewable energy: solar energy, bioenergy, wind energy hydropower, sustainable biofuel energy geothermal or geothermal energy and tidal energy. Wind energy is generated from wind turbines that are in a large open area. Wind energy is renewable, local energy that does not cause global warming and does not produce polluting gases such as carbon dioxide, nitric oxide or methane, so its harmful impact on the environment is minimal. the cost of wind is relatively high and requires many standards and lands to be used as wind fields that can be used for other purposes such as agriculture, grazing. Hydropower is generated from waterfalls, water rapids, and dams. It is also having limited power and it's relatively expensive. As for solar energy, it is one of the most suitable types of renewable energy in the Arab world due to the emergence of the sun for long periods and at a limited cost. Where solar cells are used, which are photovoltaic converters direct sunlight into electricity, which are semiconducting and light-sensitive devices surrounded by a front and back conductor envelope for electricity, types of the solar cell, crystalline silicon cells.

Proposed system

The proposed system includes three stages; first collection and pre-processing related to collecting the values from the sensors in real-time for both datasets (i.e., solar plant and weather), dropping any record that has missing values then merging both that dataset based on (primary key); the second stage focuses on split the stream of the dataset into multi-interval and remove the duplication. The final stage focuses on building the model from linear and nonlinear and compares both for implementation it with three techniques CPU, GPU, and FPGA. Figure 13.2 shows a block diagram of the proposed system.

A Wireless Sensor Network (WSN) is a network in which nodes are distributed randomly or symmetrically, depending on the requirements, to detect data and perform various actions. WSN is one of the world's largest and most widely utilized networks. Solar energy harvesting is highly common in WSN and is also utilized for energy gathering. In these WSN applications, the wireless sensor node's life cycle and performance, as well as communication channels, are critical. A sensor node is made up of four major components: a sensing unit, a transceiver unit, a processing unit, and a power unit, as well as supplementary application-specific components including a mobilizer, location detecting system, and power generator.

Sensors are one of the IoTs support technology which contains various kinds of device sensing and actuators, sensors help systems to operate in a real-time environment. Sensors are used to collect a huge amount of data which is used as an input to large data applications, therefore sensors technology is considered as an essential tool for computing and analysing data, that functions related to IoT. The analysis of huge data resulting from sensing units is performed by using Data Mining and Machine Learning for building models, specifying patterns, relation creation, and deploying the outcomes for support and make-decision.

The external effects detection on electronic sensors is divided into active and passive sensing. The active sensing will alter in reaction to external effects and generate a change in current or voltage when an excitation signal is used. In passive sensing, there is no response to external effects. Passive temperature sensing is commonly utilized such as thermocouples. Another type of sensor, which is based on electronic circuit systems, is suitable, inexpensive, and simple but it lacks when used to monitor hostile conditions such as oxidizing fluids, high temperatures, or high pressure, and they need a large amount of space.

TA40 and TA60 Sensor

The TA40 and TA60 Series air temperature sensors are effective and out-quality electronic sensors, building to determine ambient air temperature. The enhanced form using great confidence elements produces more active and precise temperature measures, the standard ranges temperature measure is (-30–50°C),. The main features of this sensor

- Microprocessor accuracy.
- Strong signal no wost for 250 m distance.
- Exchanging battery beside no need software modification
- Waterproof, strong installation, semi-conductor component

Pyranometer

A pyranometer is a sensor that converts the global solar radiation it receives into an electrical signal that can be measured. The measurement of the sun's radiation on the earth is referred to as global solar radiation. It refers to direct and diffuse radiation, the direct radiation is the amount of solar energy that reaches to surface directly from the sun above the pyranometer sensor while diffuse radiation is the reach of solar energy horizontally, that sun's light is diffused by the atmosphere, also measured by pyranometer sensor. The main features of this sensor

- Measuring both direct and diffuse radiation.
- Global radiation range (0–1400 W/m^2).

AcuDC240

AcuDC240 is a measurement of DC power, which is used for measuring controlling, getting, and saving data measured in real-time. Used for measuring significant parameters in an effective way such as current, power, energy, and voltage. The main features of this sensor

- Display data in real-time.
- Measures with high accuracy.
- The input range for direct voltage measurement is 0-1000V and for current is 0-±10A.

RCB56A1

RCB56A1 set is for the accuracy measurement: DC, AC, pulse, and irregular wave current in real-time. The main features of this sensor

- Great accuracy, regular linearity
- Wide bandwidth
- Quick reply
- overload ability

Implementation

The integration system contains multi-stages, *first stage* captures data in real-time from multi-sensors. Then merging between solar plant dataset and weather datasets. After that checking the missing values by dropping any record have missing value. *The second stage* called pre-processing includes adding some features

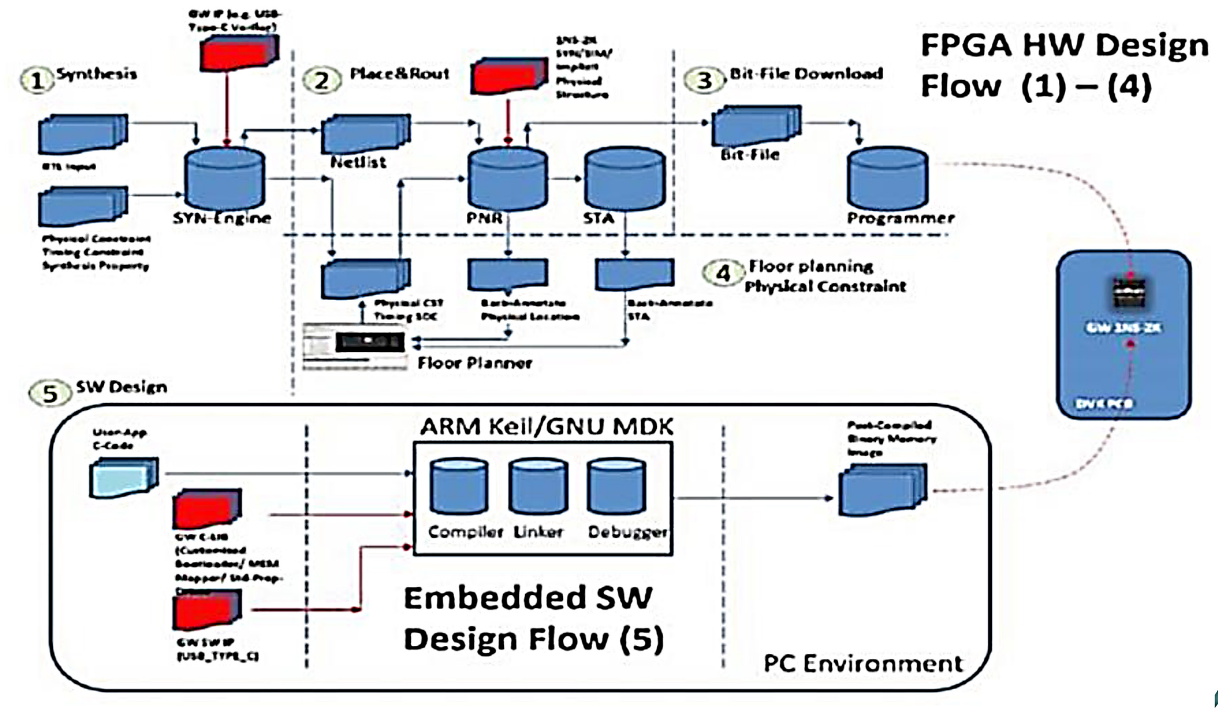


Figure 13.1 Relationship between embedded software models (linea\nonlinear) and FPGA

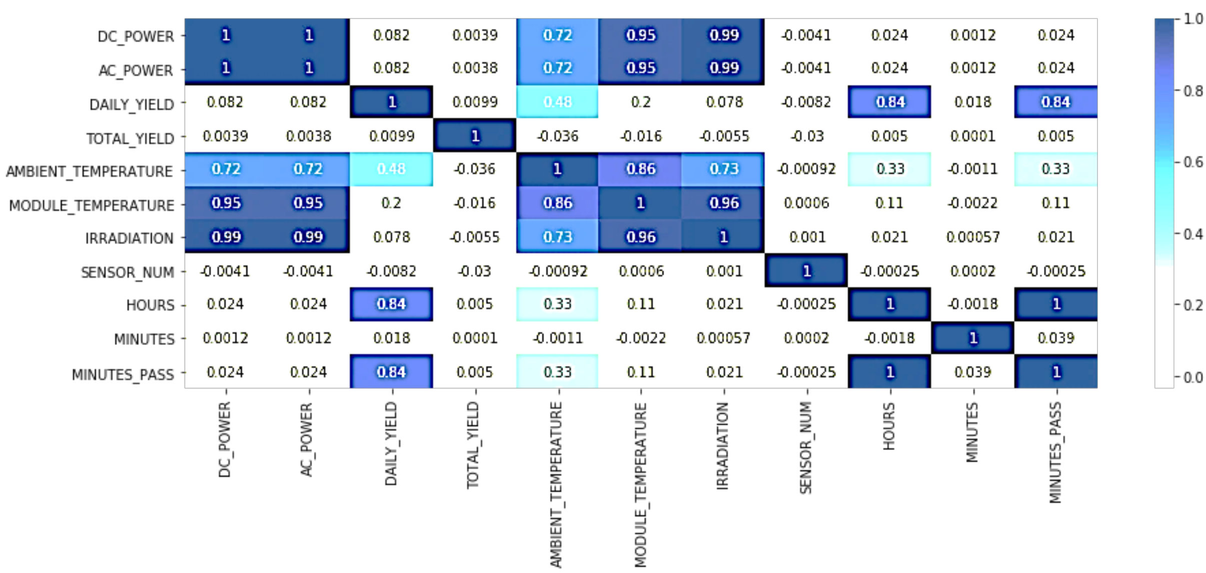


Figure 13.2 Correlation of dataset after merging datasets

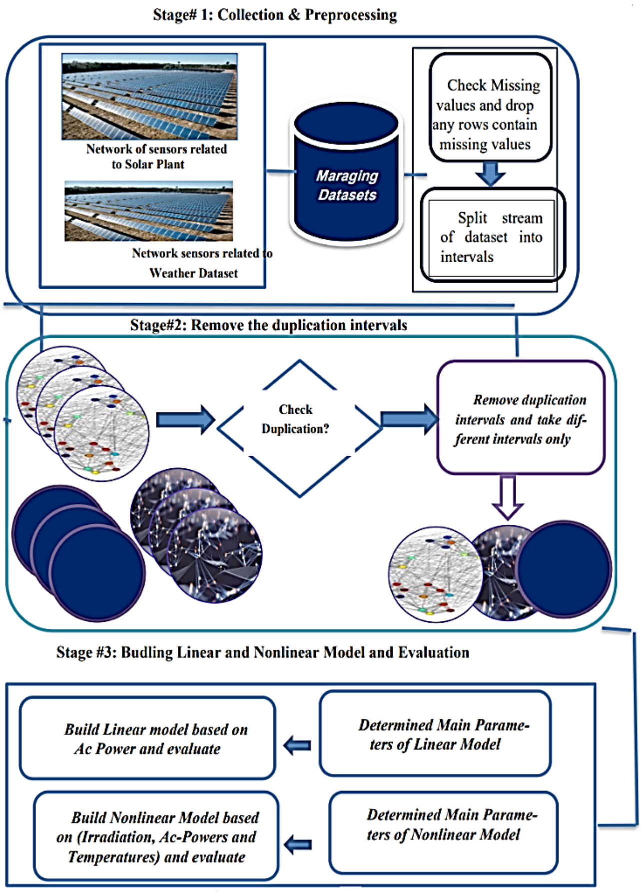


Figure 13.3 Block diagram of proposed system

that are useful in prediction, splitting the dataset into multi-intervals, then removing the duplication interval. Find the correlation among the features as explained in Fig. 3. In the third stage create LEI, and NEI models before that determining the main parameters for each model as shown in Table 13.2. Based on LEI The Relationship between DC-Power and (AC-Power\ Irradiations \Dc-Power) explain in Figures 13.5–13.7 sequentially. While; Fig. 8 shows the Dc-power generation through NEI. The comparison between the two models LEI and NEI is present in Fig. 9.

The final stage includes the implementation of the design models on three different hardwares and compares the execution time for each one as explained in Table 13.3. As a result; we can summarisation the point achieves in that paper as follow:

- Collecting the data from sensors in real-time
- Merging between solar -plant dataset and weather datasets based on two features (i.e. plant-id and date-time).
- Check missing values and drop them if found Delete duplicate intervals, and add some features that are important in prediction.
- building LEI and NEI models and evaluating them based on two points performance and time.

Conclusion

This paper presents an integrated system based on Different types of hardware to evaluation including CPU, GPU, and FPGA to predict the DC-power from the solar plant. The data contains two sets of information about two solar power plants that were acquired over 34 days:

- Power generation data include seven features (i.e., Source-key, Plant-ID, DC-power, AC-power, Yield delay, Total Yielded, Date-Time)

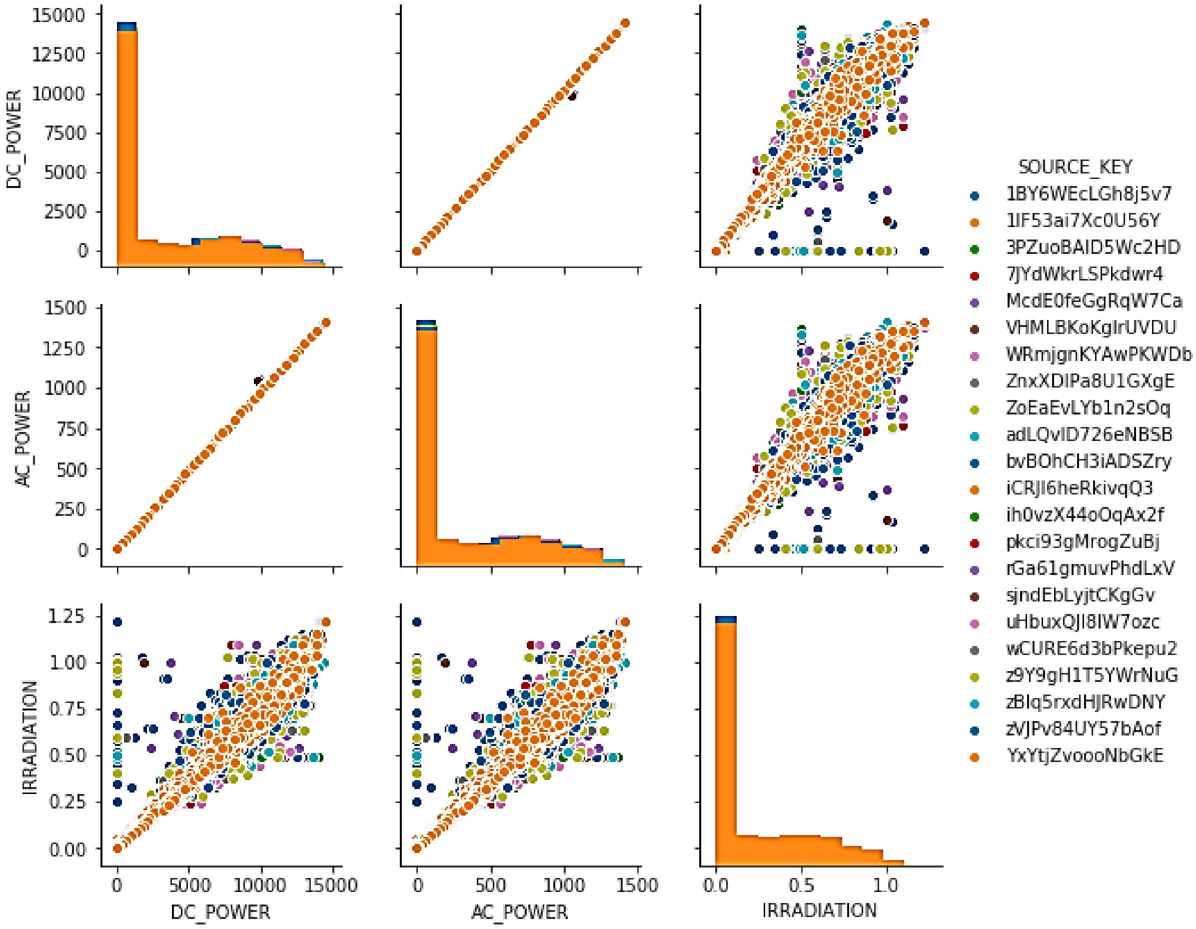


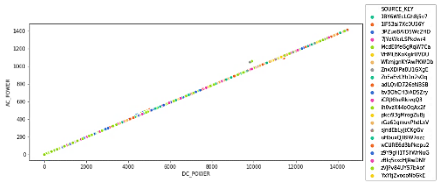
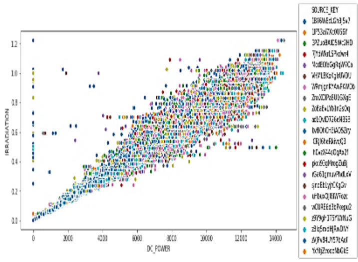
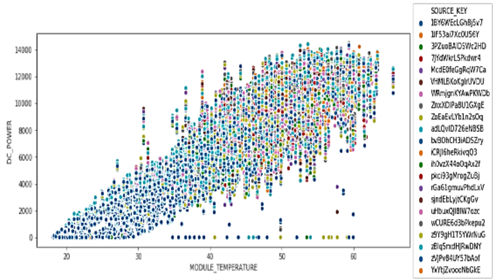
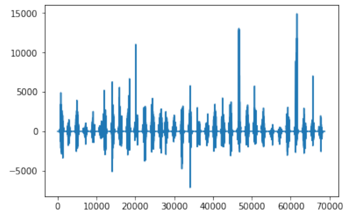
Figure 13.4 relationship among DC-power and (AC-power\irradiations\DC-power)
'popt=', array ([1.11067030e+01, -8.36585233e-10, -2.88700293e+08, -6.56012551e-02]))
'pcov=', array ([[2.95118747e-01, -3.37619553e-09, 1.17373200e+09, 6.74016006e-03], [-3.37619550e-09, 7.98285837e-14, -2.73849543e+04, -4.92535159e-10], [1.17373199e+09, -2.73849543e+04, 9.39432660e+21, 1.69319923e+08], [6.74016006e-03, -4.92535159e-10, 1.69319923e+08, 1.56495347e-04]]))

- Weather data contain six features (i.e., Source-key, Plant-ID, Irradiation, Date-Time, Temperatures, Mobility Temperatures)

After collecting both datasets in real-time maraging in the signal dataset based on both features (Date-Time and Plant-Id) to become that dataset contains nine features rather than 13. After that checking, if any record of that dataset has missing values drop it. In the second stage split the dataset into multi-intervals the time of each interval take 15 minutes; in this stage focus on removing the duplication interval and take only the different intervals to build the model. In general, the total number of intervals is 51 while after remove duplication remained only 22 intervals. Finally building two models (linear and nonlinear) and implementation based on three types of technique (CPU, GPU, and FPGA). As a result, in both models, the FPGA gives the time more reduce compare with CPU and GPU. We can summarisation the main advantages of Models as follow:

- The high correlation between DC power and AC Power
- The high correlation between power and irradiation
- Correlation between DC power, AC power, and module temperature and Ambient Temperature
- Correlation between daily yield and ambient temperature
- A nonlinear model require multi parameters must preparing but their results are best than a linear model
- Multi features affect in generated max DC-power include (AC-power, irradiance and temperature)

Table 13.2 Parameters effect in both Linear and Nonlinear Model..

Model	*Equations*	*Parameters*	*Values of P*	*Results*
Linear Model	□(□)= + ( )	$P(t)$:DC power $E(t)$: irradiance a,b : random coefficients	a=rnd() b=rnd()	 *Figure 13.5* Generation DC-power based on AC-power  *Figure 13.6* Generation DC-power based on irradiations  *Figure 13.7* Generation DC-power based on temperatures
Nonlinear Model	$P(t)=aE(t)$ $(1-b(T(t)+E(t)$ $800(c-20)-25)-$ $d\ln(E(t)))$	irradiance $E(t)$, Temperature $T(t)$ coefficients a,b,c,d popt, pcov	'popt 'pcov'	 *Figure 13.8* Generation DC-power based on NLM

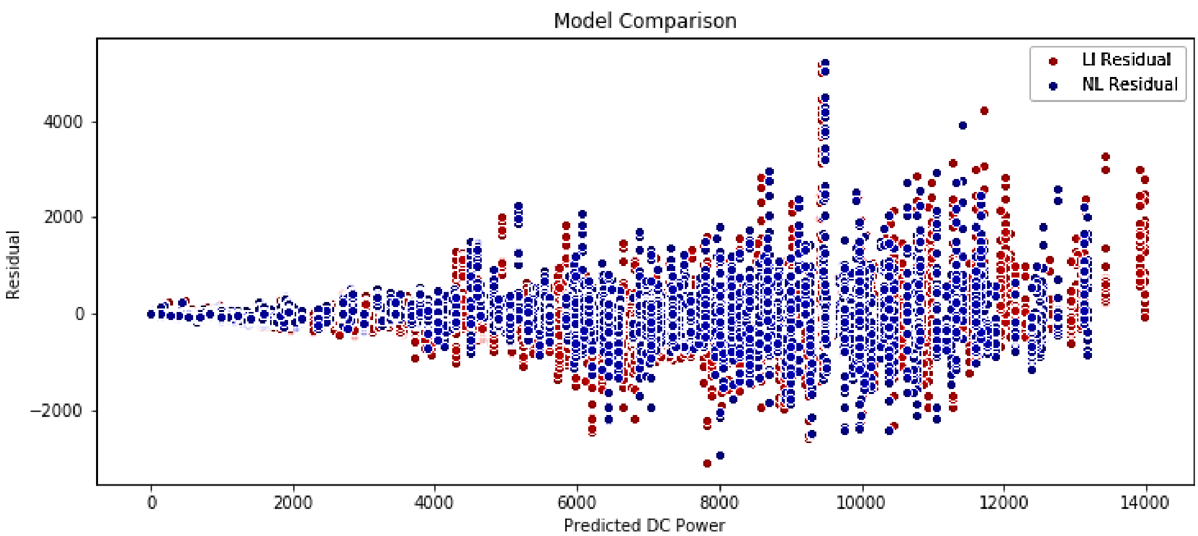


Figure 13.9 Compare between LM and NLM in generation DC-power

Table 13.3 Compare between LEI and NEI Model from Time Computation

Name of model	*CPU*	*GPU*	*FPGA*
LEI MODEL	12.597	5.992	1.004
NEI MODEL	23.994	17.023	1.962

References

Al-Janabi, S. (2015). A Novel Agent-DKGBM Predictor for Business Intelligence and Analytics toward Enterprise Data Discovery. JUBPAS. 23(2):482507.

Al-Janabi, S., Alkaim, A. F, Al-Janabi, E., and Aljeboree, A. (2021). Intelligent forecaster of concentrations (PM2.5, PM10, NO2, CO, O3, SO2) caused air pollution (IFCsAP). Neural Comput. Appl. 33:14199–14229. https://doi.org/10.1007/s00521-021-06067-7

Al-Janabi, S., Alkaim, A.F., and Adel, Z. (2020). An Innovative synthesis of deep learning techniques (DCapsNet & DCOM) for generation electrical renewable energy from wind energy. Soft Comput. 24:10943–10962. https://doi.org/10.1007/s00500-020-04905-9

Ang, K. L.-M. and Seng, J. K. P. (2021). Embedded Intelligence: Platform Technologies, Device Analytics, and Smart City Applications. IEEE Internet Things J. 8(17):13165–13182. doi:10.1109/jiot.2021.3088217

Basaran, K., Özçift, A., and Kılınç, D. (2019). A New Approach for Prediction of Solar Radiation with Using Ensemble Learning Algorithm. Arab. J. Sci. Eng. 44:7159–7171. doi:10.1007/s13369-019-03841-7

Bibri, S. E. (2018). The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability. Sustain. Cities Soc. 38:230–253. doi:10.1016/j.scs.2017.12.034

Cotfas, L. A., Delcea, C., Roxin, I., Ioanăş, C., Gherai, D. S., and Tajariol, F. (2021). The Longest Month: Analyzing COVID-19 Vaccination Opinions Dynamics from Tweets in the Month following the First Vaccine Announcement. IEEE Access. 9:3320333223. doi: 10.1109/ACCESS.2021.3059821.

Dhanraj, Joshuva, A., Ali, Mostafaeipour., Karthikeyan, Velmurugan., Kuaanan, Techato., Prem K. Chaurasiya, P. K., Jenoris, M., Solomon, Anitha Gopalan, A., and Khamphe, Phoungthong. (2021). An Effective Evaluation on Fault Detection in Solar Panels. Energies. 14:22:7770. https://doi.org/10.3390/en14227770

Dogan, A. and Birant, D. (2020). Machine Learning and Data Mining in Manufacturing. Exp. Syst. Appl. 114060. doi:10.1016/j.eswa.2020.114060

Gao, T. and Lu, W. (2020). Machine learning toward advanced energy storage devices and systems. iScience. 101936. https://doi.org/10.1016/j.isci.2020.101936

Hao, J. (2020). Deep Reinforcement Learning for the Optimization of Building Energy Control and Management. PhD Thesis, University of Denver.

~~Hochreiter, S. and Schmidhuber, J. (1997). Long Short-Term Memory. Neural Comput. 9(8):1735–1780. doi:10.1162/neco.1997.9.8.1735~~

Hossny, K., Magdi, S., Soliman, A. Y., and Hossny, A. H. (2020). Detecting explosives by PGNAA using KNN Regressors and decision tree classifier: A proof of concept. Prog. Nuc. Energy. 124:103332. doi:10.1016/j.pnucene.2020.103332

Kabir, E., Kumar, P., Kumar, S., Adelodun, A. A., and Kim, K. H. (2018). Solar energy: Potential and future prospects. Renew. Sustain. Energy Rev. 82:894900. https://doi.org/10.1016/j.rser.2017.09.094

Kaur, H. and Buttar, A. S. (2019). A review on solar energy harvesting wireless sensor network. Int. J. Comput. Sci. Eng. 7(2):398404. doi: https://doi.org/10.26438/ijcse/v7i2.398404

Khan, A., Sohail, A., Zahoora, U., and Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. Artif Intell. Rev. 53:5455–5516. https://doi.org/10.1007/s10462-020-09825-6

Lamb, J. J. and Pollet, B. G. (2020). Micro-Optics and Energy. doi:10.1007/978-3-030-43676-6

~~Mahdi, M. A. and Al_Janabi, S. (2020). A Novel Software to Improve Healthcare Base on Predictive Analytics and Mobile Services for Cloud Data Centers. Big Data and Networks Technologies, BDNT 2019, Lecture Notes in Networks and Systems. In: ed., Y. Farhaoui Y, 81. Springer, Cham, doi: https://doi.org/10.1007/978-3-030-23672-4_23~~

~~Mathew A., Amudha P., and Sivakumari S. (2021). Deep Learning Techniques: An Overview. Advanced Machine Learning Technologies and Applications, AMLTA 2020. Advances in Intelligent Systems and Computing. In: ed. A., Hassanien,~~ R., Bhatnagar , and A. Darwish, 1141. Singapore: Springer. https://doi.org/10.1007/978-981-15-3383-9_54

Megahed, T. F., Abdelkader, S. M., and Zakaria, A. (2019). Energy Management in Zero-Energy Building Using Neural Network Predictive Control. IEEE Internet Things J. 6(3):53365344. doi: 10.1109/JIOT.2019.2900558.

Miljkovic, D. (2017). Brief review of self-organizing maps. 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO). doi:10.23919/mipro.2017.7973581

Rustam, F., Khalid, M., Aslam, W., Rupapara, V., Mehmood, A., and Choi, G. S. (2021). A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis. Plos one. 16(2):e0245909. https://doi.org/ 10.1371/journal.pone.0245909.

Sah, D. K., and Amgoth, T. (2020). Renewable Energy Harvesting Schemes in Wireless Sensor Networks: A Survey. Information Fusion. 63:223247. doi:10.1016/j.inffus.2020.07.005

Samaher Al-Janabi, S. and Ayad Alkaim, A. 2022. A novel optimization algorithm (Lion-AYAD) to find optimal DNA protein synthesis. Egyp. Info. J. 23(2): 271290. https://doi.org/10.1016/j.eij.2022.01.004.

~~Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks. 61:85117. https://doi.org/10.1016/j.neunet.2014.09.003~~

Sodhro, A. H., Pirbhulal, S., Luo, Z., and De Albuquerque, V. H. C. (2019). Towards an optimal resource management for IoT based Green and sustainable smart cities. Journal of Cleaner Production, 220, 1167-1179. https://doi.org/10.1016/j.jclepro.2019.01.188.

Tan, P. N., Steinbach, M., and Kumar, V. (2016). Introduction to data mining. Pearson Education India: University of Minnesota.

Wang, J., Chen, Y., Hao, S., Peng, X., and Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119, 3-11. https://doi.org/10.1016/j.patrec.2018.02.010

Xiangdong Zhang, X., Gunasekaran Manogaran, G., and BalaAnand Muthu, B. A. (2021). IoT enabled integrated system for green energy into smart cities. Sustain. Energy Technol. Assess. 46:101208. https://doi.org/10.1016/j.seta.2021.101208.

Zhu, J., Wang, H., Zhang, Z., Ren, Z., Shi, Q., Liu, W., and Lee, C. (2020). Continuous direct current by charge transportation for next-generation IoT and real-time virtual reality applications. Nano Energy. 73:104760. https://doi.org/10.1016/j.nanoen.2020.104760