Learning Session Series

Topic: MLOps for AI Engineer and Data Scientist

Sub-topic: Introduction to MLOps
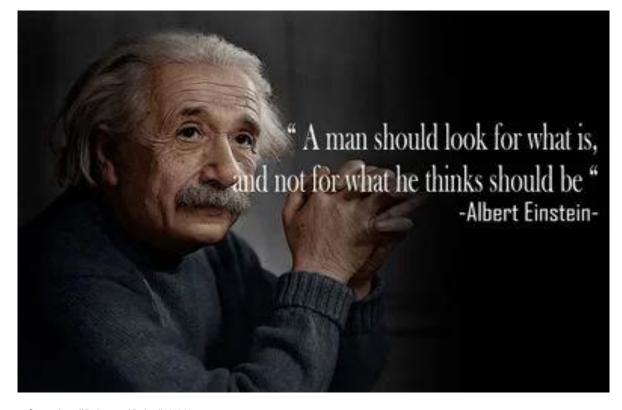
Speaker: Joseph Itopa Abubakar

November 21st, 2021

Omdena

OPEN EDUCATION BY LOCAL CHAPTERS

Learning section objective:

❖ To have general knowledge of the fundamentals of MLOps.
❖ To learn about the key components of MLOps.
❖ To have conceptual idea about APIs and API designs.
❖ Introduction to Domain(Solar energy)

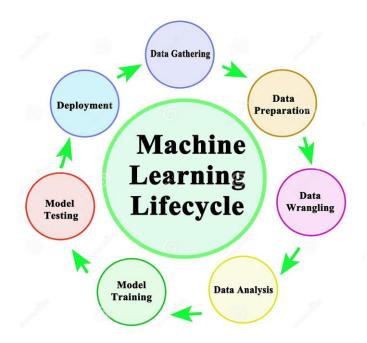" A man should look for what is, and not for what he thinks should be "
-Albert Einstein-

Agenda

- ❑ A glance at ML and MLOps Life Cycle
- ✓ Challenges facing MLOps
- ❑ Introduction to MLOps
- ✓ What is MLOps?
- ✓ Why the need for MLOps?
- ✓ Where & when do we adopt MLOps
- ✓ Components of MLOps
- ✓ Challenges and the need for APIs in MLOps
- ✓ Introduction to APIs
- ❑ Domain of interest: An introduction to renewable energy

A Glance at an AI/ML Project Life Cycle

Figure 1a: The life cycle of a typical machine learning project

Figure 1b: The life cycle of a typical deep learning project

A glance at MLOps Life Cycle
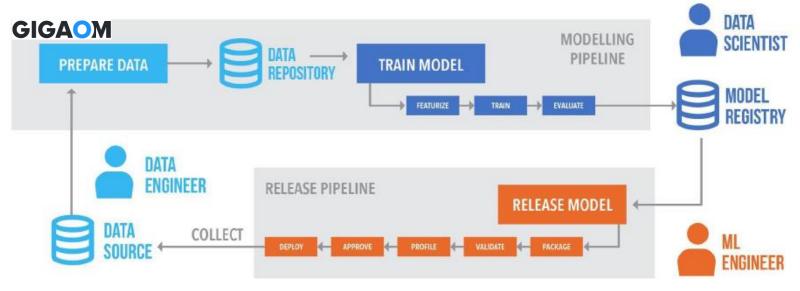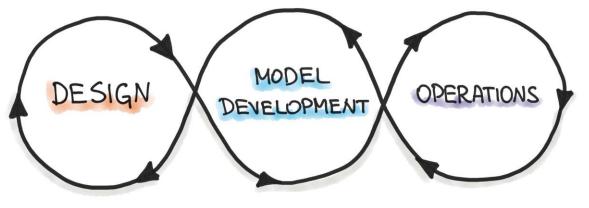
Figure 2: Incorporating systematic and repeatable workflow

A glance at MLOps Life Cycle
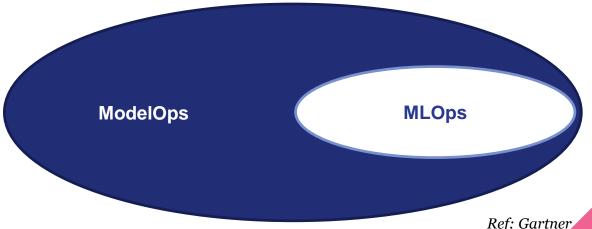
Figure 2: The life cycle of an MLOps

Introduction to MLOps

MLOps is focused on the operationalization of ML models, while ModelOps covers the operationalization of all types of AI models.

ModelOps
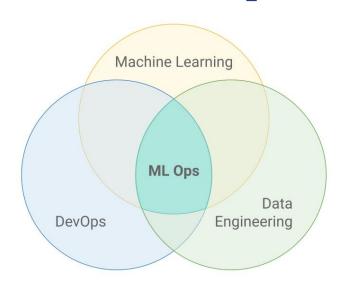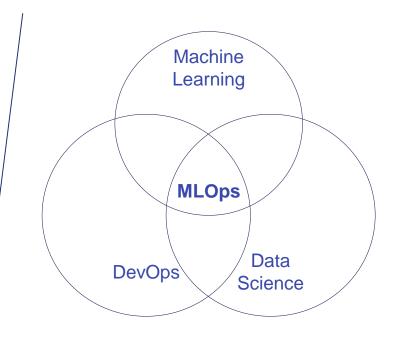
MLOps

Ref: Gartner

What is MLOps?

MLOps or **ML Ops** is a set of practices that aims to deploy and maintain machine learning models in production reliably and efficiently.

Why the need for MLOps?

According to businesswire earlier in 2021,...

MLOps =>

"seeks to **increase** automation and **improve** the quality of production models, while also **focusing** on business and regulatory requirements."

87%
of data science projects never make it into production

32%
need months to get models into production

Reference:
ttps://www.businesswire.com/news/home/20210209005426/en/New-Survey-Finds-Model-Driven-Culture-Is-Critical-for-Data-Science-Success?utm_campaign=tecton&utm_medium=blog&utm_source=datag om

Market Prospect for MLOps

MLOps Estimated Market Projection

Components of MLOps

Discover Use Case

Data Engineering

ML Pipeline

Production Deployment

Production Monitoring

Components of MLOps

| Discover Use Case | Data Engineering | ML Pipeline | Production Deployment | Production Monitoring |

Feasibility study → Understand the business → Identify possible use case → Explore data → (back to Feasibility study)

Serve Model → Prepare Data → Understand Algorithms → Algorithm Training → Model Experimentation → Evaluate model

Optimization → Deploy → Automate → Operate → Monitoring

Components of MLOps

Discover Use Case | Data Engineering | ML Pipeline | Production Deployment | Production Monitoring

Feasibility study → Understand the business → Evaluate model → Model Serving → Prepare Data → Understand Algorithms → Algorithm Training → Model Experimentation → Evaluate model

Identify possible use case → Explore data → Feasibility study

Optimization → Deploy → Automate → Operate → Monitoring → Optimization

Components of MLOps

| Discover Use Case | Data Engineering | ML Pipeline | Production Deployment | Production Monitoring |

Feasibility study

Understand the business

Explore data

Identify possible use case

Model Serving

Prepare Data

Evaluate model

Understand Algorithms

Model Experimentation

Algorithm Training

Optimization

Deploy

Monitoring

Automate

Operate

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
- Business uses
- Monitoring and management

Fix It, Fix It, Fix It

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
- Business uses
- Monitoring and management

Reference: https://www.science.org/content/article/nih-takes-steps-improve-reproducibility

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
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Challenges facing MLOps

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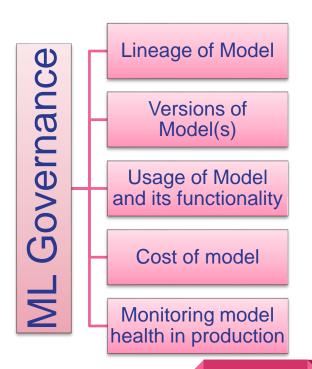- Collaboration
- Business uses
- Monitoring and management

ML Governance

- Lineage of Model
- Versions of Model(s)
- Usage of Model and its functionality
- Cost of model
- Monitoring model health in production

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
- Business uses
- Monitoring and management

Scalability

- Distributed ML
- Programming language of choice
- Large Scale Feature Store e.g. Redis
- Experiment management

Reference: https://neptune.ai/blog/how-to-scale-ml-projects

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
- Business uses
- Monitoring and management

Reducing the gap between the departments, industries, and companies.
~ Natalie Garda

Reference: https://www.iottechexpo.com/2017/10/ai/iot-machine-learning-ml-ai-why-collaboration-key/

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
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Find ML use case

Manually analyzing data

Software decision-making
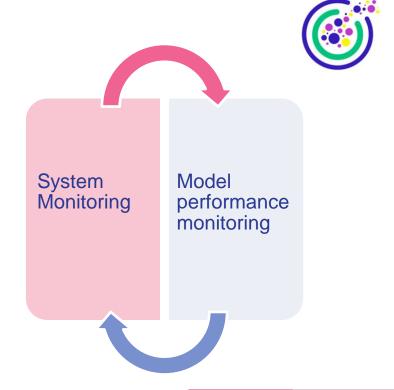
Prioritize on them

Value And Data availability

Reference systems

Reference: https://www.datarevenue.com/en-blog/the-ai-machine-learning-usecase-checklist
https://drive.google.com/file/d/12BlCf4Y3ijFhZduCSKc_DhcN56QAjp_J/view

Challenges facing MLOps

- Deployment and automation
- Reproducibility of models and predictions
- Diagnostics
- Governance and regulatory compliance
- Scalability
- Collaboration
- Business uses
- Monitoring and management

System Monitoring

Model performance monitoring

Reference: https://towardsdatascience.com/machine-learning-monitoring-what-it-is-and-what-we-are-missing-e644268023ba
https://neptune.ai/blog/ml-model-performance-monitoring

Where & when do we adopt MLOps

Machine learning use case frequency

- ➤ **Enterprises**
- ➤ **Startups**

- ✓ **Business use-case**
- ✓ **Production phase**

DevOps vs MLOps

Tools for MLOps

- ✓ KubeFlow
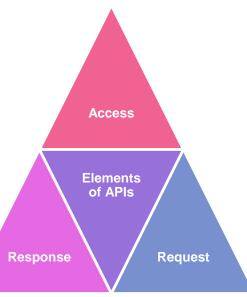
- ✓ MLFlow

- ✓ Algorithmia

- ✓ Pachyderm

Tea Break | Quiz

1) Concerning MLOps/ModelOps, identify the correct statement among the options below:
a) ModelOps is a sub-domain of MLOps.
b) MLOps is a sub-domain of ModelOps.
c) All of the above.
d) I'm hungry and not interested.

2) Which of the following is a tool for MLOps
a) DataOps.
b) Ensemble.
c) MLFlow.
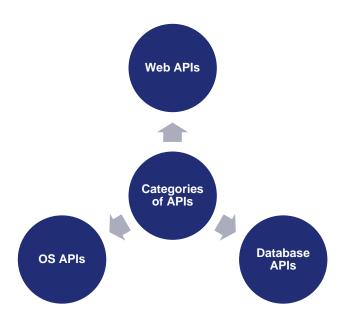d) Non of the above.

Introduction to APIs

APIs are rules or guidelines that define the way applications or devices can connect, and communicate.

A RESTful(or REST – REpresentational State Transfer) APIs are those that follows the REST architectural principles.

Introduction to APIs
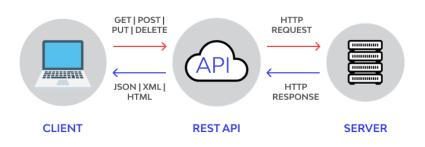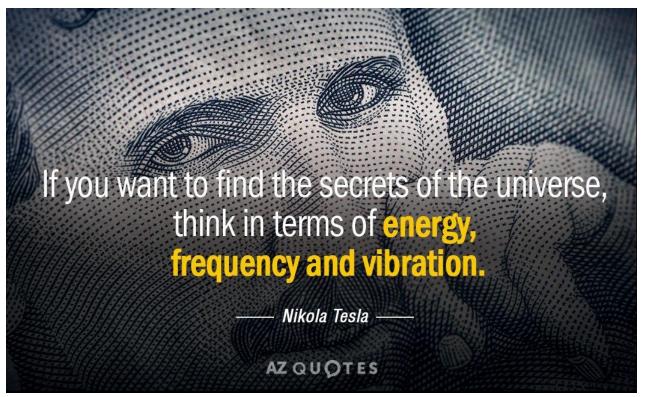

Figure 3a: Categories of MLOps

Figure 3b: Structural Architecture of RESTful API

Tea Break | Quiz

1) Which of the followings do we need to request and also to receive response from our API
a) GET
b) PUT
c) POST
d) DELETE

2) Identify which of the options below is not an element of APIs
a) Response
b) Post
c) Access
d) Request
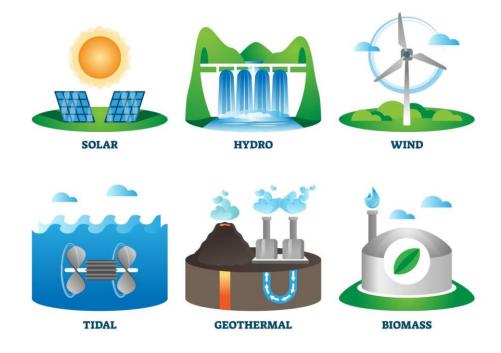
Domain of interest: An introduction to Renewable Energy

If you want to find the secrets of the universe, think in terms of **energy, frequency and vibration.**

— Nikola Tesla —

AZ QUOTES

Source: https://www.azquotes.com/author/14543-Nikola_Tesla

Domain of interest: An introduction to Renewable Energy

Figure 4: Types of Renewable Energy

Energy collected from renewable sources that will replenish itself within the human timescale is referred to as renewable energy.

Abuja city as a case study

Abuja

Figure 5: Map of Nigeria
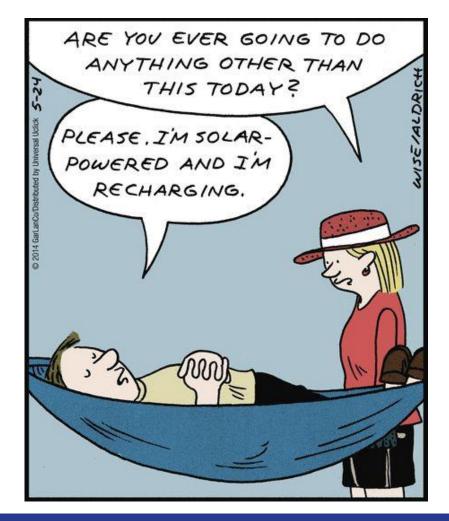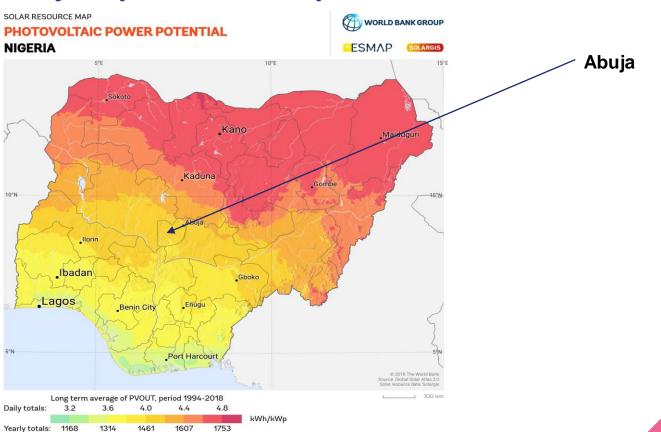
Abuja city as a case study

Figure 6: Photovoltaic Power Potential of Nigeria from 1994 - 2018
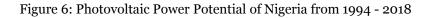
Reference: https://bit.ly/3cg4UEQ

Nigeria Historical Direct Normal Irradiation

DNI, which is also known as beam radiation is the radiance by the earth surface from the source located above the atmosphere excluding atmospheric losses.

DHI irradiance is the radiation received by the earth surface as a result of scattered light rays by the atmosphere.

Abuja

Long term average of DNI, period 1994-2018

Daily totals:	1.8	2.2	2.6	3.0	3.4	3.8	4.2	4.6	5.0
Yearly totals:	657	803	949	1095	1241	1387	1534	1680	1826

kWh/m²

© 2019 The World Bank
Source: Global Solar Atlas 2.0
Solar resource data: Solargis

100 km

Figure 6: DNI of Nigeria from 1994 - 2018

DNI vs DHI vs GHI

- Direct Normal Irradiance (DNI)

- Diffuse Horizontal Irradiance (DHI)
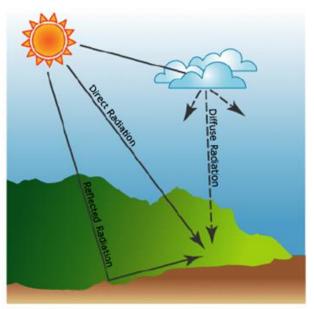
  Source: nrel.gov

- Global Horizontal Irradiance (GHI)

Source: esri.com

GHI= DHI + DNI x cos(z)

Figure 7: Comparism of DNI, DHI, and GHI

DNI vs DHI vs GHI - cont'd
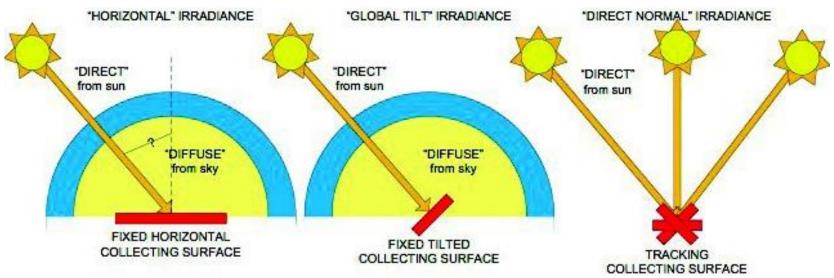
Figure 8: Comparism of DNI, DHI, and GHI

Nigeria Historical Global Horizontal Irradiation

GHI, is the total irradiance from the Sun to a horizontal surface of a specific location that is perpendicular to the earth.

GHI= DHI + DNI x cos(z)

Abuja
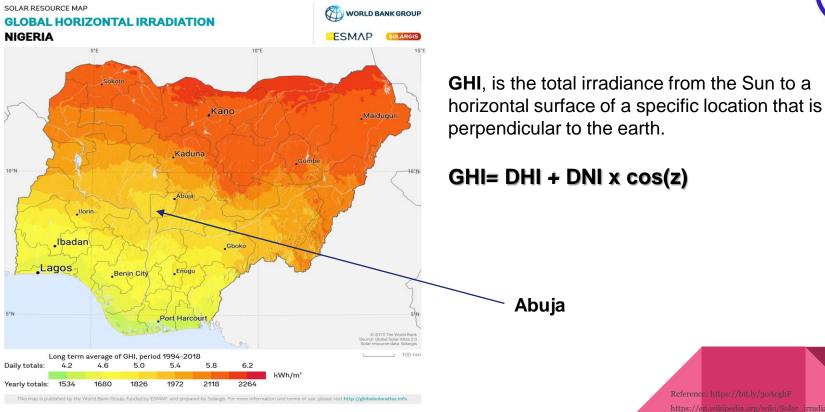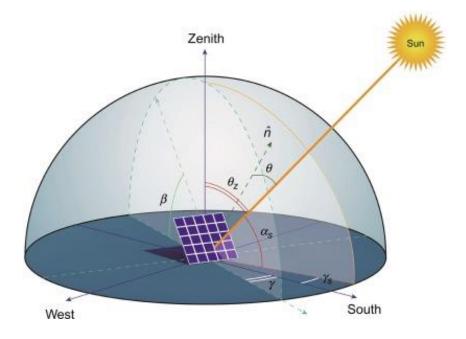
Figure 8: DNI of Nigeria from 1994 - 2018

Solar Irradiations- Zenith Angle

Figure 9: Diagrammatical representation of zenith angle

Θ_z - Zenith Angle

α_s – Elevation Angle

Domain of interest: An introduction to Renewable Energy
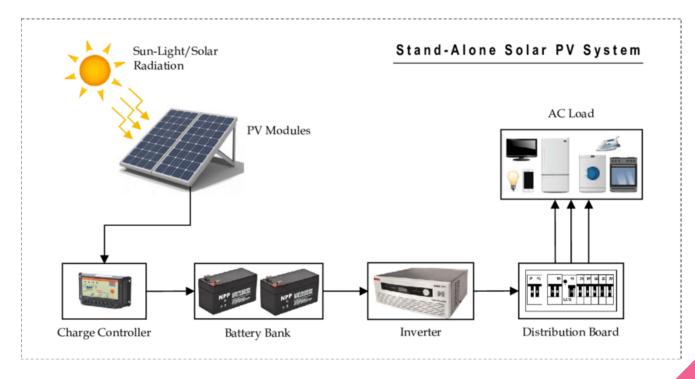
Figure 10: A stand-alone solar PV system

Domain of interest: An introduction to Renewable Energy
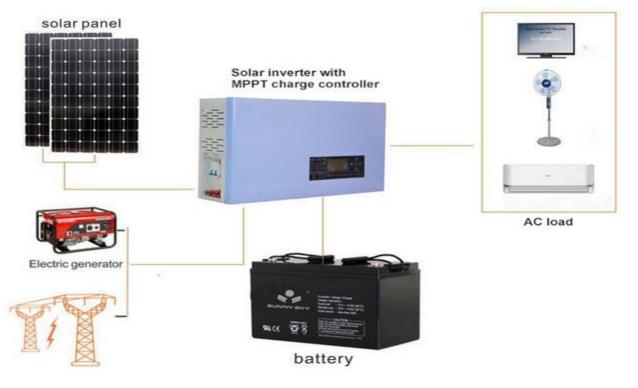
Figure 11: A Hybrid Solar PV System

Domain of interest: An introduction to Renewable Energy
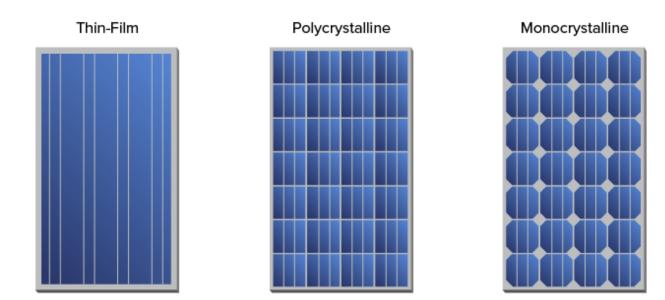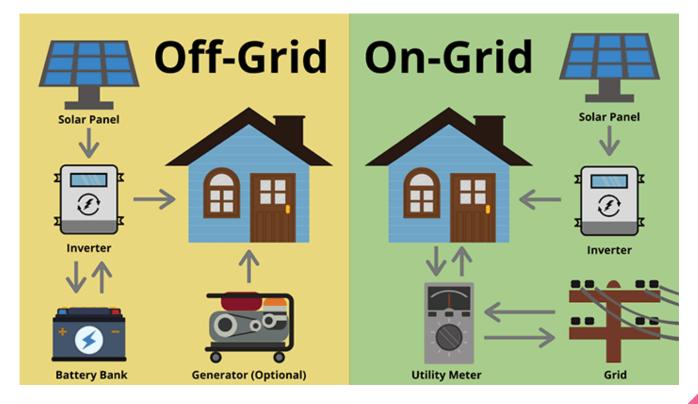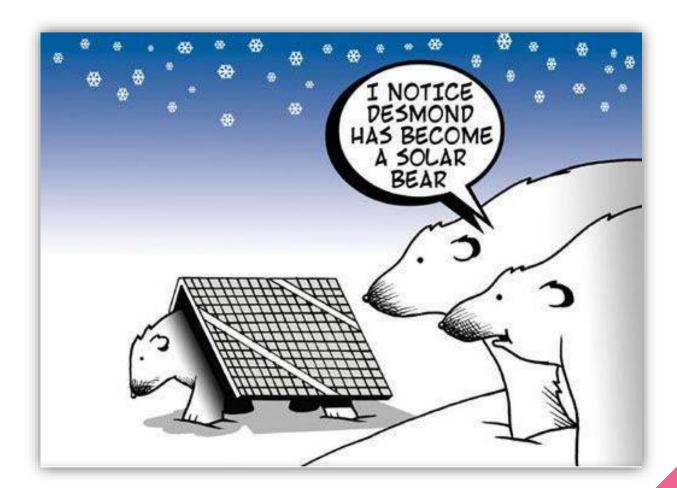
Figure 12: Most common type of PV Modules

Domain of interest: An introduction to Renewable Energy

Figure 13: Off-Grid vs On-Grid Configuration

Tea Break | Quiz

1) Geo-thermal is a type of renewable energy, True or False:
a) True
b) False
c) None of the above.

2) Which of the following is used to control electric current from PV modules?
a) Charge controller
b) Battery
c) Inverter with no in-built charge controller.
d) Non of the above.

RECAP

❑ A glance at ML and MLOps Life Cycle.

❑ Introduction to MLOps/APIs: Elements and categories of API.

❑ Domain of interest: An introduction to renewable energy.

RECOMMENDED READING

- https://medium.com/illumination/introduction-to-mlops-f877ccf10db1#:~:text=The%20origins%20of%20MLOps%20goes%20back%20to%202015%20from%20a,reach%20%244%20billion%20by%202025

- https://docs.microsoft.com/en-us/learn/modules/start-ml-lifecycle-mlops/

- https://neptune.ai/blog/life-cycle-of-a-machine-learning-project

- https://www.analyticsvidhya.com/blog/2021/07/deepdive-into-the-emerging-concpet-of-machine-learning-operations-or-mlops/

- https://www.datarobot.com/wiki/machine-learning-life-cycle/

ASSIGNMENT

I.   Register with a(or all) the cloud service providers:

▪   https://aws.amazon.com/premiumsupport/knowledge-center/create-and-activate-aws-account/

▪   https://azure.microsoft.com/en-us/free/

▪   https://console.cloud.google.com/freetrial?pli=1

▪   https://hub.docker.com/

II.   Register an account with solar cast:

▪   https://toolkit.solcast.com.au/register?_ga=2.85277145.1510370701.1638305380-843673236.1635755031

III. Share screenshot(s) of your successful registrations on slack and your full name.

REFERENCE

- https://en.wikipedia.org/wiki/MLOps
- https://medium.com/illumination/introduction-to-mlops-f877ccf10db1#:~:text=The%20origins%20of%20MLOps%20goes%20back%20to%202015%20from%20a,reach%20%244%20billion%20by%202025
- https://databricks.com/session/project-mlflow-infrastructure-for-a-complete-machine-learning-life-cycle-2
- https://docs.microsoft.com/en-us/learn/modules/start-ml-lifecycle-mlops/
- https://developers.redhat.com/blog/2021/05/11/the-machine-learning-life-cycle-part-1-methods-for-understanding-data
- https://cloud.google.com/blog/products/ai-machine-learning/making-the-machine-the-machine-learning-lifecycle
- https://www.researchgate.net/figure/Life-cycle-for-a-deep-learning-model_fig3_345388655
- https://neptune.ai/blog/life-cycle-of-a-machine-learning-project
- https://towardsdatascience.com/the-machine-learning-lifecycle-in-2021-473717c633bc
- https://www.analyticsvidhya.com/blog/2021/07/deepdive-into-the-emerging-concpet-of-machine-learning-operations-or-mlops/
- https://www.analyticsvidhya.com/blog/2021/05/machine-learning-life-cycle-explained/
- https://www.datarobot.com/wiki/machine-learning-life-cycle/