International Proceedings

The 7th ASEAN Smart Grid Congress

12 - 13 December 2024, at Chiang Mai Rajabhat University, Chiang Mai, Thailand

Distributed Generation for Smart Grid

Smart Mobility (EV)

Energy Management for Smart Grid

Climate Change

"Smart Microgrid Appropriate for ASEAN"

Smart microgrid

Battery & Energy Management

Intelligent Appliances & Smart Building

Social /Policy/ Mechanism – Smart Grid

Energy Resilience

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International Proceedings

The 7th ASEAN Smart Grid Congress

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Asian Development College for Community Economy and Technology (adiCET),
Chiang Mai Rajabhat University, Mae Rim Campus (CMRU),
Thailand

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Universiti Teknologi MARA (UiTM),
Shah Alam, Malaysia

Vellore Institute of Technology (VIT),
Vellore Campus, India

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adiCET

Message from the Dean

Asian Development College
for Community Economy and Technology

The 7^{th} ASEAN Smart Grid Congress brings together a diverse array of participants including academics, government representatives, industry professionals, entrepreneurs, and students. It is a dynamic platform for collaboration, innovation, and the exchange of ideas for smart grid technologies and renewable energy systems. This year's Congress is particularly special, as it is a part of the 100^{th} Anniversary of Chiang Mai Rajabhat University. Chiang Mai Rajabhat University has been a beacon of knowledge and innovation for a century, serving its community with unwavering dedication to education, research, and service. This milestone underscores the university's key role in shaping the leaders, innovators, and changemakers of tomorrow. Microgrids can change the future of every remote and underserved village by providing lights for teaching and healthcare, for economic productivity. Smart grids, in return, will make us have more efficient and sustainable enterprise of our energy resources. Working together, ASGC-7 represents a very special forum that brings participants together, this year in a hybrid format that allows us to reach out to an even larger audience. Diversity of perspectives will surely drive innovation and collaboration forward. Whether joining in person or virtually, your contribution to this Congress is not valued any less.

I would like to extend my deep appreciation to all those who have made this event possible: speakers, participants, industrious organizers, and sponsors. This will indeed ensure the success of this Congress and be part of its long-lasting effect. Let this be a platform that creates meaningful connections among us, and moves us toward a greener and brighter future for ASEAN smart grid and beyond.

Asst. Prof. Dr. Hathaithip Sintuya
Dean
Asian Development College
for Community Economy and Technology (adiCET)
Chiang Mai Rajabhat University

Solar Research Institute

Message from the Director

Solar Research Institute (SRI)

On behalf of Solar Research Institute (SRI), it is an honor and a privilege to be able to work with the esteemed colleagues at Asian Development College for Community Economy and Technology (adiCET), Chiang Mai Rajabhat University. As co-hosts of this significant gathering, we are pleased to contribute to fostering collaboration and innovation in the fields of smart microgrids, energy management, advanced materials, and climate resilience.

The congress comes at a pivotal moment when the urgency to transition towards a more sustainable and resilient energy future has never been greater. The ASEAN region, with its dynamic economies and unique environmental challenges, serves as a vital arena for implementing transformative solutions in energy systems. The topics explored in this congress—ranging from innovative microgrid designs to cutting-edge energy materials and adaptive strategies for climate resilience—reflect the multidimensional approach required to address these complex challenges.

This event is more than a platform for the exchange of ideas; it is a call to action. The research and solutions presented here will undoubtedly shape the future of energy systems in our region, contributing to a smarter, more efficient, and climate-resilient ASEAN. As we gather the brightest minds from academia, industry, and government, let us seize this opportunity to foster meaningful collaborations that will inspire impactful innovations.

We extend our heartfelt gratitude to all contributors, presenters, and attendees for their invaluable participation. May this congress not only expand our understanding of smart grid technologies but also strengthen our shared commitment to building a sustainable future for generations to come.

Prof. Ir. Dr. Nofri Yenita Dahlan
Director
Solar Research Institute (SRI)
College of Engineering, Universiti Teknologi MARA (UiTM)

SMART CAMPUS with DEMAND RESPONSE CHALLENGE and OPPORTUNITY

Maerim
Rooftop : 876 kWp
Carport : 122 kWp

Wiang Bua
Rooftop : 260 kWp
Carport : 130 kWp

Rooftop and Carport Solar

ENZY Energy Management System

Smart Street Lighting

Smart Street Light System
Smart Street Light with IoT
309 Sets

Battery Energy Storage

Size : 100 kW/200 kWh

Battery Energy Storage

EV Charger

EV Car

EV Golf Cart
14 seats, 7.5 kW/72V - 2 units

EV Charger
Pulsar Plus : Type2, 7.4 kW- 2 Units

Quasar : CHAdeMo DC Bi-Directional
Charge 7.4kW, Discharge 7.2 kW - 1 unit

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Mr. Sovanna Phoeurn	Cambodian-Thai skills development institute under the ministry of labor, Phnom penh city, Cambodia
Mr. Benoit Marcoux	OPAL-RT Technology, Cannada

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Mr. Chan Thavysak	Electricite du Laos: EDL, Laos
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Ms. Piyaporn Sinnnart	PTS Combination Co., Ltd., Thailand
Dr. Wilailak Pokakul	LEONICS COMPANY LIMITED, Thailand
Dr. Wuttipong Suphonthana	LEONICS COMPANY LIMITED, Thailand
Mr. Thanatat Soponananchai	FATHOPES ENERGY (THAILAND) CO., LTD., Thailand

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Agenda

The 7th ASEAN Smart Grid Congress: Smart Microgrid for ASEAN
Date: 12 – 13 December 2024, Chiang Mai, Thailand

12 December 2024 **Venue:** Asian Development College for Community Economy and Technology (adiCET), Chiang Mai Rajabhat University, Mae Rim campus, Chiang Mai, Thailand	
Time	**Activity**
08:00 – 09:00	Depart from Chiang Mai Night Bazaar to adiCET
09:00 – 09:30	Registration and Reception
09:30 – 09:40	Opening Performance
09:40 – 09:50	**Welcome Speech & Introduction** Asst. Prof. Dr. Hathaithip Sintuya Dean, Asian Development College for Community Economy and Technology, Chiang Mai Rajabhat University, Thailand
09:50 – 10:00	**Opening Speech** Assoc. Prof. Dr. Chatree Maneekosol Acting President, Chiang Mai Rajabhat University, Thailand
10:00 – 10:05	**Sponsor Recognition**
10:05 – 10:15	Setting the Scene **Smart Microgrid Research & Development in ASEAN** Asst. Prof. Dr. Sulak Sumitsawan ASGC Chairman
10:15 – 10:30	Break & Photo Session
	Keynote Session:
10:30 – 10:45	**Hawaii's Renewable Energy and Smart Grid Progress, Implementation, and Key Lessons Learned on the Path to 100% RPS by 2045** Dr. Richard E Rocheleau Director of HNEI Institute University of Hawaii, USA

12 December 2024 **Venue:** adiCET, Chiang Mai World Green City, Chiang Mai, Thailand	
Time	**Activity**
10:45 – 11:00	**NEDO Role of Microgrid Technology Promotion for ASEAN Countries** Mr. Kawamura Hironori Chief Representative of NEDO Bangkok Office, NEDO, Japan
11:00 - 11:15	**Smart Microgrid and Digital Transformation in China** (online) Dr. MA Minxiang Deputy Director-General, Yunnan Provincial Academy of Science and Technology, China Assoc. Prof. Dr. Vivia Luo Yunnan University, China
11:15 – 11:30	**Smart Microgrid in Thailand** (Video) Ms. Munlika Sompranon Director of Division of Solar Energy Development Department of Alternative Energy Development and Efficiency (DEDE), Ministry of Energy, Thailand
11:30 – 11:45	**Emerging Technologies for Climate Change Mitigation and Smart Grid Advancement in the U.S.** Dr. Richard Carlin Science Advisor for Innovation and Climate Change Science Advisor for Innovation and Climate Change NAVFAC Engineering and Expeditionary Warfare Center (EXWC)
11:45 – 12:00	**Q&A**
12:00 – 13:30	Lunch

12 December 2024 **Venue:** adiCET, Chiang Mai World Green City, Chiang Mai, Thailand			
Time	**Activity**		
13:30 – 16:00	**Oral Presentations (parallel sessions in hybrid format)** (Presentation 15 mins/ Q&A 5 mins)		
Venue:	Bird House Meeting Hall	AREC Building	Bamboo Meeting Hall
Session topic:	**A: Smart microgrid**	**B: Energy Management and Material**	**C: Climate Change & Resilience**
Subtopic	- Distributed Generation for Smart Grid - Battery & Energy Management	- Energy Management for Smart Grid - Smart Mobility (EV) - Intelligent Appliances & Smart Building	- Climate Change & Clean Energy - Nanotechnology and Materials for Energy and Environment - Energy Resilience
Session Chairs	Prof. Dr. Nofri Yenita Dahlan, UiTM, Malaysia	Dr. Nono Darsono, BRIN, Indonesia	Dr. Kampanart Silva, ENTEC, Thailand
	Dr. Vorachack Kongphet, NUOL, Lao PDR	Asst. Prof. Dr. Rotjapun Nirunsin MJU, Thailand	Assoc. Prof. Dr. Azlin Mohd Azmi, UiTM, Malaysia
Session Coordinators	UiTM Mr. Tengku Nazmi Ms. Siti Shahada Shamshuddin adiCET Dr. Thananchai Sataklang Mr. Sovana Phoeurn	UiTM Mr. Muhammad Afiq Abd Jalil Ms. Nurul Aqilah Mahmud adiCET Mr. Narakorn Songkittirote Mr. Chan Tavysak	UiTM Mr. Muhammad Zulhamizan Ahmad Ms. Nurul Farhana Zulkefli adiCET Dr. Sasiprapha Kaewdang Mr. Bounkham Tanthavong
16:00 – 18:00	Networking Break at adiCAFE Site Visit – *the Smart Microgrid and Smart Community at adiCET*		
18:00 – 21:00	Banquet at Chiang Mai World Green City *Night market-style open-air banquet under the stars, featuring northern and central Thai cuisine*		

<table>
<tr><th colspan="4">13 December 2024
Venue: adiCET, Chiang Mai World Green City, Chiang Mai, Thailand</th></tr>
<tr><th>Time</th><th colspan="3">Activity</th></tr>
<tr><td>08:00 – 09:00</td><td colspan="3">Depart from Chiang Mai Night Bazaar to adiCET</td></tr>
<tr><td>09:00 – 09:15</td><td colspan="3">**Invited Presentation**
Microgrid Systems Using Real-Time Simulators and examples
Mr. Benoit Marcoux
Business Development Manager – Asia, OPAL-RT TECHNOLOGIES</td></tr>
<tr><td>09:15 – 09:30</td><td colspan="3">**Smart campus with demand response challenge & opportunity**
Mr. Weerayut Srithiam
Chief, Smart Energy Solutions Business Department
Innovative Energy Solutions Business Management Division
Electricity Generating Authority of Thailand (EGAT), Thailand</td></tr>
<tr><td>09:30 – 10:30</td><td colspan="3">**Site visit of Chiang Mai World Green City & Chiang Mai Rajabhat University** *(via bus around the Mae Rim Campus)*
Smart Microgrid: Full Feeder Community Microgrid
Asst. Prof. Dr. Hathaithip Sintuya, adiCET</td></tr>
<tr><td>10:30 – 11:00</td><td colspan="3">Break</td></tr>
<tr><td>10:30 – 12:00</td><td colspan="3">**Collaboration workshops**
The goal of this workshop is to foster collaboration and knowledge sharing among ASEAN stakeholders and international partners on key aspects of smart microgrid development.</td></tr>
<tr><td>Venue:</td><td>Bird House Meeting Hall</td><td>AREC Building</td><td>Bamboo Meeting Hall</td></tr>
<tr><td>Collaboration topic:</td><td>**A: Emerging Research on Smart Microgrid for ASEAN**
Discuss the latest innovations and identify research priorities and collaboration opportunities for enhancing microgrid technology in the region.</td><td>**B: Capacity Building for Smart Microgrid Development in ASEAN**
Explore strategies for building expertise, skills, and technical capabilities necessary for effective microgrid implementation.</td><td>**C: Standard and Testing of Smart Microgrid**
Explore possibilities for a common framework for standards and testing opportunities to ensure reliable, efficient, and scalable microgrid solutions.</td></tr>
<tr><td>Facilitator and Note Takers</td><td colspan="3">Asst. Prof. Dr. Worajit Setthapun, adiCET
Mr. Rafiqin Muhammad Huzai Bin Ramli, Temasek Polytechnic, Singapore
Mr. Justin Lim Zheng Qin, Temasek Polytechnic, Singapore</td></tr>
<tr><td>12:00 – 13:30</td><td colspan="3">Lunch (Box lunch)</td></tr>
<tr><td>13:30 - 15:00</td><td colspan="3">Cultural tour or Free time
Chiang Mai City Tour with Tram ride and professional tour guide
(Please sign up for the cultural tour at the registration table)</td></tr>
<tr><td>15:00 – 16:00</td><td colspan="3">Depart back to Chiang Mai Night Bazaar</td></tr>
</table>

Oral Presentation Agenda

12 December 2024

Room A (Bird House Meeting Hall), Topic: Smart microgrid

Sub-topic: Distributed Generation for Smart Grid and Battery & Energy Management

Session Chairs:		**Prof. Dr. Nofri Yenita Dahlan (UiTM, Malaysia)** **Dr. Vorachack Kongphet** (NUOL, Lao PDR)	**Session Coordinator:** UiTM Student adiCET Student	
No.	Time	Code	Article Title	Format
1	13:30 – 13:45	DG003	Studying and Analyzing the Economics and Engineering of a 290 kWp Hybrid Wind+Solar System for Electricity Generation at Bann Raya Resort, Racha Island, Phuket, Thailand *Waiwit Udayachalerm, Wirachai Roynarin, Worachate Sangsida, Sirisak Pangvuthivanich, Kwanchai Choicharoen, Panu Pratumnopharat*	On-site
2	13:45 – 14:00	DG004	E-Infinity Ecosystem: Peer-to-Peer Energy Trading Using X-Changer and Energinx Smart Meters for Reverse Power Flow Prevention *Puttapong Somjai, Kittisak Khuwaranyu, Paisarn Muneesawang, Rachasak Phanumpha, Duangkamol Ruen-ngam*	On-site
3	14:00 - 14:15	BT001	Comparison of PSO optimization and feedback control methods for energy management in hybrid photovoltaic with grid-tied system Hideki Khakhai, Thipwan Fangsuwannarak, Jirut Rhianprayoon	On-site
4	14:15 – 14:30	BT002	Assessing Techno-Economic Impacts of Hybrid Renewable Energy System With Energy Storage For Campus Buildings In Malaysia Using HOMER *Mardhia Adriana, Nofri Yenita Dahlan, Muhammad Azfar Shamil Abd Aziz*	On-site
5	14:30 – 14:45	BT003	Evaluating Battery Energy Storage System (BESS) Sizing for Substation Investment Deferral Using Load Profile Analysis in Thailand *Temsiri Prompook, Sorawut Jittanon, Nipon Ketjoy, Wisut Chamsa-ard, Chakphed Madtharad, Tawat Suriwong*	On-site
6	14:45 – 15:00	CC004	Design of 5 kW Low Speed Wind Turbines for Air Compresses Application. *Worachate Sangsida, Wirachai Roynarin, Waiwit Udayachalerm, Sirisak Pangvuthivanich, Kwanchai Choicharoen, Panu Pratumnopharat*	On-site
7	15:00 – 15:15	CC006	Design a 100kWh Hybrid Photovoltaic System at UiTM Campus using PVsyst *Mohd Husni Mohd Som, Siti Zaliha Mohammad Noor, Khairunisa Nadrah Md Zahir, Suleiman Musa, Nur Syamimi Dzulkamal, Pusparini Dewi Abd Aziz*	Online
8	15:15 – 15:30	DG002	Calibration and Performance Analysis of a 50 MW Large-Scale Solar PV System in the Eastern Region of Peninsular Malaysia Across Two Monsoon Seasons *Nur Fadhilah Jamaludin, Nofri Yenita Dahlan, Sridhar Sripadmanabhan Indira*	Online
9	15:30 – 15:45	DG005	Enhancing Optimal Unit Commitment via Ant Lion Optimizer with Photovoltaic Uncertainty *Muhammad Aidil Adha Aziz, Zuhaila Mat Yasin, Zuhaina Zakaria*	Online

12 December 2024

Room B (AREC Building), Topic: Energy Management and Material

Sub-topic: Energy Management for Smart Grid, Smart Mobility (EV),
and Intelligent Appliances & Smart Building

Session Chairs: **Dr. Nono Darsono** (BRIN, Indonesia) **Asst. Prof. Dr. Rotjapun Nirunsin** (MJU, Thailand)				Session Coordinator: UiTM Student adiCET Student
No.	Time	Code	Article Title	Format
1	13:30 – 13:45	EM003	Application of Machine Learning Models in Solar Power Prediction Based on Multilevel Stacking Ensemble Approach *Chun-Liang Tung, Chien-Yu Lu, Ta-Ching Chou, Sanyam Kukreti*	On-site
2	13:45 – 14:00	EM007	Data-Driven Solutions for Effective Community Energy Monitoring Using a Hybrid Framework of Smart Meters and Surveys *Thanachai Sataklang, Hathaithip Sintuya, Worajit Setthapun*	On-site
3	14:00 - 14:15	EM008	IoT Monitoring System Development for Collect Building Energy Consumption *Narakorn Songkittirote, Thanachai Sataklang, Worajit Setthapun, Hathaithip Sintuya*	On-site
4	14:15 – 14:30	EV002	Techno-Economic Feasibility and Environmental Assessment of a Grid-Connected PV System for EV Charging in Brunei Darussalam *Sheik Mohammed Sulthan, Ang Swee Peng, B Sri Revathi, Muhammad Norfauzi, Saiful Bahri Hj Md Ja, Äôafar, Law Kah Haw*	On-site
5	14:30 – 14:45	SB001	Solar PV Soiling Study *Rajasekar Natarajan, Harish Aggarwal, Pokuri Siva Krishna, Murali S, Rashmi Ranjan Das, Chinmaya Sahu*	On-site
6	14:45 – 15:00	CC002	Energy Performance Enhancement of the Office Building: Economic and Environmental Impact of Achieving nZEB *Bhumitas Hongvityakorn, Pruk Aggarangsi, Prajak Kittirattanaviwat*	On-site
7	15:00 – 15:15	SB002	Applications of an Automated Nutrient Solution Chilling System for Growing Hydroponic Lettuces in Tropical Conditions *Paween Kriangkasem, Surachai Narrat Jansri, Phatcharida Lawan, Atthaphong Phiantae*	Online
8	15:15 – 15:30	CC001	Integrated IoT and Machine Learning Framework for Real-Time Monitoring and Mitigation of Industrial Gas Leaks *Ashwini kumar, K.C. Sriharipriya, J Christopher Clement, Linga Reddy, G.K. Rajesh*	Online
9	15:30 – 15:45	EM005	Harnessing Digital Twins: A New Frontier for Electrical Systems in Industrial Plants *Hossein Zeynal, Ahmad Kor, Zuhaina Zakaria*	Online
10	15:45 – 16:00	EM006	Development of Test Bed and Communication Technology Evaluation for Advanced Metering Infrastructure (AMI) and Smart Grid applications *Shashitheran Karuppiah, Dr.Lo Chin Kim*	Online

12 December 2024

Room C (Bamboo Meeting Hall), Topic: Climate Change & Resilience

Sub-topic: Climate Change & Clean Energy, Nanotechnology and Materials for Energy and Environment, and Energy Resilience

Session Chairs: **Dr. Kampanart Silva** (ENTEC, Thailand) **Assoc. Prof. Dr. Azlin Mohd Azmi** (UiTM, Malaysia)			**Session Coordinator:** UiTM Student adiCET Student	
No.	**Time**	**Code**	**Article Title**	**Format**
1	13:30 – 13:45	CC003	A case study on carbon credit trading in photovoltaic systems at the large academy, focusing on break-even point and passive income *Suwicha Sokul, Peerapon Chanhom, Keerati Chayakulkheeree, Thipwan Fangsuwannarak*	On-site
2	13:45 – 14:00	CC005	Study on measures to promote renewable energy and energy efficiency and conservation towards net-zero carbon emission *Kampanat Thapmanee, Khemrath Vithean, Pidpong Janta, Rungtiwa Phoonsuk, Nuwong Chollacoop, Kampanart Silva*	On-site
3	14:00 - 14:15	CC010	Biochemical methane potential of co-digestion from food waste and watermelon rinds *Titiwath Faksomboon, Kittikorn Sasujit, Jutaporn Chanathaworn, Ratchadaporn Puntharod, Puwadon Chumpoochai, Rotjapun Nirunsin*	On-site
4	14:15 – 14:30	NM003	Electrospun chitin-based nano-membrane from mushroom waste for water filtration of nano-plastics removal *Shih-Yun CHANG, An-Jie LUAN, Chen-Yeon CHU, Yi-Hsin CHIEN*	On-site
5	14:30 – 14:45	ER003	Waste-to-Energy and Potential for Enhancing Regional Energy Resilience *Wichuda Pumpoung, Napat Jakrawatana*	On-site
6	14:45 – 15:00	CC009	Empowering Remote Communities with Renewable Energy Education: A Game-Based Learning Approach *Narakorn S., Wanwiset A., Nattapat L., Thananchai S., Sasiprapha K., Artidtaya M., Surachai N. J., Hathaithip S., Preecha S., Att A., Sutthinan C., Amnat K., Surasak N., Chatree M., Watcharapong W., Panlop S.*	On-site
7	15:00 – 15:15	ER001	Impacts of Transformer Saturation Characteristics on Ferroresonance using Ritz Method *Muhammad Saád Bin Haji Bini, Swee Peng Ang, Sheik Mohammed Sulthan, Nor Asiah binti Muhamad, Kah Haw Law, Muhammad Norfauzi*	Online
8	15:15 – 15:30	ER002	An Investigation on Energy and Electricity Status of Malaysia *Wu Zhi Shan, Christina Chin May May, Novita Sakundarini, Akhil Garg*	Online
9	15:30 – 15:45	CC007	Floating Photovoltaic (FPV) Project Appraisal for potential Malaysia Reservoirs *Siti Zaliha Mohammad Noor, Khairunisa Nadrah Md Zahir, Nurul Iman Arina Razlan Adli, Suleiman Musa, Pusparini Dewi Abd Aziz*	Online
10	15:45 – 16:00	CC008	Analysis on Energy Import and Energy Export Patterns of Residential Consumers *Siti Maisara Murniyati Muin, Chin Kim Lo, Hui Mun Looe*	Online

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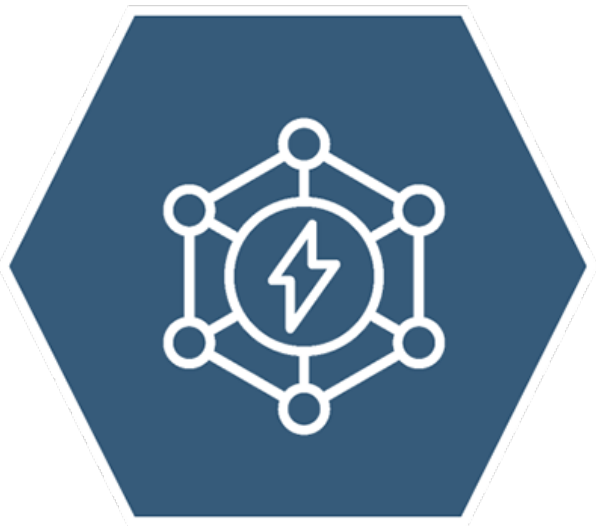

Distributed Generation for Smart Grid

Calibration and Performance Analysis of a 50 MW Large-Scale Solar PV System in the Eastern Region of Peninsular Malaysia Across Two Monsoon Seasons

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Abstract—In an effort to harness sustainable energy solutions, Malaysia has shifted its attention to the development of diverse configurations of Large-Scale Solar Photovoltaic (LSSPV) systems. This shift is driven by the country's plentiful solar radiation, a renewable and clean energy source. However, the efficiency of these solar systems is influenced by the variable conditions associated with the country's monsoon seasons, affecting critical components like inverters and transformers, which are vital for grid-connected power delivery. To address these challenges, this paper presents a calibration and performance analysis of a 50 MWAC LSSPV system located in the eastern region of Peninsular Malaysia using MATLAB Simulink. The preprocessed and cleaned data from iSolarCloud is utilized to enhance the accuracy of the simulations thus ensuring the model closely reflects real-world conditions. The performance of the calibration model based on the active power tolerance at the Point of Common Coupling (PCC) is evaluated during both the southern and northern monsoon seasons, in accordance with the standards and guidelines set by the Malaysia Energy Commission and Tenaga Nasional Berhad (TNB). These findings offer valuable insights for maintaining and optimizing existing systems, as well as supporting future LSSPV expansions and improvements in Malaysia and similar tropical regions.

Keywords— Large-Scale Solar Photovoltaic (LSSPV) systems, Point of Common Coupling, MATLAB Simulink, iSolarCloud, Malaysia Energy Commission, Standard Test Condition, Photovoltaic System

Studying and Analyzing the Economics and Engineering of a 290 kWp Hybrid Wind+Solar System for Electricity Generation at Bann Raya Resort, Racha Island, Phuket, Thailand

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Abstract - The high electricity production costs and reliance on fossil fuels on Thailand's islands have significantly contributed to global warming. This study presents the design and analysis of a hybrid renewable energy system for Racha Yai Island, Phuket, to reduce electricity costs, enhance energy self-sufficiency, and mitigate environmental impacts. Due to the island's limited space and favorable wind and solar resources, a 290-kilowatt hybrid system—combining solar and wind energy—was designed to replace the existing diesel generators. The system included a 10-kW wind turbine and a 280-kW solar array. Wind energy production was estimated using the Wind Atlas Analysis and Application Program (WAsP), while solar energy output was calculated using HelioScope software. The system was expected to generate approximately 436,000 kWh annually, with 14,454 kWh coming from wind energy and 422,405 kWh from solar energy, meeting a steady load demand of 60 kW. Economically, the project achieved a net present value (NPV) of 1,928,445 baht, an internal rate of return (IRR) of 13.96%, and a payback period of 7.06 years. Additionally, the system was projected to reduce greenhouse gas emissions by approximately 245,077 kgCO2e annually, contributing to more excellent energy stability and environmental sustainability on the island.

Keywords - solar cell system, low-speed wind turbine, greenhouse gases

I. INTRODUCTION

The global transition towards renewable energy has gained significant momentum, particularly in island and remote regions facing unique energy challenges. Thailand's islands, characterized by high electricity production costs and substantial dependence on fossil fuels, represent critical areas for sustainable energy transformation [1]. Recent developments in renewable energy technologies have made hybrid systems increasingly viable, combining solar and wind power to address energy stability and environmental sustainability [2].

The electricity landscape in Thailand's island communities has traditionally relied on diesel generators, which incur high operational costs and contribute substantially to greenhouse gas emissions. A notable recent example is Banpu NEXT's pioneering microgrid installation on Koh Lipe, which successfully demonstrated a 24-hour renewable energy supply for a resort, showcasing the practical potential of integrated renewable energy systems in island settings [3].

Climate challenges underscore the urgency of renewable energy adoption. Recent studies have highlighted that islands are particularly vulnerable to climate change impacts, with unpredictable weather patterns intensifying the need for resilient, local energy solutions [4]. Solar and wind hybrid systems offer a promising approach to mitigating these challenges by generating decentralized, clean energy.

Technological advancements have significantly improved hybrid renewable energy systems' efficiency and economic feasibility. Innovations in low-speed wind turbines and high-efficiency solar panels have expanded the potential for renewable energy in regions with moderate wind and solar resources [5]. Moreover, improvements in energy storage technologies have addressed intermittency challenges, making hybrid systems more reliable and attractive for remote locations.

This study builds upon recent research by focusing on a 290 kWp hybrid wind and solar system at Bann Raya Resort on Racha Yai Island, Phuket. By comprehensively analyzing the system's technical performance, economic viability, and environmental benefits, the research aims to contribute valuable insights into renewable energy implementation strategies for island communities.

I. THEORY

A. *Wind Power Calculation*

It is well known that the equation generally provides the theoretical wind power per given swept area by a wind turbine, as in (1):

$$P_W = \frac{1}{2}\rho A V_0^3 C_P \tag{1}$$

The power output of a wind turbine (PW) depends on air density (ρ), the rotor's swept area ($A = \pi r^2$ or $\pi d^2/4$), wind velocity (V), and the power coefficient (C_P), which represents the efficiency of converting wind energy into usable power. The output is directly proportional to the square of the rotor diameter and the cube of wind speed. Notably, doubling the wind speed increases power output by eight times. However, capturing all of the wind energy is impossible, as doing so would stop airflow and make further energy extraction impossible.

B. *Quantum theory of light*

The photoelectric effect occurs when electrons are ejected from a material once the incident light reaches a particular threshold frequency. Below this frequency, no electrons are emitted. In 1905, Albert Einstein explained this phenomenon by proposing that light consists of discrete wave packets, or photons, each carrying energy. He suggested that when a photon strikes an electron, it ejects the electron, revealing the particle-like nature of light. Einstein also noted that long-wavelength radiation does not cause electron emission because its photons lack sufficient energy [10], [11], [12].

Planck's theory [9] states that a photon's energy is proportional to its frequency, governed by the Planck constant. This relationship can be expressed mathematically as in (2):

$$E = \eta\varpi = \eta\chi/\lambda \tag{2}$$

Where E is the photon's energy, h is Planck's constant (approximately 6.626×10^{-34} J·s), v is the photon's frequency in hertz (Hz), c is the speed of light in a vacuum (approximately 3.00×10^{8} m/s), and λ is the wavelength of the photon. This equation explains how solar panels generate electricity: when sunlight strikes the surface, photons transfer their energy to electrons in materials like silicon, dislodging them and producing electricity. The power of photons depends on their wavelength; shorter wavelengths (e.g., blue light) have more energy than longer ones (e.g., red light), affecting solar panel efficiency.

C. *Investment Concept*

The net present value (NPV), calculated as the difference between net cash inflows and outflows over a given period, is used to assess capital projects and investments. For NPV, the formula (3) is:

$$N\Pi\varsigma = \sum_{\tau=0}^{T} \frac{NX\Phi_\tau}{(1+\kappa)^\tau} \tag{3}$$

NCF_t represents net cash flow in each period, k is the discount rate or required return, and t is the time from 0 (present) to T (total periods). The NPV measures the value that an investment adds to a company. A project is considered favorable if the NPV is positive, as it indicates that future cash inflows exceed costs, creating value. If NPV is negative, the project is deemed unprofitable, destroying value.

D. *Methodology*

A hybrid renewable energy system comprising wind and solar energy with a total capacity of 290 kilowatts was examined at the RAYA Resort on Racha Yai Island in Phuket, located at a latitude of 7.60°N and a longitude of 98.37°E. Fig. 1 depicts the main components of the hybrid renewable energy system.

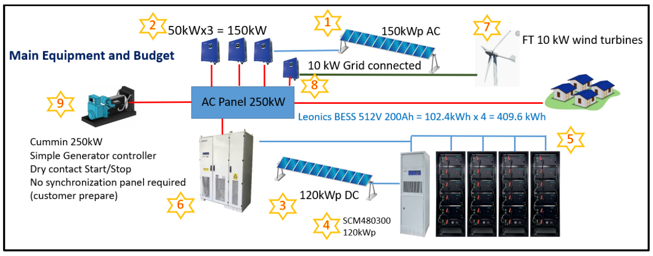

Fig. 1. Main Equipment of the hybrid renewable energy system.

As shown in Fig. 1, the system's main components were a 150 kW PV module for the AC grid and battery charging (1), three 50 kW on-grid inverters supporting the PV module (2), a 120 kW PV module on the DC side for battery charging (3), charge/discharge control units (4), a 400 kWh lithium battery energy storage system (5), a 250 kW grid and load control unit for peak load management (6), a 10 kW low wind speed turbine for nighttime battery charging (7), a 10 kW on-grid wind turbine with an inverter (8), and a 250 kW diesel generator for backup. WAsP software assessed wind energy, while HelioScope estimated solar energy production.

E. *Wind Energy*

A 10 kW low-speed wind turbine, designed by Thai researchers, was chosen for this study as a significant advancement in electricity generation. It could start at wind speeds of 2.5 m/s without an initial power supply and featured rotor blades, a generator, and a control system for optimal performance and safety. Built to withstand fluctuating winds, it had an automatic restart for gusts over 12 m/s and used materials suited to Thailand's hot, humid climate, ensuring efficiency at low wind speeds typical of tropical regions while minimizing noise impact.

Two models were used to assess wind speed and direction: the World Bank's data provided baseline wind conditions, which were further analyzed with Denmark's Wind Atlas Analysis and Application Program (WAsP). The data was compared with Spain's VORTEX wind speed model. To reduce risks during the pre-construction phase, wind power density at 10 and 50 meters was measured at Ban RAYA Resort, Racha Yai Island, to evaluate wind energy potential.

F. Solar Energy

HelioScope, a well-known national research computer model, was used to analyze solar irradiance data, providing insights into the amount of sunlight available and the potential power output of the solar panels. It was examined at the RAYA Resort on Racha Yai Island in Phuket, located at a latitude of 7.60°N and a longitude of 98.37°.

G. Financial Analysis

The financial analysis assessed the project's feasibility by evaluating costs for critical components like solar, wind, battery systems, diesel generators, and control systems. The net present value (NPV), internal rate of return (IRR), and payback period were calculated using these costs. The results demonstrated the project's financial viability, highlighting the economic benefits and the timeframe for recovering the investment.

H. Environmental Benefit Analysis

The environmental benefits analysis of the hybrid renewable energy system at The RAYA Resort, Racha Yai Island, Phuket, included calculating the reduction in greenhouse gas emissions using the following (4):

$$CO_2 \text{ Reduction } (kgCO_{2e}) = \text{Electricity Generated (kWh)} \times \text{Emission Factor } (kgCO_{2e}/kWh) \qquad (4)$$

The emission factor represents the CO2 saved per unit of electricity generated from renewable sources like solar or wind instead of fossil fuels. This calculation estimated the total reduction in greenhouse gas emissions, contributing to a cleaner, more sustainable environment for the resort and surrounding areas.

II. RESULT AND DISCUSSION

A. Wind energy production

The preliminary wind speed analysis at Ban RAYA Resort, Racha Yai Island, Phuket, using the World Bank model, showed an average wind speed of 4.2 m/s at 10 meters and 5.81 m/s at 50 meters. This data was processed using the Wind Atlas Analysis and Application Program (WAsP) developed by the Wind Energy Department at Risø DTU, Denmark. The WAsP model results revealed an average annual wind speed of 4.41 m/s at 10 meters and 4.90 m/s at 50 meters.

The simulation of electricity generation at various wind speeds at Ban RAYA Resort, Racha Yai Island, Phuket, was conducted at a height of 18 meters above ground level. This analysis used a 10-kW low-speed wind turbine as the starting point. As illustrated in Fig. 2, the turbine generated 1.65 kWp of electricity at a wind speed of 4.6 m/s. This wind speed was used to determine the electrical output throughout the entire year. It was discovered that the low-speed wind turbine with a capacity of 10 kW installed in the project area generates approximately 39.6 kWh per day or 14,454 kWh per year.

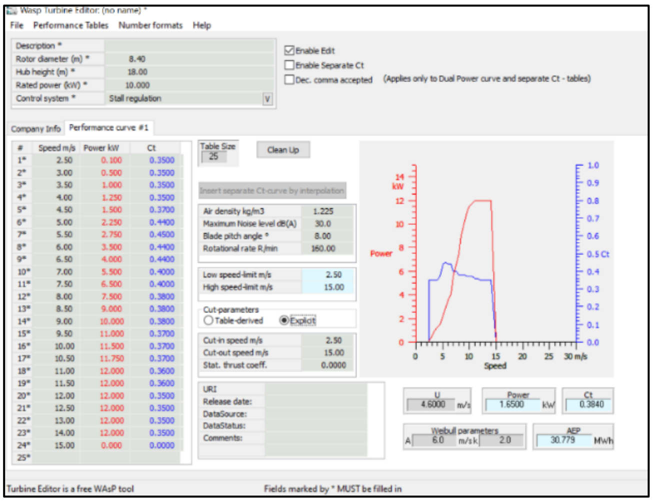

Fig 1. The simulation of electricity generation.

Furthermore, the relationship between wind speed, power output, and wind turbine operation shows that as wind speed increases, power output rises gradually, then more rapidly, until it reaches the maximum or rated power. After reaching this level, the output remains constant despite further increases in wind speed until the turbine shuts down at extremely high wind speeds (cut-out speed) of 15 m/s to prevent damage. At wind speeds up to 10 m/s, the turbine's power output increased, reaching rated power around 10–12 m/s. Beyond this, the turbine maintained or reduced output, and at 14 m/s or higher, it stopped operating to avoid damage.

Table 1. shows the performance summary of the wind farm. The wind farm was designed with 10 kW turbines at a 30 m tower height, achieved over 91.7% efficiency, had a capacity factor exceeding 29.3%, and operated at an average wind speed of 5.8 m/s at the project site.

Table 1. Performance Summary of the Wind Farm

Parameter	Unit	Value
Efficiency	%	91.70
90% (Capacity Factor)	%	29.30
Annual Energy Production (AEP)	MWh/y	25,711
Average Wind Speed	m/s	5.80 (Tower - 30 m)
Benefit-Cost Ratio (B/C)	-	1.31
Internal Rate of Return (IRR)	%	11.17

B. Solar Energy Production

The simulation results of the solar energy system's electricity generation using the HelioScope program by FT ENERGY revealed that installing a 280 kWp solar system at Ban RAYA Resort, Racha Yai Island, Phuket, produced an annual electricity output of approximately 422.4 MWh. The monthly solar electricity output, as shown in TABLE II, found that in March, the system generated a maximum electricity output of approximately 52,136.8 kWh, followed by January, which had a potential electricity production of up to 47,298.7 kWh.

Table 2. Monthly Solar Energy from HelioScopes Model

Month	GHI	POA	Shaded	Nameplate	Grid
	(kWh/m^2)	*(kWh/m^2)*	*(kWh/m^2)*	*kWh*	*kWh*
January	166.5	181.3	179.6	47,298.7	40,678.3
February	165.4	174.7	173.6	45,795.3	39,166.2
March	194.8	198.8	197.6	52,136.8	44,444.3
April	173.4	170.3	169.1	44,436.8	38,095.5
May	157.0	150.2	149.0	39,044.0	33,652.9
June	146.0	138.7	137.5	35,964.7	31,183.8
July	151.80	145.20	143.90	37,673.50	32,669.3
August	146.50	143.30	142.00	37,193.00	32,249.6
September	142.60	143.30	142.00	37,247.60	32,276.2
October	148.10	153.70	152.50	40,112.10	34,532.8
November	130.90	139.40	138.10	36,262.20	31,344.3 0
December	132.30	142.80	141.30	37,093.80	32,112.0

C. Financial Analysis Result

The investment budget for the hybrid renewable energy system, shown in TABLE III, included costs for critical components like the solar system, wind system, battery, diesel generator, and control system, totaling around 30 million baht. The island's investment cost was approximately three times higher than on the mainland, primarily due to the high logistics expenses of transporting equipment, with each boat shipment costing around 400,000 baht. Additionally, the absence of expert staff on the island increased costs due to high staffing expenses.

Table 3. Investment Budget for A Hybrid Renewable Energy System

No	Main Equipment/System List	Price (MBaht)
1	Solar system	12,5000,000.00
2	Wind system	3,000,000.00
3	Battery system	5,000,000.00
4	Diesel Generator	2,000,000.00
5	Control System	5,500,000.00
6	Others	2,000,000.00
	Total	**30,000,000.00**

The financial analysis in this study assumed the installation of a 280-kW solar system, a 10-kW wind turbine, a 400-kWh battery for energy storage, and a 250-kW diesel generator for backup, as shown in TABLE IV. When the hybrid system could not generate electricity, the diesel generator would take over, with a production cost of 25 baht per unit, based on the 2023 average diesel price of 32.73 baht per liter. The solar system was expected to generate an average of 1,091 kWh per day, operating for 4.60 hours, while the wind turbine was projected to produce 14,454 kWh annually, or about 39.60 kWh per day.

Table 4. Feasibility Analysis Assumption

No	Analysis Assumption	Unit	Specification
1	Installed capacity	kWp	290.00
2	Total investment	Baht	30,000,000.00
3	Average hour of solar energy	Hour/day	4.60
4	Performance ratio (Expected)	%	81.81
5	Average hour of solar energy	Hour/day	3.76
6	Plant factor	%	0.00
7	Daily electricity production	kWh/day	1,131.15
8	Yearly electricity production	kWh/year (Net working day)	412,869.28
9	Electricity injected into grid from Day-off	kWh/year (Net working day)	0.00
10	Demand Charge	Baht/kW	74.14
11	Electricity Increase by	%	0.00

The financial analysis result, as presented in TABLE V, showed a net present value (NPV) of 1,928,445 baht, an internal rate of return (IRR) of 13.96%, and a break-even period of 7.06 years, indicating that the project is financially viable with moderate returns and a reasonable payback period.

Table 5. Result of IRR, NPV, and discount rate

No	Analysis List	Unit	Result
1	Internal Rate of Return, IRR	%	13.96
2	Net Present Value, NPV	Baht	1,928,445.00
3	Check NPVIRR	Baht	0.00
4	PV Rate	%	10.00

D. Environmental Benefit Analysis Result

The environmental benefits analysis of the hybrid renewable energy system at The RAYA Resort, featuring a 10 kWp wind turbine and a 280 kWp solar system, showed a significant reduction in greenhouse gas emissions. Based on the principle that each kWh of electricity generated from wind or solar reduces emissions by 0.561 $kgCO_{2e}$, the project's estimated annual generation of 422,405 kWh resulted in a reduction of approximately 245,077.89 $kgCO_{2e}$ per year, demonstrating the project's positive environmental contribution.

III. CONCLUSION

The installation of renewable energy at the Bann RAYA Resort Hybrid Renewable Energy Project on Racha Yai Island, Phuket, consisted of a hybrid system that combined a 10 kW wind turbine with a 290 kW ground-mounted solar panel system. A study using simulation software to evaluate the energy potential in the area showed that the wind resources were suitable for electricity generation, with each low-speed wind turbine estimated to have produced approximately 14,454 kWh per year. Solar energy, analyzed using the proprietary software HelioScope, was projected to generate around 422,405 kWh annually. We will conduct the site analysis for further work by comparing the actual data with the software Pvsystem and the HelioScope program. The combined electricity output from both technologies was estimated at approximately 436,000 kWh/year. The project generated a net present value (NPV) of 1,928,445 baht and an internal rate of return (IRR) of 13.96%, achieving a payback period of 7.06 years. Furthermore, the new system significantly improved the island's electricity stability compared to the previous, more polluting system, resulting in a reduction of approximately 245,077 kg CO_{2e}/year in greenhouse gas emissions.

IV. ACKNOWLEDGMENT

The researchers would like to express their sincere gratitude to the team at the Thailand Renewable Energy for Community Association, FT Energy Co., Ltd., the Research and Service Center for Energy, Faculty of Engineering, the Rajamangala University of Technology Thanyaburi, and all supporting team members who contributed to the study of this project. The research team appreciates everyone's support and facilitation of the research efforts.

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E-Infinity Ecosystem: Peer-to-Peer Energy Trading Using X-Changer and Energinx Smart Meters for Reverse Power Flow Prevention

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Abstract — The rapid advancement of energy management technologies has catalyzed the development of peer-to-peer (P2P) energy trading platforms, revolutionizing energy production and consumption dynamics. In Thailand, this shift is exemplified by the E-Infinity Ecosystem, a P2P energy trading platform powered by X-Changer and Energinx smart meters, designed to prevent reverse power flow and optimize energy distribution. This paper presents an experimental study on the application of the E-Infinity Ecosystem within a ceramic factory, where one building acts as a producer and another as a consumer. The system leverages distributed energy resources (DERs) and facilitates direct energy transactions, offering a user-friendly interface and advanced energy management tools. The results demonstrate that Energinx and X-Changer enable efficient real-time energy sharing between buildings, minimize energy waste, and ensure grid stability. Furthermore, the study explores the technological, regulatory, and economic challenges facing the adoption of P2P energy trading systems in Thailand. The findings emphasize the potential of decentralized energy markets to promote renewable energy integration, reduce costs, and foster community participation in the energy sector. This work contributes to the advancement of decentralized energy systems, aligning with Thailand's national energy policies and global sustainability goals.

Keywords — Peer-to-Peer Energy Trading, Distributed Energy Resources, Energinx Smart Meters, X-Changer Trading Platform, Renewable Energy Integration

Enhancing Optimal Unit Commitment via Ant Lion Optimizer with Photovoltaic Uncertainty

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Abstract — This paper introduces a new approach for addressing the unit commitment problem by including solar photovoltaic (PV) integration. The uncertainties associated with photovoltaic (PV) output are classified into three distinct categories based on their varying levels of penetration. The data utilized in this study pertains to the IEEE 39-bus system, which incorporates 10-unit generators. The analysis considers various system restrictions in the unit commitment process, including power balancing, system reserve requirements, generator generation limits, and minimum up and down time constraints. The Ant Lion Optimizer (ALO) is a proposed solution for the unit commitment problem, drawing inspiration from the hunting behavior of the ant lion. In this study, the performance of the suggested method is evaluated and compared with that of the Dynamic Programming (DP) technique. The evaluation is conducted in terms of generation scheduling, total operating cost (TOC), and calculation time. Based on the findings, it can be concluded that the ALO technique demonstrates superior performance in generation scheduling, resulting in reduced total operating costs (TOC) when compared to the DP technique. The integration of photovoltaic (PV) systems into the grid infrastructure results in an annual cost savings of approximately $6,612,705.

Keywords — Evolutionary computation, forecast uncertainty, Power generation planning, Power system economics, Solar power generation

Battery & Energy Management

Comparison of PSO optimization and feedback control methods for energy management in hybrid-solar with grid-tied system

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Abstract — Reducing global warming is very important today. It is considered another option to reduce global warming. Renewable energy is, therefore, another way to reduce these problems. But renewable energy systems are volatile and uncertain. Battery energy storage systems (BESS) are an essential part of storing surpass energy from daily unstable solar energy for photovoltaics (PV). This paper presents an optimal BESS charging-discharging schedule strategy using Particle Swarm Optimization (PSO) technique to reduce electricity costs and compares the results with EMS feedback control peak shaving mode to achieve the lowest electricity cost for loading in the dormitory. We have looked at the characteristics of the BESS G-cell 100 kW/227.2 kWh battery. The result shows the PSO and FBC an energy reduction of 83.7% and 82.1 respectively, and electricity bill reduction of 85.5% and 84.1% respectively.

Keywords — Energy Management, Battery Energy storge system, Particle Swarm optimization, Optimal charging and discharging schedule.

Assessing Techno-Economic Impacts of Hybrid Renewable Energy System with Energy Storage For Campus Buildings In Malaysia Using HOMER

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Abstract — Hybrid renewable energy systems (HRES) combined with energy storage offer a viable strategy to lessen reliance on fossil fuels and minimize carbon emissions in the search for sustainable energy solutions. This study assesses the techno- economic effects of installing a hybrid renewable energy system for a university campus building in Malaysia. The grid connected system consists of solar photovoltaic (PV) along with battery energy storage systems (BESS). A thorough analysis is carried out to optimize system setup using the HOMER program, taking into account factors like energy generation, storage capacity, and economic viability. The results illustrate the viability and benefits of incorporating renewable energy into campus infrastructure, showing considerable potential for cost savings and environmental benefits. Additionally, HRES with BESS demonstrates superior environmental performance by producing the fewest emissions, underscoring its benefits in reducing harmful outputs and promoting sustainability. This article serves as a model for sustainable energy planning in similar tropical locations by offering insightful information on the real-world use of HRES with BESS.

Keywords — Hybrid renewable energy systems (HRES), solar photovoltaic (PV), battery energy storage systems (BESS), net energy metering (NEM), Energy Management System (EMS), HOMER

Evaluating Battery Energy Storage System (BESS) Sizing for Substation Investment Deferral Using Load Profile Analysis in Thailand

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Abstract — As Thailand's electricity demand continues to rise due to rapid economic and industrial development, there is a need to find new approaches to maintain grid stability and defer costly infrastructure investments. This study presents a method to determine the optimal battery size for Battery Energy Storage Systems (BESS) in distributed substations, focusing on peak demand that exceeds transformer capacity during electricity tariff periods in Thailand. A method was proposed to determine the appropriate BESS sizing by analyzing load profiles, detecting overload periods, and calculating battery capacity requirements. Key parameters, including the energy needed for discharging (Eneed) and energy available for charging (Eallow), were used to define the BESS size and optimize its operation. Among different load profiles, the pattern with a distinct difference between peak-time overload and off-peak low consumption offered the most significant potential for delaying substation upgrades, while other profiles show less capacity for deferral. The study reveals that BESS size was significantly influenced by load profile patterns, particularly the relation between Eallow and Eneed, but not by the load growth rate. Future research should evaluate additional factors, such as investment and maintenance costs, cost-benefit analyses, and alternative solutions, to further inform substation investment deferral decisions.

Keywords — load profile, overload, BESS sizing, substation, peak shaving

Smart Mobility (EV)

Techno-Economic Feasibility and Environmental Assessment of a Grid-Connected PV System for EV Charging in Brunei Darussalam

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Abstract — Electric Vehicles (EVs) are increasingly becoming popular globally due to their environmental benefits and sustainability. However, electric vehicles are charged by the electricity generated primarily by natural gas, which defeats the purpose of having EVs to reduce carbon emissions. Additionally, adding charging stations for EVs can burden the grid and potentially disrupt load demand. This research aimed to study the effectiveness of a solar-powered EV charging station in Brunei Darussalam. The study analyzed the collected data in terms of technical, economic, and environmental aspects. It found that a 10-kW photovoltaic (PV) system can produce between 3.91 and 4.57 kWh/kWp in a day. The average performance ratio and system efficiency are 0.78 and 16.9%, respectively. When assessing the economic feasibility under the selected conditions, due to the extremely cheap electricity cost in the country and the high initial investment cost, integration of PV would be beneficial mainly for residential buildings with more than 3000 kWh consumption per month and the charging would be free of cost with zero emission. On the contrary, under the commercial tariff system, the payback period of the commercial solar-powered EV charging station is 4.6 years, and the ROI is 81.72%. In addition to that, using a PV system for charging can eliminate carbon emissions.

Keywords — EV charging station, grid-connected PV system, economic analysis, technical analysis, carbon emissions

Intelligent Appliances & Smart Building

Solar PV Soiling Study

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Abstract - The identification of photovoltaic (PV) panel soiling using artificial intelligence (AI) is critical for optimizing solar PV plant efficiency. This paper proposes a modified convolutional neural network (CNN) model to classify different types of PV panel soiling. Our approach, tested on a dataset of solar panel images, improves the speed and accuracy of classification, achieving a 98.95% success rate. The method enables focused and efficient cleaning strategies by identifying specific types of pollutants on the panels, ultimately enhancing the overall system performance. We compare the proposed method with existing algorithms, showcasing the enhanced performance in detecting soiling on PV panels. Additionally, the paper discusses the implications of the results for future solar plant maintenance techniques.

Keywords - Solar PV, Soiling, Artificial Intelligence, Modified Convolutional Neural Network, Image Classification, Solar Panel Maintenance

Applications of an Automated Nutrient Solution Chilling System for Growing Hydroponic Lettuces in Tropical Conditions

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Abstract - Hydroponic farming is gaining popularity in Thailand as an alternative to traditional agriculture, driven by increasing consumer demand for clean, safe, and pesticide-free produce. Growing cool season crops like lettuce in tropical climates can be challenging, particularly in maintaining optimal temperatures for plant growth. This study incorporated a nutrient solution cooling (NSC) system into a dynamic root floating technique (DRFT) hydroponic to regulate water temperature (WT) between 22-|25 °C and promote lettuce growth under tropical conditions. A split-plot experimental design was used to compare the growth performance of green-leaf and red-leaf lettuce cultivars under controlled WT (with NSC) and ambient WT (without NSC) conditions. Growth parameters including root length (RL), leaf length (LL), and fresh weight (FW) were measured. The results showed that the NSC system significantly improved RL, LL, and FW for both lettuce cultivars compared to ambient WT conditions. An economic analysis, based on a 10-year investment period at a 5% annual interest rate, revealed that the NSC system had a higher benefit-to-cost (B/C) ratio compared to the traditional hydroponic culture. The analysis also suggested that increasing the scale of production further improves the B/C ratio, making the NSC system economically viable for larger hydroponic operations. In conclusion, integrating the NSC system into hydroponic setups within tropical environments can enhance lettuce growth and economic returns, making it a valuable strategy for improving productivity and sustainability in hydroponic farming.

Keywords - hydroponic lettuce, tropical conditions, water chiller, temperature control system, internet of things

Energy Management for Smart Grid

Application of Machine Learning Models in Solar Power Prediction Based on Multilevel Stacking Ensemble Approach

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Abstract - Prediction of solar radiation is critical in various applications including photovoltaic (PV) power generation and micro grid management. Due to the non-stationary and non-linear nature of solar irradiance, accurate prediction is essential for reliable PV plant operation. In this research, we compared the efficiency of six types of machine learning models, namely random forest (RF), extreme gradient boosting (XGBoost), k-nearest neighbors (KNN), linear regression (LR), multi-layer perceptron (MLP) along with support vector regression (SVR) as a meta-model. We did this by using three level stacking approach to increase precision of solar power generation predictions. In this research we are using private dataset and public dataset. The private data used in this research was collected from the University of Tartu, Estonia between 20-9–2020 and 17-10-2021. Furthermore, we utilize open-source datasets from Kaggle to forecast solar energy output and assessed the models using four metrics: Mean Squared Error (MSE), R-squared (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In examining the suggested stacked model to the individual models, we can see that the stacked model outperforms them significantly. Specifically, the stacking model achieved a MSE values of 0.0091 indicating very low error and a substantial increase, in accuracy compared to the standalone models. Moreover, the stacking model showed values, for R^2 (0.9903) and MAE (0.0578) further emphasizing its predictive abilities.

Keywords - Photovoltaic, Grid management, Support vector regression, Stacking

I. INTRODUCTION

A. Research Background

Solar energy can be a dependable and sustainable source of energy that can deliver considerable benefits for the environment and economy. As among the most promising renewable energy resources, solar energy is capable of meeting global energy demands [1]. Despite the growth in solar power generation, precise estimates of solar power production are necessary for productive use of solar energy. Forecasting solar energy accurately can optimize solar energy use, reduce reliance on other energy sources, and improve energy efficiency. Through accurate forecasting, renewable energy waste can be avoided, and grid power can be reduced. Many factors influence solar power generation, such as weather conditions, environmental factors, geographical location, and time of day. Solar energy output will also vary depending on factors such as solar elevation angle, haze effect, and cloud cover [2]. Therefore, accurate solar power predictions require sophisticated modeling techniques that can capture the complexity and nonlinearity of these factors.

Forecasting solar energy resources has traditionally been done by using empirical and conventional models, but their accuracy has been inadequate [3]. Fortunately, artificial intelligence-based techniques have been effective in addressing these issues. Utilizing machine learning algorithms, solar power generation can be predicted based on historical data. The algorithms learn from the data by utilizing statistical models to find associations and patterns, then apply this knowledge to forecast outcomes. A deep learning algorithm such as multilayered perceptron (MLP) is one of the most used methods for predictive modeling [4]. Moreover, random forest models offer a traditional approach to predicting solar power production, providing a model that can be interpreted [5].

Utilizing ensemble techniques like stacking can enhance the precision of solar power forecasting by amalgamating various models [6]. Combining the results of several base models into one ensemble learning technique called stacking allows for the creation of predictions that are more accurate. Stacking models can be particularly effective in situations where individual models may perform poorly due to overfitting, underfitting, or noise in the data. In this paper, we construct a multi-tier stacking framework for solar power prediction, integrating various machine learning algorithms to augment the precision of solar power predictions.

B. *Motivation and Objectives*

The objective of this research is to examine the principles and methods of predictive modeling as well as the applications of various model types for forecasting solar power. Additionally, this paper aims to create and assess a stacking model for solar power prediction that combines three level modeling and numerous machine learning techniques. A meta-model combines the results of several base models, such as SVR, random forest, MLP, KNN, linear regression, and XGBoost. This study used a number of performance indicators, such as MAE, MSE, RMSE, and R^2 to assess the suggested model's performance. This study explored the benefits and limitations of these methods and identify the challenges associated with solar power prediction. The proposed stacking model can help enhance the accuracy of solar power forecasts and optimize the use of solar energy. The results of this study can be valuable for researchers, policymakers, and energy companies interested in enhancing the potential benefits of solar energy.

II. LITERATURE REVIEW

A. *Understanding Renewable Energy for Sustainable Development*

Energy serves as the foundation for human survival and is crucial for the sustainable growth of the economy. Recent years have seen a rise in interest in solar power prediction. The need for renewable energy has emphasized the importance of accurate solar power prediction to reduce energy costs and dependency on grid power. By accurately forecasting solar energy availability, utilities and grid operators can optimize the balance between supply and demand, ensuring that solar power is efficiently integrated into the energy mix. Moreover, precise solar power prediction is crucial for maximizing the benefits of solar energy systems. For instance, in a solar photovoltaic on-grid system, as shown in fig. 1, sunlight is converted by solar panels into direct current (DC) energy, which is subsequently converted by a grid-connected converter into AC electricity for consumption in houses and input into the grid.

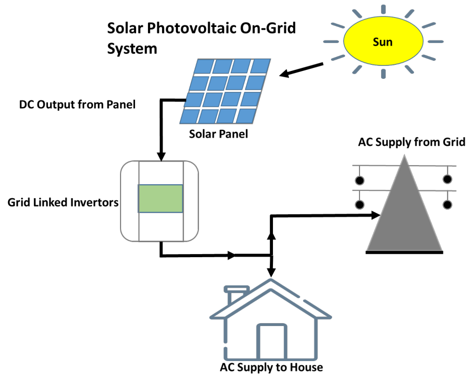

Fig. 1. Conversion of solar energy into AC and DC power

B. *Role of Machine Learning to predict Solar Power Generation*

a) Random Forest

A 2018 study by Yen and colleagues presented a hybrid model with an emphasis on using machine learning methods, particularly Support Vector Machine (SVM) and Random Forest, to estimate solar output power [7]. Metrics like MAE, RMSE, mean forecast error (MFE), and mean absolute scaled error (MASE) are used to assess the effectiveness of these models. The experimental results are presented, providing insights into the effectiveness of SVM and RF algorithms in predicting solar output power. However the results shows RF performs slightly better than SVM prediction results.

In a different study, Liu and Sun integrate K-means clustering and Principal Component Analysis (PCA) with a Random Forest algorithm that is optimized using Differential Evolution Grey Wolf Optimizer [8]. The optimal Random Forest parameters are effectively chosen by the optimization method, which filters and minimizes data noise using PCA and K-means. Comparative tests revealed that the prediction accuracy and resilience of this combined model are greatly increased.

b) Linear Regression

A study by Mathur and colleague shows a comparative analysis of linear regression, Poisson regression and Lasso regression models has been performed using weather data such as temperature, humidity, and light intensity to forecast the generated electric power of a solar plant and understand its behavior. The results indicate that compared to the Poisson and Lasso regression models, the linear regression model forecasts the output power of PV systems more correctly [9].

The goal of a different study by Kaushik and colleagues [10] is to use machine learning techniques like Decision Tree Regression, Random Forest Regression and Linear Regression to attain accurate short-term forecasting. The suggested models show 99% accuracy, according to the results.

c) XG Boost

A study conducted by Moosa and colleagues investigated the utilization of machine learning algorithms for forecast solar radiation for optimal solar energy generation [11]. Their study compared the performance of three prominent algorithms: Extreme Gradient Boosting (XGB), Random Forest, and Artificial Neural Network (ANN). Through rigorous analysis, the results demonstrate that XGB outperforms both Random Forest and ANN in terms of accuracy, as indicated by the lowest Root Mean Square Error (RMSE).

Further, the research by Quoc-Thang Phan et al. demonstrated that the fusion of Kernel PCA and XGBoost provides a potent strategy for enhancing the accuracy of short-term solar power forecasts. The model's ability to handle nonlinear relationships and its robust performance under varying weather conditions make it a valuable tool for managing the challenges posed by the intermittency of solar PV generation. The results highlight how cutting-edge machine learning approaches can improve the dependability and effectiveness of renewable energy systems [12].

d) K-Nearest Neighbor

The study by Ramli and colleagues investigated the factors affecting solar power generation in Malaysia and identified those with strong correlations to solar power output. Using these factors, the k-nearest neighbor method was employed to anticipate solar power generation for the following month. Findings indicated that the k-nearest neighbor method outperformed the artificial neural network, evidenced by its lower root mean square error, making it a more accurate prediction tool for solar power generation in the region [13].

In 2018 Fei Wang et al. [14] conducted a study using two commonly used classification methods namely K-nearest neighbors (KNN) and support vector machines (SVM), are employed to categorize daily local weather patterns for DAST solar PV power forecasting. The result shows KNN is more responsive to the training dataset length and can achieve greater accuracy.

e) Multi-layer Perceptron

El Badaoui et al. (2013) employed MLP neural networks to predict the global solar radiation in the area of Sebt El Guerdane, Agadir, Morocco [15]. In this study, the MLP model outperformed linear regression in forecasting solar radiation accurately. The research is pertinent to renewable energy research, especially optimizing the use of solar energy through artificial neural networks.

Another study by Abdullah et al. (2019) used the Sharda University PV dataset 2022 Edition for various regression models for predicting power output [16]. The performance of these regression models has been evaluated and compared using metrics such as projected vs. actual value charts, mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and R2-score, among others. Simulation outcomes demonstrate that the multilayer perceptron regressor outperforms alternative methods, with an RMSE of 17.870 and an R2 score of 0.9377.

f) Support Vector Regression

A study finding by Alfadda and colleagues, explored the solar power prediction using SVR, Polynominal regression and Lasso. The findings indicate that the SVR model outperforms other regression models when the appropriate set of features is selected [17].

Further, Kasireddy et al. [18] applies machine learning algorithms to past weather data, such as temperature, dew, wind, the amount of clouds, and visibility, using the following algorithms: Lasso regression, linear regression, support vector regression (SVR) and ridge regression. Analysis shows that the SVR algorithm surpasses the other methods in predicting solar energy output.

g) Stacked Model

The primary aim of stacking is to decide which model combination is optimal for a given application. Additionally, Al-Haji and associates suggested an ensemble learning strategy to improve the precision of solar energy predictions one day in advance [19]. The methodology entails combining the predictions generated by recurrent neural networks and support vector regressor through a stacking technique. Their results unequivocally establish the supremacy of the ensemble model over individual models and other fusion techniques utilized for solar energy forecasting. Al-Haji and colleague's research not only presents the promising results achieved by the ensemble approach but also emphasizes the significance of larger training datasets in further improving the model's performance.

In 2018 Zhou et al. [20] employed the Stacking algorithm, combining multiple base Support Vector Machines (SVM) to forecast PV power output. Their findings indicate a notable improvement in the efficiency of the proposed model compared to traditional methods.

In conclusion, the literature review suggests that models like random forest, XGB, SVR, KNN, MLP, Linear regression are efficient in predicting solar power. Stacking methods combining various models provide an effective way to reduce bias and improve accuracy. However, our review of the literature indicates a scarcity of research on multilevel stacking. Future research should explore complementary methods to improve the accuracy and scalability of solar power prediction.

III. METHODOLOGY

The methodology section involves data description, initial data preprocessing, feature engineering, and exploratory analysis. Individual models, including Linear Regression, Random Forest, XGBoost, KNN, MLP and SVR, are applied to predict solar energy production. Stacking techniques are employed at multilevel, combining diverse models and utilizing SVR as the meta-model. The models are then tested and evaluated on performance metrics, including mean squared error, root mean square error, R-squared, and mean absolute error.

A. Dataset Description

In this research, we have used two types of dataset, private dataset and public dataset. The private dataset is collected from the University of Tartu, Estonia to forecast solar energy production. The data contains attributes such as Index10, Humidity, Temperature(C), Global Horizontal Irradiance (GHI), Hour, Month, Output power and previous output. The dataset provides every 30 min data, 1hour data and 4 hour data between 20-9–2020 and 17-10-2021. The 30 min interval dataset comprises 17864 observations, 1 hour dataset consists of 8932 data record, and 4 hour interval dataset has 2233 data records. Below fig. 2 shows the location of Estonia solar power plant.

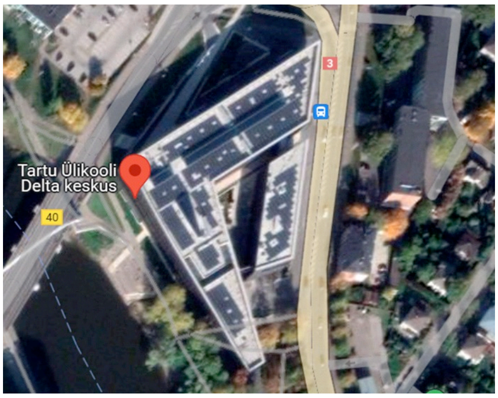

Fig. 2. PV map of delta center

Source: *Delta Centre - University of Tartu - Google Maps*

Additionally, we utilized open-source datasets from Kaggle to assess and authenticate the effectiveness of our predictive model. The datasets were obtained from two solar power facilities in India, spanning 34 days of entries. Each dataset comprises two categories of files: power generation data and weather sensor data. After merging and cleaning the two dataset we get 3158 records for plant 1 similarly for plant 2 we get 3259 records. Also we get nine variables which includes several important feature like Irradiance, module temperature, ambient temperature and AC power which then evaluated for final prediction.

B. *Data Preprocessing*

The data undergoes multiple preprocessing steps which includes, dealing with missing values, dropping irrelevant columns, identifying and handling outliers and normalizing the data to a uniform scale. Additionally, the output power is transformed using the square root to achieve a more normalized distribution. Standard scaling is applied to the features for better model performance. As the data contained different units and scales, normalization was performed before model training to ensure a uniform scale in the input data. Normalization ensures that the input features to the model are of the same magnitude and range.

The Estonia dataset was relatively clean, with emphasis placed on organizing the data appropriately. Outlier detection focused on negative values and top system capacity. Upon visual examination, no outliers were found in the dataset. For Public dataset both sensor data and weather data then merge to obtain the dataset with multiple features for prediction. The dataset then underwent pre-processing steps including filling missing values, removing duplicate entry when merging two datasets and scaling features to a consistent range. Outlier detection and removal step performed using the Interquartile Range (IQR) method.

C. *Data Splitting*

After preprocessing the raw data, then the data is categorized into two parts: a training set and a test set. The training dataset is utilized to construct and train a diverse set of algorithm, while the test dataset served as the key metric for evaluating the overall performance of the ensemble and individual models implemented in the code. The partition of the dataset is performed in the ratio 80% for training dataset and 20% for testing dataset.

D. *Computational Models*

Predicting the power output of panels using machine learning involves analyzing weather data and performance of the model. ANN has proven effective in previous studies which resulted to the selection of MLP, a kind of ANN for predicting the PV systems power output. Moreover RF and XGBoost were picked as the tree based models, for this research. Previous studies have shown that RF usually achieves accuracy levels. While XGBoost is not commonly used for output power prediction it has become popular for its performance among tree based models. Considering the correlation of weather data with nearby values KNN is also explored, highlighting the greater influence of closer neighbors. The selection of linear regression is due to its simplicity and effectiveness in modeling relationships between variables in meteorological data, making it suitable for data with linear characteristics. SVR is chosen for its modeling of data making it suitable, for the nonlinear characteristics of meteorological data. Finally, to enhance overall forecasting accuracy, the predictions of several different models are combined using the stacking approach.

a) Random Forest

Random forests represent a supervised machine learning method extensively employed in regression and classification assignments, consistently delivering outstanding outcomes even in cases where hyperparameters are not finely adjusted. A Random Forest operates similar to a cooperative decision-making group within machine learning. By amalgamating insights from multiple trees, it enhances predictions, culminating in a more robust and precise model overall. The RF model is trained and evaluated similarly to LR, assessing its performance against the established metrics.

b) XGBoost

XGBoost, an open-source tool, enables the efficient and proficient application of gradient boosting, an ensemble machine learning technique utilized for both classification and regression tasks. In regression predictive modeling, where the objective is to predict numerical values like monetary amounts or measurements, XGBoost proves to be a fitting choice. It employs a variety of differentiable loss functions in conjunction with gradient descent optimization for model fitting. This method, akin to neural networks, minimizes the loss gradient during model fitting, hence the term gradient boosting.

c) K-Nearest Neighbor

KNN, a non-parametric approach in machine learning, is utilized for both classification and regression tasks. In numerical target prediction scenarios, KNN retains all training instances and generates predictions based on measures of similarity [21]. In a basic implementation of KNN regression, the procedure entails calculating the mean of the numerical target values from the K nearest neighbors within the training dataset. Similar to its classification counterpart, the regression variant of KNN employs the same distance-measuring functions.

d) Multi-Layer Perceptron

A feed-forward neural network (FFNN) including consecutive layers of neurons connected by synaptic weights is called a Multi-Layer Perceptron (MLP) [22]. The three interwoven layers that make up MLP are as follows: an output layer that makes assumptions about the input signals, a hidden layer that does complex calculations, and an input layer that receives input signals. The hidden layer's complexity allows the MLP to estimate any continuous function. In this instance, the MLP uses its low complexity and flexibility to combine basic learners to provide final predictions.

e) Linear Regression

Linear regression is a statistical method used to model the linear association between one or multiple independent variables and a dependent variable. Simple regression is defined as modeling the dependent variable with only one independent variable. Simple linear regression equation is shown as in (1).

$$Y = \beta_0 + \beta_1 x + \epsilon \qquad (1)$$

Where β_0 is the intercept, designating the y-axis intersection point, β_1 represents the slope of regression line, x denotes independent variable whereas y denotes dependent variable. Furthermore, the term ϵ refers to the error term.

f) Support Vector Regression

SVR is a potent regression technique that finds a hyperplane in a high-dimensional space to maximize data point separation. Support Vector Regression (SVR), as opposed to Support Vector Machines (SVMs), is used to find the continuous space hyperplane which best fits the data points. The steps involved in the procedure are to represent all of the input variables onto a high-dimensional feature space, find the hyperplane with the largest margin (distance) between it and the closest data points, and reduce prediction error. Mathematical formulation of SVR is shown in as (2).

$$\mathrm{Min}\frac{1}{2}\|\omega\|^2 \qquad (2)$$

Where min indicates that the goal is to minimize the following expression, $\|\omega\|^2$ represents the squared euclidean norm of the weight vector and the term $\min\frac{1}{2}\|\omega\|^2$ is a regularization term which is used to prevent overfitting.

Support Vector Regression (SVR) entails optimizing a cost function aimed at reducing the disparity between predicted and observed values. SVR employs a kernel function to elevate the data into a higher-dimensional realm, facilitating the identification of a hyperplane. Objective function of SVR is shown in as (3).

$$min\frac{1}{2} \parallel \omega \parallel^2 + C\sum_{i=1}^{N} (\xi_i + \xi_i^*) \qquad (3)$$

Where C denotes number of errors in training, ξ_i is the slack variable which measures the deviation above the margin, ξ_i^* is the slack variable which measures the deviation below the margin and the sum $\sum_{i=1}^{N}(\xi_i + \xi_i^*)$ aggregates these deviations for all data points.

g) Stacked Model

In machine learning, stacking is an ensemble approach wherein several different base models are trained, and the predictions from these models are used as input characteristics for a meta-model, enhancing overall predictive performance. In this proposal the first level consists of Individual models, namely XGBoost, KNN, Linear Regression and RF, independently generate predictions. The predictions from XGBoost and KNN are amalgamated and utilized as inputs for a Multi-Layer Perceptron (MLP), while the predictions from Linear Regression and Random Forest are combined and used as inputs for SVR in the second level of stacking. Subsequently, the predictions from the MLP and SVR models at the second level are conjoined and serve as a dataset for a meta-model positioned at the third level, ultimately providing the final prediction. Fig 8 represent the proposed staking model.

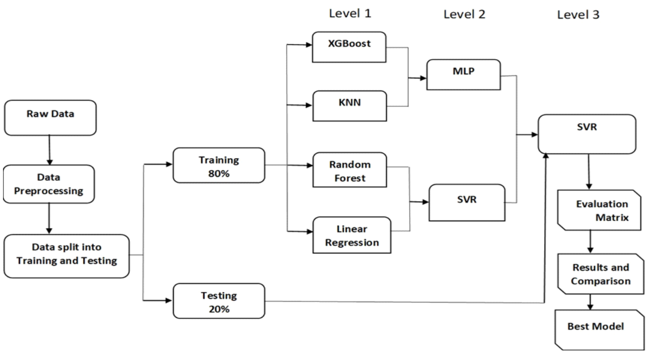

Fig. 3. Visual representation of proposed model

At first, the individual models, namely XGBoost, KNN, Random Forest, and Linear Regression, are trained separately. The predictions generated by XGBoost and KNN models are combined into one dataset for further processing in the subsequent level, while similarly, the combined predictions from Random Forest and Linear Regression models form another dataset for the subsequent level.

Two stacking models are constructed at the second level. The first stacking model combines Random Forest and Linear Regression, while the second stacking model combines KNN and XGBoost. The meta-model for both stacking models are SVR and MLP. Base models are trained by training set, and their predictions form the input for the meta-model at second level. The stacking models are then evaluated on the test set using the defined metrics.

In the third level, the predictions from the second level stacking models are combined, forming a new dataset. A third level stacking model is constructed using SVR as the meta-model. The combined result from the second level goes to meta-model for training as well as for testing the new dataset. This three-level stacking approach is designed to leverage the complementary strengths of different models. The test set is employed to evaluate the model's performance following its training with aggregated predictions.

The advantage of employing a stacking approach in machine learning lies in its ability to enhance predictive accuracy by integrating diverse models at multiple levels, thereby mitigating the limitations of individual models and leveraging their complementary strengths. This ensemble technique effectively combines the predictive outputs of various base models through strategically designed meta-models, fostering a more robust and adaptable system that often outperforms individual models, particularly when faced with complex and non-linear relationships within the data.

E. Evaluation Metric

The efficacy of all models is rigorously evaluated using the test dataset. We have used four metrics to evaluate the models' performance: Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R-squared (R^2). Performance metrics can be measured in a variety of ways, but there is no general consensus on which ones are acceptable [23]. The goal is to evaluate the accuracy and resilience of individual models to ensemble models. In addition, the effectiveness of the ensemble models is evaluated by comparing them to the best-performing individual model.

IV. RESULTS AND ANALYSIS

In this part, we plan to use both models and combined models to predict PV power output. Our data originates from two sources; data, from Estonia and public data from India. For the dataset we will analyze time intervals of 30 minutes, 1 hour and 4 hours. On the other hand for the dataset that includes India Plant 1 and Plant 2 we will focus on intervals of every 15 minutes.

By comparing how well individual models perform against combined models with these datasets and time intervals our goal is to gain insights into their abilities in different scenarios. This holistic approach allows us to assess how data granularity affects model accuracy and reliability. Through this research we aim to pinpoint the modeling methods to improve the precision of solar PV power forecast, across different geographical locations and time frames.

A. Prediction Performance

This section displays the outcome of evaluating the proposed stacked model and shows the comparison between standalone model and proposed model on the basis of the metrics on different datasets. It also includes an analysis of the model's internal learning operation and examines the effect of the forecast horizon on the modeling.

Fig 4–6 shows the collection of graphs which illustrates the actual versus predicted values for various regression models applied to the different datasets which includes Estonia's 30 min interval dataset and India's Plant 1 and plant 2 dataset. Each scatter plot represents different models, including Linear Regression, Random Forest, SVR, XGBoost (XGB), KNN, MLP and Stacked model, with the projected output values on the Y-axis and the actual output values depicted on the X-axis. In each plot, the red dashed line indicates the line of perfect prediction where the actual values would exactly match the predicted values.

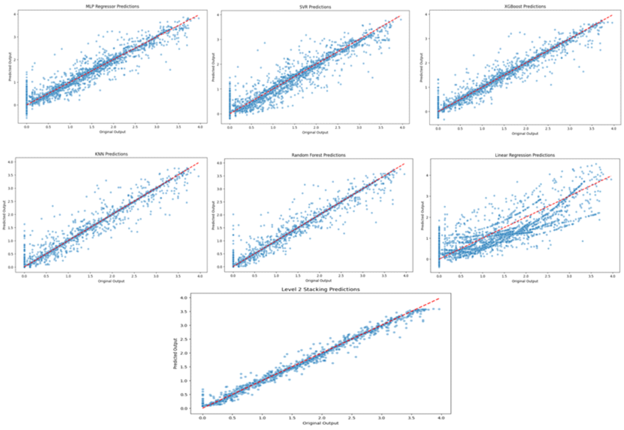

Fig. 4. Predicted output Y axis and actual output X axis for 30 Min interval dataset

Fig. 4 displays high performance of a stacked model over individual model by plotting the predicted output against the original output, showing a robust positive correlation. The scatter plot demonstrates that the predictions closely follow the red dashed line, which represents perfect predictions. The spread of data points surrounding the line is tighter compared to other models graph, indicating that the Level 2 stacking model achieves higher accuracy and less variability in its predictions.

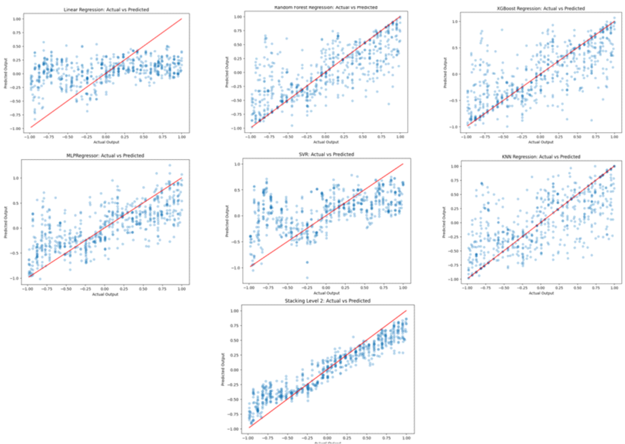

Fig. 5. Predicted output Y axis and actual output X axis for India Plant1 dataset

Fig. 5 depict the actual versus predicted values for seven regression models for India Plant 1 dataset, where the Linear Regression model exhibits a moderate scatter and some deviation, the Random Forest and XGBoost models display tighter clustering around the fit line suggesting greater accuracy, the MLP Regressor indicates higher variance and potential overfitting, the SVR shows reasonable clustering but more dispersion compared to the ensemble models, the KNN Regression model presents a significant spread indicating challenges in pattern recognition, and the Stacking model demonstrates the densest clustering around the fit line, thus harnessing the strengths of all individual models to achieve enhanced predictive performance.

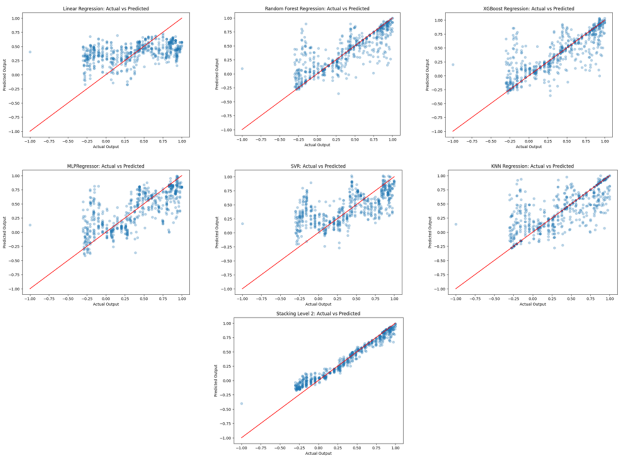

Fig. 6. Predicted output Y axis and actual output X axis for India Plant2 dataset

Fig. 6 illustrate the actual versus predicted outputs for various models for India Plant 2 dataset. Linear Regression exhibits a broad spread, indicating lower accuracy. Random Forest Regression offers improved predictions with points nearer to the red line. XGBoost Regression further enhances accuracy but still shows some dispersion. MLP Regression demonstrates moderate spread with several predictions deviating from the line. SVR displays a tighter clustering around the red line, highlighting its prediction effectiveness. KNN Regression shows significant spread, suggesting lower prediction accuracy and the Stacking model, which amalgamates these individual models, showcases superior performance with points closely aligned along the red line, signifying a marked improvement in predictive accuracy.

Overall, the models with tighter clusters of points around the red dashed line show better predictive performance. The above graphs suggests that the stacking approach improves the model's predictive performance, leading to more precise alignment with the actual values.

B. Performance Evaluation

The study evaluates multiple models which includes LR, RF, XGBoost, KNN, SVR, and MLP, with the following hyper parameters: max_iter, activation, hidden_layer_sizes, solver, and learning_rate for MLP Regressor; n_neighbors and p for KNN; n_estimators, learning_rate, max_depth, and subsample for XGBoost; and default settings for the remaining models. Hyperparameters are essential to machine learning models because they affect how well the training procedures work [24].

While performing model testing we get the results of evaluation metrics on the Estonia 30 Min Interval test data for various models are shown in the table 1. Using four metrics, the table compares the performance of many machine learning models which includes XGBoost, MLP, RF, KNN, SVR, LR and Stacking Model using a dataset with 30-minute intervals, showing that the Stacking Model achieves the lowest MSE (0.0091), highest R² (0.99033), lowest MAE (0.0578), and lowest RMSE (0.0957), indicating superior performance, while Linear Regression performs the worst with the highest MSE (0.2592), lowest R² (0.7264), highest MAE (0.3919), and highest RMSE (0.5091). The Stacking Model demonstrates the best output across all metrics, denoting it is the most accurate and reliable model for this dataset.

Table 1. Evaluation metrics for Estonia 30 min interval dataset

Models	MSE	R^2	MAE	RMSE
Stacking Model	**0.0091**	**0.9903**	**0.0578**	**0.0957**
Random Forest	0.0276	0.9707	0.0688	0.1664
KNN	0.0311	0.9671	0.0631	0.1764
SVR	0.0626	0.9338	0.1512	0.2503
XGBoost	0.0301	0.9681	0.0807	0.1736
MLP	0.0522	0.9448	0.1361	0.2286
Linear Regression	0.2592	0.7264	0.3919	0.5091

Table 2 displays the performance metrics of various machine learning models on Estonia 1hour interval dataset, showing that the Stacking Model outperforms others with the lowest MSE (0.0099), highest R-squared (0.9897), lowest MAE (0.0722), and lowest RMSE (0.0997), followed by models like Random Forest, KNN, SVR, XGBoost, MLP, and Linear Regression in descending order of performance based on these metrics.

Table 2. Evaluation metrics for Estonia 1 hour interval dataset

Models	MSE	R^2	MAE	RMSE
Stacking Model	**0.0099**	**0.9897**	**0.0722**	**0.0997**
Random Forest	0.0338	0.9651	0.0749	0.1838
KNN	0.0413	0.9572	0.0817	0.2033
SVR	0.0607	0.9372	0.1564	0.2463
XGBoost	0.036	0.9627	0.0898	0.1898
MLP	0.0558	0.9422	0.1517	0.2363
Linear Regression	0.2465	0.7451	0.3884	0.4965

Table 3 data showcases the performance metrics of multiple machine learning models over a Estonia 4 hour interval dataset. It reveals that the Stacking Model surpass the performance of other models with the lowest Mean Squared Error (0.0134), highest R-squared (0.9726), lowest MAE (0.0899), and lowest RMSE (0.1158). Other models that perform similarly but with increasing error values and decreasing R-squared values in that order are Random Forest, XGBoost, SVR, KNN, MLP, and Linear Regression.

Table 3. Evaluation metrics for Estonia 4 hour interval dataset

Models	MSE	R^2	MAE	RMSE
Stacking Model	**0.0134**	**0.9726**	**0.0899**	**0.1158**
Random Forest	0.031	0.9366	0.0872	0.1762
KNN	0.0523	0.8932	0.0999	0.2288
SVR	0.0481	0.9017	0.144	0.2195
XGBoost	0.0278	0.9431	0.0888	0.1669
MLP	0.0531	0.8916	0.1689	0.2305
Linear Regression	0.1804	0.632	0.3353	0.4248

Table 4 displays the performance indicator of several ML models on India Plant 1 dataset, indicating that the Stacking Model achieves the best output with a MSE of 0.047, an R² of 0.868, a MAE of 0.173, and a RMSE of 0.218, followed by Random Forest and XGBoost with MSE of 0.155, R² of 0.57 for RF and MSE of 0.172, R² of 0.523 for XGB. The K-Nearest Neighbors model shows average performance with an MSE of 0.195 making it less accurate than Stacking

Model, Random Forest, and XGBoost. The SVR model performs poorly compared to the above models, with an MSE of 0.284, R^2 of 0.214, MAE of 0.414, and RMSE of 0.533, indicating higher prediction errors and lower accuracy. Overall, the Stacking Model proves to be the most efficient and effective approach for this dataset, while the Linear Regression model is the least effective model.

Table 4. Evaluation metrics for India Plant1 Dataset

Models	MSE	R^2	MAE	RMSE
Stacking Model	**0.047**	**0.868**	**0.173**	**0.218**
Random Forest	0.155	0.57	0.272	0.394
KNN	0.195	0.459	0.315	0.442
SVR	0.284	0.214	0.414	0.533
XGBoost	0.172	0.523	0.284	0.415
MLP	0.192	0.467	0.346	0.439
Linear Regression	0.322	0.111	0.47	0.567

Table 5 provides a comprehensive comparison of various regression models based on their performance metrics. It highlights that the Stacking model markedly surpasses the other models, achieving a remarkably low MSE of 0.009, an impressively high R^2 value of 0.942, a minimal MAE of 0.0746, and a very low RMSE of 0.099. Random Forest has an MSE of 0.058, an R^2 of 0.657, an MAE of 0.147, and an RMSE of 0.241, which indicates it performs reasonably well but not as proficiently as the Stacking Model. Both KNN and MLP display moderate performance, with KNN having an MSE of 0.079, R^2 of 0.532. Conversely, SVR and Linear Regression demonstrate inferior performance, with SVR having an MSE of 0.107, R^2 of 0.364, MAE of 0.252, and RMSE of 0.328, and Linear Regression faring the worst with an MSE of 0.139, R^2 of 0.18, MAE of 0.306, and RMSE of 0.372. Collectively, this table conclusively illustrates that the Stacking Model is the most effective methodology for forecasting the power output of the India Plant 2 dataset, delivering the highest accuracy and lowest error rates among the evaluated models.

Table 5. Evaluation metrics for India Plant2 Dataset

Models	MSE	R^2	MAE	RMSE
Stacking Model	**0.009**	**0.942**	**0.0746**	**0.099**
Random Forest	0.058	0.657	0.147	0.241
KNN	0.079	0.532	0.18	0.281
SVR	0.107	0.364	0.252	0.328
XGBoost	0.062	0.63	0.149	0.25
MLP	0.077	0.544	0.211	0.277
Linear Regression	0.139	0.18	0.306	0.372

C. *Comparison of different model on different dataset*

On comparing the different models from different dataset shows stacking model superior performance across almost all metrics and intervals, particularly noticeable in the 30-minute and 1-hour datasets where it gets the smallest MSE, MAE, and RMSE, and highest R^2. Random Forest and XGBoost also perform well as individual model for private dataset while Linear Regression shows the weakest performance with the highest MSE, RMSE, and lowest R^2 consistently. Upon comparing the results from the Estonia and India datasets, a marked decline in performance metrics, particularly R-squared (R^2) values, is evident when transitioning from the Estonia dataset to the India datasets. The Stacking Model exhibits a notable R^2 reduction from the Estonia dataset to the India Plant 1 dataset, decreasing by approximately 10.43% (from 0.9897 to 0.868). Additionally, the R^2 further diminishes by about 4.77% on comparing the Estonia dataset to the India Plant 2 dataset (from 0.9897 to 0.942). This reduction in R^2 values is accompanied by an uptick in error metrics, such as MSE, MAE and RMSE, indicating a decline in the model's performance when applied to the India datasets.

This comparison underscores that the models perform more effectively on the Estonia datasets, likely due to disparities in data quality, feature relevance, or inherent characteristics of the datasets. The significant increase in errors and reduction in R^2 values for the India Plant 1 and Plant 2 datasets suggest that these datasets might require a different modeling approach, more rigorous data preprocessing, or the integration of more complex features to improve model performance. Overall, this comparison underscores the paramount importance of choosing models that are meticulously tailored to the unique attributes and requirements of the dataset and the predictive task at hand. Stacking Model, although generally effective, demonstrates variable performance across different datasets, emphasizing the necessity for model adaptability and dataset-specific optimization.

V. CONCLUSION

A multi-level stacking ensemble model was used in this study to improve prediction accuracy over a number of datasets with different time intervals. The study applied a variety of machine learning algorithms, such as XGBoost, MLP, k-NN, Random Forest, Linear Regression, and SVR, ordered hierarchically from Level 1 to Level 3, using a systematic method with three unique stages of model integration. Rigorous data cleaning processes have been implemented to address outliers and missing values, ensuring the robustness and reliability of the predictions.

XGBoost, k-NN, Random Forest, and Linear Regression were the basic models used by Level 1 of the stacking ensemble. For each model to capture different aspects of the data dynamics, 80% of the preprocessed data was used during training. XGBoost and Random Forest employed boosting and bagging techniques to concentrate on ensemble learning, whereas k-NN utilized its capacity to identify local regularities in the data, and Linear Regression analyzed the linear correlations. Using increasingly complex models like MLP and SVR, Level 2 saw the integration of Level 1 outputs with the goal of synthesizing the original predictions into a more refined output, minimizing variance and maybe capturing non-linear interactions that single models would miss. In order to correct and enhance the predictions made by Level 2 by focusing on the residuals and enhancing the final prediction accuracy, Level 3 employed a second SVR to serve as the meta-learner. The ultimate adjustment layer was supplied by this top-level model, guaranteeing that the ensemble's predictions are as near to the target values as feasible.

The performance of this complex stacking architecture was then rigorously evaluated using an evaluation metric, comparing the results to those of individual models to determine the most effective approach. Better performance was shown by the ensemble model compared to typical single-model techniques, as indicated by reduced error metrics (MSE, MAE, RMSE) and improved R-squared values across various intervals and datasets.

This study underscores the significance of choosing the most suitable machine learning algorithms for inclusion in the stacking ensemble, showing that a comprehensive evaluation of different algorithms leads to superior performance outcomes. With its layered integration of several machine learning models, this structured ensemble approach offers an effective tool for handling complicated prediction tasks in a variety of domains, from financial modeling to energy forecasting. The ensemble model's performance in this work supports more research and application of stacking approaches, especially in domains where complex data and prediction accuracy are important considerations.

This study significantly enhances prediction accuracy, demonstrating that such advanced techniques can effectively capture the diverse and non-linear patterns present in solar power data. The incorporation of models that can handle data from various geographical regions has proven essential, as it allows for more robust and generalized predictions that account for differing weather patterns and solar irradiance levels.

Future research could further optimize the architecture by experimenting with different combinations of base and meta-learners, potentially incorporating more advanced machine learning models or deep learning approaches, considering better quality of data to further enhance the predictive power and efficiency of the ensemble system. Moreover, implementing a rigorous feature selection process is crucial to ensure that independent variables exhibit a strong correlation with the dependent variables. Finally, the practical application and impact of the proposed model have been thoroughly assessed, indicating that it can effectively enhance solar energy utilization, inform policy decisions, and support energy management strategies. In future research, we could gather an extensive collection of datasets from diverse locations worldwide to thoroughly understand regional disparities and to develop a prediction model that is versatile and applicable across different locations, states, and countries. By overcoming these challenges, this research not only optimizes solar power prediction but also enables the seamless incorporation of solar energy into the electrical grid, thereby contributing to advancement of renewable energy solutions.

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Harnessing Digital Twins: A New Frontier for Electrical Systems in Industrial Plants

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Abstract - Digital Twinning technology is being implemented in the operational process of industrial plants to increase predictability and efficiency. As a virtual real-time twin, it monitors the performance of each physical asset under certain operating conditions. That extends the life span of electrical components, which permits predictive maintenance with improved operational efficiency while reducing emissions and improving safety conditions. While applying DT technology, prioritization of critical components in the industrial electrical system exhibits great importance. Based on the findings, the MV motors and panels are identified as the most critical components of continuous and reliable industrial processes where great attention is being paid to closely monitor their operational status and procure urgent actions in advance. Given that, the contribution will try to provide a realistic route for the applications of this technology to close the gaps between the advantages and the large-scale use in managing industrial electrical systems. This can be helpful for moving towards smarter and more sustainable operations of the industrial sector that can adapt to the energy evolution.

Keywords - Digital Twins, Artificial Intelligence, Industrial Plant, Plant Information Management System.

I. INTRODUCTION

One of the major drivers of new generations of innovation and optimization in industrial, oil, gas, and petrochemical plants is the maturity of digital twins and cyber-physical systems [1]. They provide virtual replicas of physical assets and processes, with monitoring in real time, predictive analytics, and simulation capabilities that elevate operations and decision-making. Hence, industrial plants would be able to connect to those systems that integrate physical elements with digital technologies, creating intelligent systems that allow for seamless communication, control, and optimization of operations [2].

Digital Twins (DT) and Cyber-Physical System (CPS) have a high potential in the oil, gas, and petrochemical industry if it is able to utilize prediction maintenance, optimization of production processes, and continuity of operation in complex and hazardous environments in order to increase safety, reliability, and sustainability [1]. While the convergence of DT and CPS drives operational excellence, it also ushers in smart manufacturing practices, unlocking new opportunities for cost savings, innovation, and competitive advantage within industrial and energy sectors. Their relation with DT and CPS for industrial plants is interrelated and very complicated. Both complement each other in optimizing plant operations and their efficiency [3].

DT technology creates a kind of virtual representation over the physical assets and the processes, further giving real-time insight with predictive analytics for better decision-making abilities and overall improved performance [4]. On the other hand, the CPS combines the physical component with digital technology to provide seamless communication, monitoring, and control over industrial processes in a networking environment. This DT and CPS synergy of the industrial plant may now be understood as an enabling capability toward smart, cyber-physical systems wherein the physical assets are mirrored by their digital twins such that operators are able to monitor, analyze, and optimize plant operations in real time [5]. The manufacturing plants will move several production processes to an automated environment, thus reducing downtime, improving safety, and being more efficient in terms of overall performance, therefore ushering in the era of smart manufacturing and digital transformation by utilizing the functions of both technologies. It is the technology of the DT that revolutionized the field of industrial plants, introducing enormous development in design, monitoring, and maintenance processes. In recent times, much interest and investment have been developing regarding DT, and researchers and industry professionals are looking at the possible benefits and challenges that may be lurking behind the realization of this technology within different industrial sectors [6].

This review covers all the diversified aspects of digital twins in industrial plants, including applications, advantages, limitations, and future directions. A digital twin is a virtual replica of any physical asset, system, or process emulating the actual physical counterpart in real time. It means a digital twin is empowered through the integration of sensors data, machine learning algorithms, and simulations whereby operators and engineers are allowed to track, analyze, and optimize more perceptively the performance [7].

The concept of a digital twin came from Michael Grieves back in 2002. In the recent times, it has gained much prominence in manufacturing, energy, and healthcare sectors [8], [9].

Applications of digital twins in industrial plants vary from predictive maintenance and process optimization to product design and remote monitoring. Since a digital twin can analyze real-time data from sensors embedded in machinery, it has the ability to predict and warn against potential failures or upcoming maintenance, thus minimizing downtime while enhancing operational efficiency. They also allow operators to simulate a number of scenarios that may be helpful in the optimization of processes regarding production and resources and allow engineers to try out new product designs quickly by virtual testing [10-12].

It is very advantageous to make use of digital twins in an industrial setting. They serve to enhance the performance by optimizing processes for reduced operational costs, derived from insights gained from real-time data. Digital twins further allow informed decision-making through the simulation of different scenarios, hence informing strategic choices that drive business growth [13]. Predictive maintenance capabilities reduce unplanned downtime by identifying potential issues early, while real-time monitoring enhances safety through the detection of hazards and improves safety protocols.

Industrial plants greatly benefit from such digital twins, but putting them into place is not very easy. Integration of data coming from different sources may be rather challenging and is linked with high needs of resources and expertise. Such increased connectivity and data exchange also raises security concerns, insofar as that may expose the connected systems to cybersecurity risks. Moreover, the high costs of creation and benefits reaping from digital twins, together with a lack of skills in specialized domains like data analytics and machine learning, remain broad challenges for many organizations [12], [13]. These include interoperability between different digital twin platforms, AI and machine learning for enhancing analytics, edge computing to avoid latency, and integration of the digital twin with a digital thread for an integrated flow of information throughout the product's life.

The practical utilization of digital twin technology in a petrochemical plant would be to make replicas for monitoring and optimization by means of complex processing units that are distillation columns, reactors, and heat exchangers. Building virtual versions of these key assets would let operators simulate several operating conditions, predict performance outcomes, and find ways to improve processes [14]. For instance, digital twins can monitor temperature and pressure levels in real time, predict equipment failures before they happen, optimize energy use for maximum production efficiency while minimizing downtime. The integration of digital twins with advanced analytics and AI algorithms also enables the elaboration of predictive strategies for maintenance; this may enable the petrochemical plants to be more proactive regarding maintenance needs in general, thus avoiding costly unplanned shutdowns. The overall implication of deploying digital twins at a petrochemical plant would translate into a data-driven, optimized operation that ensures reliability for a sustainable and safety-assured production process.

The implementation of digital twins within electrical systems at industrial, oil and gas, and petrochemical plants introduces a revolutionary new way of thinking about the management and optimization of critical infrastructure. By creating virtual replicas of electrical assets, including transformers, switchgear, and distribution panels, operators can gain real-time insight into performance, predict maintenance needs, and troubleshoot issues in a proactive manner. In industrial plants, the employment of DT for electrical systems allows operators to monitor energy consumption, understand inefficiencies that have been built into the current setup, and maintain optimized power distribution to further improve operations and reduce costs [15], [16]. In oil , gas and petrochemical industry, DT presents views of the electrical infrastructure across remote sites, right down to every minute detail, thus allowing for centralized monitoring and control that ensures a reliable supply of power and prevents critical operation downtime.

Also, digital twin utilization for electrical systems in the industrial, oil and gas, and petrochemical plants will provide a holistic approach toward asset management and maintenance [16]. Accordingly, operators will be able to view the health of their equipment with real-time data from sensors and IoT devices and make informed decisions on possible failures, thereby planning maintenance activities wiser to minimize disruptions and increase uptime. Industrial digital twins enable the simulation of different cases for the optimization of the electrical system, ensuring that production is achieved with minimum energy consumption and degradation to the environment. In the oil and gas and petrochemical industries, electrical system digital twins are of paramount importance in the delivery of continuous power to critical operations with minimum possibility of failure of critical equipment, hence enhancing safety and regulatory compliance in an overall complex and hazardous environment.

DT thus has huge potential to bring in real-time insights, predictive capabilities, and optimization opportunities in industrial plants. Though there are challenges with respect to data integration, security, cost, and skills, continuous research and developments in technology will make the digital twin a far more pervasive reality across industries in the future. This, however, will probably see the role of digital twins at industrial plants expand as the organization continues to embrace digital transformation-driving innovation, efficiency, and competitiveness for many more years.

II. DIGITAL TWINS FRAMEWORK

Generally speaking, DT can be divided into three parts: the physical object, the virtual representation, and the interface that connects the two systems. Figure 1 illustrates the overall architecture of a typical DT. The physical system refers to any real-world system currently in existence, including but not limited to industrial plants, smart grids, learned transportation systems, advanced manufacturing, and smart cities. This physical system can serve many users, while changes in the operational environment take place. The changes demand corresponding actions from the physical system. Yet, updating the physical model of reality to conform to complex operational changes is not trivial. In that respect, the DT can use a simplified physical model, and under the data of the changed environment, it can simulate different scenarios and give advice to the tangible system for its following actions.

As can be seen in Figure 2, furthering a possible usage for an actual system that driven by DT required three major components that are comprised of the physical sub-system, the

Figure 1. Digital Twins overall structure

AI model, and the DT model. IoT gateways connected to each physical system collect data from that physical system and consolidate it. Communication protocols are used to send the data out from the physical system to the AI model. The AI model analyses the data and builds the models concerning the condition of the physical system. Then, the AI model stores the trained model as a DT model to represent the digital representation of the physical system configuration. In addition, if the physical system configuration has not changed, the DT model can advise the physical system based on the obtained data.

The AI model will update its model, considering changes in the physical system, and change the DT model further to support functions of the physical system when the configuration of the physical system changes or when a different response is required under the same kind of circumstances. In the same vein, it should also be noted that DT can help in managing and controlling the operation of physical systems.

III. PROPOSED MODEL DEVELOPMENT

The typical single line diagram (SLD) for an industrial plant is shown in Figure 3.

As one can witness in Figure 3, a variety of electrical loads (lighting, HVAC system, electro pumps, AC/DC motors, UPS, cathodic protection system, etc.) are demonstrated in SLD which are mostly prevailing in every industry especially in Oil /Gas and Petrochemical sectors [17].

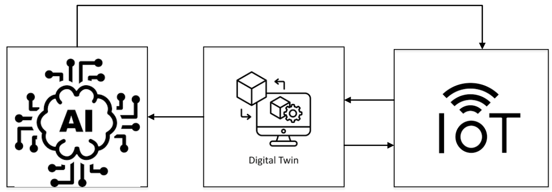

Figure 2. DT and AI

In Figure 4, the schematic array of electrical equipment in an actual and typical industry is shown. As can be seen in both Figures 3 and 4, the most crucial and vital electrical equipment in continuous operation of industrial process are those of MV/LV switchgear/panel and the electrical motors. Therefore, a great deal of attention shall be paid when driving digital twins for such industrial plant with a massive number of electrical motors and MV switchgear.

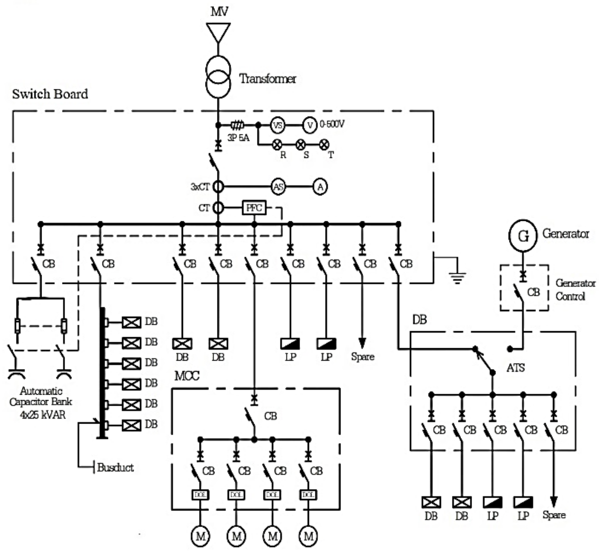

Figure 3. Typical single Line Diagram for industrial plant

The main intent is to develop DT for electrical system, in this vein, the focus will be laid on two critical component of MV/LV motors and switchgears by means of relevant and affordable IOT system and measurement sensors.

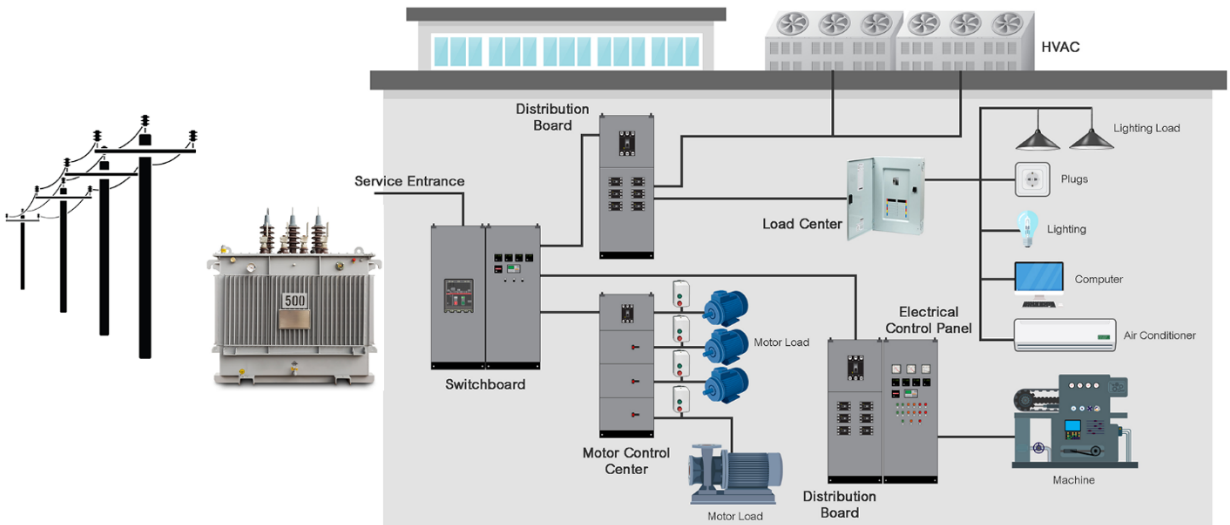

Figure 4. Power Distribution in industrial plant

That is to make a data stream to gradually build the equivalent digital representation of reality of current operation and health status of the aforementioned critical electrical components.

Electrical installations in large industrial plants, due to the insignificance of the initial EPC costs, are less compared to other parts of the projects, but they are of double importance. Considering the nature of loads and the sensitivity and dependence of industrial processes on continuous power supply, this matter will require a special attitude. Any possible failure in the electrical network of the plant will cause severe financial losses. Due to the multiplicity of dynamic loads (low and medium pressure engines), industrial drive systems and low and medium pressure panels, in addition to special considerations in the initial design, will require intelligent monitoring of the functional status and prevention of possible defects in the future.

With the emergence of the 4th industrial revolution, with the benefit of technologies such as the IOT, robotics, AI and machine learning, the process of intelligentization has been greatly improved in all industrial sectors [8-10]. In this regard, the initial efforts for intelligentization in the oil, gas and petrochemical industry have started in the last few years, but these plans have been limited merely to sectors such as HSE and hazard prediction.

The use of online data of sensitive electrical equipment (motors and MV panels) allows the technical inspection department to make appropriate decisions by real-time monitoring of data, data mining results and machine learning algorithms. The study of international companies such as the Saudi Aramco oil company or the South African Sasol and Chinese Sinapec companies shows that the use of this data, of course, in the production process in the oil, gas and petrochemical industries, in addition to increasing production, has resulted in significant savings for them.

The present proposal intends to study and select high-sensitivity electrical equipment (motors and medium-pressure valves) in an industrial plant and present an implementation plan (hardware and software) for intelligentization and technical decision-making based on data. In the continuation of the analysis, the improvement of operational indicators, continuity of production, monitoring of the situation, early troubleshooting, acceleration of operations and management of technical assets will be reported in detail.

After the stage of design, implementation, testing and updating, which is carried out and delivered by the experts of this company in the form of a special project with time and cost control, the hardware platform including servers and all information at the site or central office the employer and will be placed under his control. Updates, further analysis of data and processes and other services will be continued in the form of a technical support contract.

The acquired data according to Figure 5 perform filtering, warehousing, data processing and analysis based on machine learning algorithms. The development of a suitable platform for data mining and monitoring a large amount of continuous data will be an integral part of the implementation stage. furthermore, if required, the outputs and simulation results can be transferred to Android platform and the real-time display of the functional status of the key electrical equipment for the industrial plant, such as MV/LV motor and panels, will be presented on the smartphones of supervisors and technical managers

This system collects, stores and analyzes the required data of the complex based on the client's requirements. Based on the needs and definition of the employer, a group of managers, engineers and operators and other factory personnel, especially financial affairs, can use the results and analyzes of this system for immediate decisions or any other needs. This system allows this. that the Key Parameters of the complex be available to the senior managers of the complex in the platform of a separate App in any place and online.

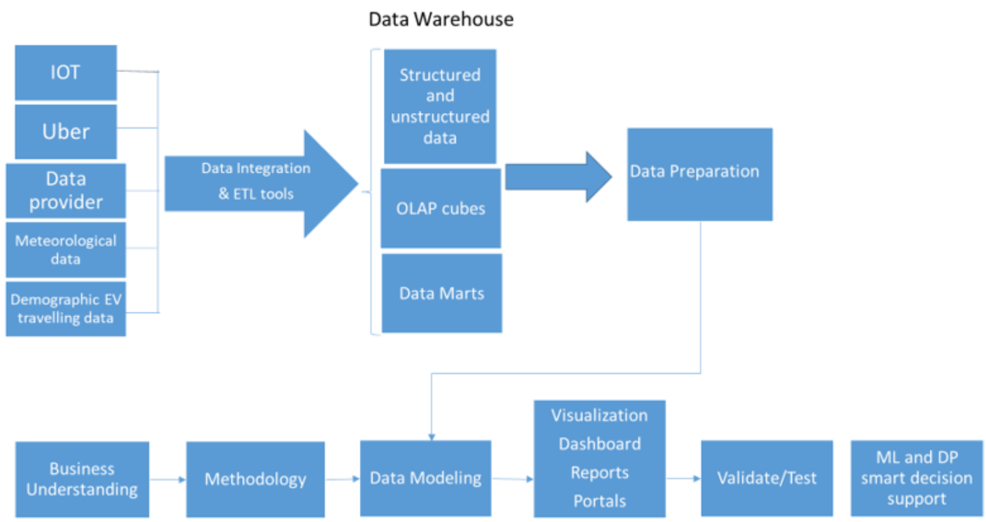

Figure 5. The proposed model

results to calculate the price of services and the consumption utility of each of the complexes in terms of comparison with the defined level of sudden differences, explaining the reasons for changes and other needs.

The client applications of this Microsoft-based system enable personnel to easily access this high-resolution data and view the current status of the plant, while the system also provides a very clear and detailed picture of past operations which also procures the analyzes that can be used to optimize suggestions in advance, such as improving quality control and maintenance processes. Software applications such as maintenance management, accounting, modeling can use this system for additional decisions.

Using the data stored in this system allows you to make decisions for any action and reports quickly and ultimately leads to increased production and reduced operating costs. In addition, the mentioned system helps to improve performance and reduce waste.

IV. CONCLUSION

In current practice, the digitalization of almost all industrial sectors is driven by the 4th Industrial Revolution technologies like IoT, robotics, AI, and machine learning. The oil, gas, and petrochemical industries digitalization in the recent decade has focused on HSE and hazard prediction. Online data coming from such sensitive electrical equipment like motors and MV panels allows real-time monitoring and making informed decisions based on data mining and machine learning. Similarly, studies conducted for such companies as Saudi Aramco, Sasol, and Sinopec demonstrate that the production process topped with such data increases output and provides substantial cost savings. This paper aims to identify the key electrical equipment in the industrial plant and develop a plan of implementation regarding hardware-software, which will enable digitalization and data-driven decision-making for the improvement of operational indicators. The objectives are threefold: ensuring continuity of production, enhancement of situation monitoring for early troubleshooting, and optimization of technical asset management.

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Data-Driven Approaches to Community Energy Monitoring: A Hybrid Framework Utilizing Smart Meters and Surveys

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Abstract - Smart meters and community surveys form an economical hybrid framework for community energy monitoring in this study. In Kued Chang, Chiang Mai, Thailand, the study targets smart meter deployment to address financial issues associated with extensive installation in the Mae Ta Man Community. This targeted method is improved by thorough community surveys that collect numerical and descriptive data to understand energy consumption trends. The hybrid framework analyses community energy dynamics, including peak demand periods, appliance inefficiencies, and household energy consumption. Real-time data from smart meters and detailed survey responses enable in-depth energy usage analysis and targeted strategies to improve efficiency and reduce consumption. The data showed evening energy consumption spikes due to older, less efficient appliances. These findings highlight community-driven energy efficiency efforts like upgrading obsolete appliances and changing peak consumption habits. The proposed framework could improve energy management in small and rural communities while being cost-effective. The study uses representative sampling for smart meter installation to collect high-resolution data without the financial burden of universal coverage. Community surveys provide a complete energy dynamics picture by documenting household demographics, appliance usage, and behavioral patterns. This approach's adaptability to community contexts is its strength. The hybrid model is ideal for diverse small or rural environments because it adapts to demographics, infrastructure, and energy needs. For financially strapped communities, smart meters ensure data collection to guide energy strategies while remaining cost-effective. Quantitative and qualitative data improve decision-making, enabling localised energy conservation strategies that fit community infrastructure. The hybrid framework inspires other communities to improve energy management sustainably and economically. This approach balances technological accuracy with community involvement to ensure that energy interventions are effective and appropriate for the context, promoting energy sustainability and resilience.

Keywords - Community Energy Monitoring, Smart Meters, Surveys, Hybrid Framework, Cost-Effective, Data-Driven Solutions

IoT Monitoring System Development for Collecting Building Energy Consumption

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Abstract - Smart monitoring system utilizing IoT technology was created and installed to improve real-time monitoring and energy efficiency in household energy usage. The system utilized ESP32 microcontrollers, industrial-grade meters, and the MQTT protocol to monitor energy consumption in nine residences inside the Mae Ta Man Community. The system exhibited reliability, attaining an average data loss of about 10%, with a maximum loss of 45%. Analysis of community energy consumption revealed peak usage periods from 8:00 to 10:00 and 17:30 to 20:00, primarily attributed to cooking and lighting, with phantom energy accounting for up to 15% of daily consumption. Immediate feedback and behavioral modifications resulted in a 10–15% enhancement in energy efficiency. This system is engineered for scalability and adaptability, offering actionable information to enhance energy management and facilitating wider use to promote global energy conservation initiatives.

Keywords - Smart Energy Monitoring System, Real-time Data Collection, Consumer Behavior, Energy Management

Climate Change & Clean Energy

Energy Performance Enhancement of the Office Building: Economic and Environmental Impact of Achieving nZEB

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Abstract - This paper presents a comprehensive analysis of the energy performance enhancement of an Office Building aimed at achieving Nearly Zero Energy Building (nZEB) Level 1 status. The current setup includes a 160 kW photovoltaic (PV) system and a 45 kWh energy storage system (ESS). Through optimized system analysis, the study proposes an upgrade to a 200 kW PV system and a 275 kWh ESS, which is expected to achieve an energy reduction of 87.62% to meet the nZEB Level 1 classification. The primary objectives are to evaluate the economic and environmental impacts of this integration, with a focus on energy savings, cost-benefit analysis, and greenhouse gas (GHG) emissions reduction. Results indicate that the implementation of the PV system and ESS leads to an annual energy savings of approximately 255,834 kWh, translating to a cost savings of about $30,700 per year based on an electricity rate of $0.12 per kWh. The simple payback period is estimated at 10.22 years. Environmentally, the project achieves an annual GHG emissions reduction of approximately 119.588 tons CO2e, decreasing emissions from 136.482 tons CO_{2e} to 16.894 tons CO_{2e} per year, significantly contributing to sustainability goals and climate change mitigation efforts. The findings demonstrate that achieving nZEB Level 1 status in the Office Building is both technically feasible and economi- cally viable. The significant energy savings and environmental benefits highlight the value of upgrading renewable energy systems. This study serves as a model for other facilities aiming to enhance energy performance and sustainability.

Keywords - Nearly Zero Energy Building, Energy Manage- ment, Clean Energy, Energy Economic.

I. INTRODUCTION

The building sector is a significant contributor to global energy consumption and greenhouse gas (GHG) emissions, accounting for approximately 40% of global final energy use [1] and a staggering 37% [2] of global emissions. This high carbon footprint is largely due to the production and use of materials such as cement, steel, and aluminum. As urbaniza- tion accelerates and the demand for energy-intensive amenities grows, there is an urgent need to enhance energy efficiency and integrate renewable energy sources within buildings to mitigate environmental impacts [3] and achieve sustainability goals.

While Zero Energy Buildings (ZEBs) [4] represent the ideal in sustainable building design, achieving a perfect net-zero energy balance can be technically and economically challenging due to factors like fluctuating energy demands and variable renewable energy production. Nearly Zero Energy Buildings (nZEBs) have emerged as a practical solution to this challenge, aiming to closely approach the ZEB standard within the constraints of current technology, economics, and site conditions. nZEBs are designed to have high energy perfor- mance, with most of their limited energy requirements being met by renewable energy produced on-site or nearby. This approach acknowledges the challenges of absolute net-zero energy while emphasizing reduced energy consumption and increased renewable use. Achieving nZEB status is not only a technical challenge but also an economic and environmental imperative, aligning with global sustainability goals and efforts to reduce greenhouse gas emissions.

This paper focuses on the Energy Research and Develop- ment Institute (ERDI) Building as an Office building case study for achieving nZEB lv1 status, as defined by the Society of Heating, Air-Conditioning and Sanitary Engineers of Japan (SHASE) [5]. According to SHASE Japan's standards, nZEB Level 1 corresponds to an energy reduction of 87.5% to 100% compared to baseline consumption. The Office Building in this paper currently operates with a 160 kW photovoltaic (PV) system and a 45 kWh energy storage system (ESS). Based on optimized system analysis, the study proposes upgrading to a 200 kW PV system and a 275 kWh ESS to meet the nZEB lv1 classification, as shown in Figure 1.

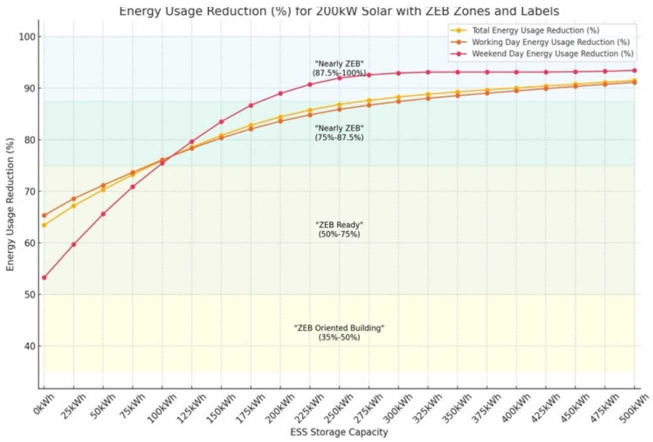

Fig. 1. Energy reduction for a 200 kW solar system with ZEB zones, showing total consumption reaching nZEB Level 1 at 275 kWh ESS capacity.

This configuration is projected to achieve an energy reduc- tion of 87.62%, effectively placing the building within the nZEB Level 1 classification.

The SHASE Japan standard provides a comprehensive framework for evaluating building energy performance, em- phasizing not only energy efficiency but also the utilization of renewable energy sources. By adhering to this standard, the ERDI Office Building sets a benchmark for excellence in energy performance within the region and contributes to the global efforts in promoting sustainable building practices.

The primary objectives of this research are:

- To assess the energy performance enhancement achieved through the integration of the PV system and ESS, quantifying the reduction in energy consumption and validating compliance with nZEB Level 1 standards set by SHASE Japan.

- To evaluate the economic impact, including initial invest- ment, operational savings, payback period, to determine the financial viability [7] of achieving nZEB Level 1 status.

- To analyze the environmental benefits by calculating the reduction in GHG emissions and assessing the contribu- tion to sustainability goals and climate change mitigation efforts.

In order to achieve these objectives, a systematic approach was adopted to analyze the energy performance, economic viability, and environmental impact of the Office building. The following section outlines the materials and methods used in this study, providing a detailed overview of the data collection, system specifications, and analytical techniques employed to evaluate the building's progress towards achieving nZEB Level 1 status from SHASE Japan standard.

II. MATERIAL AND METHODS

This study focuses on the Energy Research and Develop- ment Institute, Chiang Mai University (ERDI-CMU) Office building, which functions as an office facility with an average energy demand of approximately 100 kW. The building is currently equipped with a 160 kW solar photovoltaic (PV) system and a 50 kW/45 kWh energy storage system (ESS). The

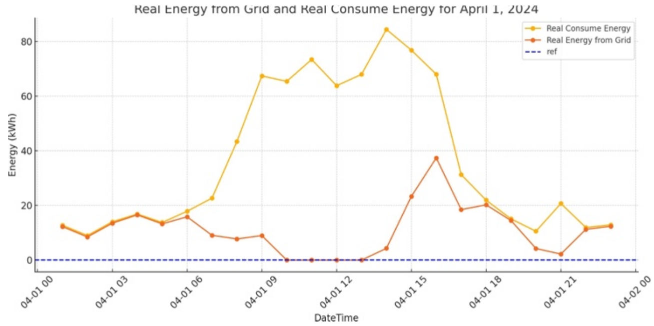

Fig. 2. Comparison of real energy consumption and grid energy usage for April 1, 2024.

From Fig 2. The top graph illustrates the real consume energy throughout the day, while the bottom graph shows the energy drawn from the grid. The data highlights the building's energy usage patterns, demonstrating an approximate 64% reduction in grid dependency due to the integration of solar PV generation and the ESS. Existing setup has achieved a total energy reduction of 64.21%, categorizing the building within the ZEB Ready classification (50%–75% energy reduction), as defined by the Society of Heating, Air-Conditioning, and Sanitary Engineers of Japan (SHASE) standards, as shown in Figure 2. To elevate the building's energy performance to Nearly Zero Energy Build- ing (nZEB) Level 1 status (87.5%–100% energy reduction) according to SHASE, the proposed system involves upgrading to a 200 kW PV system and a 275 kWh ESS. This section details the methodologies employed to assess the economic and environmental impacts of this upgrade, including data col- lection over a six-month period, system design, simulation of energy performance, economic evaluation, and environmental impact assessment.

A. Data Collection

The study gathered data on building energy consumption, solar PV generation, ESS behavior over six months. This data provides a comprehensive view of the building's energy performance as shown in Figure 3.

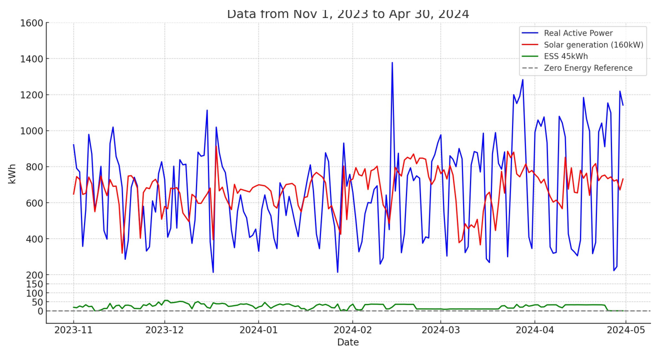

Fig. 3. Daily energy usage comparison from Nov 1, 2023, to Apr 30, 2024, showing Real Active Power, Solar Generation (160kW), ESS 45kWh

1) Building Energy Consumption Data, Comprehensive en- ergy consumption data were collected over a six-month period, from November 2023 to May 2024.

2) Solar PV Generation Data Existing 160 kW PV System Output: Solar generation data were collected concurrently over the same six-month period.

3) Energy Storage System Data The charging and discharg- ing cycles of the existing 50 kW/45 kWh ESS were tracked.

4) Cost Data in Thailand Data Existing PV Cost, ESS Cost, Electricity grid rate in Thailand [8] [9] [10].

B. Equations

1) Calculate Energy Reduction Fraction (E_{rf})

$$E_{rf} = \frac{\text{Energy Reduction (\%)}}{100} \tag{1}$$

2) Calculate Initial GHG Emissions Before Energy Reduc- tion

$$\mathrm{GHG}_{\mathrm{after}} = \mathrm{GHG}_{\mathrm{before}}(1 - E_{rf}) \tag{2}$$

$$\mathrm{CC}_{\text{per year}} = \text{Annual GHG Reduction} \tag{3}$$

$$Ann.\,\mathrm{CC}_{\mathrm{Revenue}} = Ann.\,GHG_{Reduction} \tag{4}$$

3) Total Initial Investment Cost

$$Solar\ PV_{Cost} = System\ (kW) \times Cost_{kW} \tag{5}$$

$$ESS_{\mathrm{Cost}} = ECC_{Capacity}(kWh) \times Cost_{kWh} \tag{6}$$

$$\mathrm{Tot}al_{\text{System cost}} = Solar\ PV_{Cost} + ESS_{Cost} \tag{7}$$

$$Ann._{\text{Maint Cost}} = Total_{System\ Cost} \times 2\% \tag{8}$$

$$Ann._{Net\ Saving} = Ann._{Cost\ Saving} - Ann._{Maint\ Cost} \tag{9}$$

$$PB = \frac{Total_{System\ Cost}}{Ann._{Net\ Saving}} \tag{10}$$

The preceding equations outline the methodologies used to calculate key metrics for this study, including the energy re- duction fraction, greenhouse gas (GHG) emission reductions, carbon credit revenue, and financial investment analysis. These equations provide a framework for assessing the building's en- ergy performance, the impact of solar PV and ESS integration, and the potential return on investment. The results obtained from these calculations are presented in the following section.

III. RESULT

The analysis of upgrading the Office building's energy sys- tems reveals significant economic and environmental benefits associated with the integration of a 200 kW photovoltaic (PV) system and a 275 kWh energy storage system (ESS). This proposed upgrade is compared with the current system, which consists of a 160 kW PV system and a 45 kWh ESS, to evaluate improvements in energy reduction, cost savings, and greenhouse gas (GHG) emissions reduction.

The building's estimated daily energy consumption stands at 800 kWh, leading to an annual consumption of 292,000 kWh when accounting for 365 days of operation. The integration of the current 160 kW PV system and 45 kWh ESS achieves an energy reduction of 64.21%, translating to annual energy savings of approximately 187,511 kWh. In contrast, the pro- posed upgrade to a 200 kW PV system and a 275 kWh ESS enhances the energy reduction percentage to 87.62%, resulting in higher annual energy savings of about 255,834 kWh.

Economically, the total system cost for the current setup is calculated at $169,900, derived from the solar PV cost of $1,000 per kW (totaling $160,000 for 160 kW) and the ESS cost of $220 per kWh (totaling $9,900 for 45 kWh). The proposed upgrade incurs a higher total system cost of

$260,500, with $200,000 allocated for the 200 kW PV system and $60,500 for the 275 kWh ESS. Both estimates include installation costs and are based on average retail prices in Thailand for the years 2023–2024. An annual maintenance cost, estimated at 2% of the total system cost, amounts to $3,398 for the current system and $5,210 for the proposed upgrade.

The annual cost savings are influenced by the electricity grid rate, which is set at $0.12 per kWh. For the current system, the annual energy savings of 187,511 kWh result in cost savings of $22,501. Subtracting the maintenance cost, the net annual savings amount to $19,103. The proposed upgrade, with higher energy savings of 255,834 kWh, leads to annual cost savings of $30,700. After accounting for the increased maintenance cost, the net annual savings for the upgraded system are $25,490.

When evaluating the financial viability, the simple payback period for the current system is approximately 8.89 years, calculated by dividing the total system cost by the net annual savings. The proposed upgrade has a slightly longer payback but it remains within an acceptable range considering the lifespan of the systems. The increase in net annual savings by $6,387 per year.

Environmentally, the impact of upgrading the energy sys- tems is substantial. Using an emission factor of 0.465 kg CO2e per kWh, the baseline GHG emissions for the building are calculated at 135.780 tons CO2e per year, based on the total annual energy consumption of 292,000 kWh without any energy reduction measures. The current system reduces GHG emissions by approximately 87.192 tons CO2e per year, decreasing the emissions to 48.588 tons CO2e annually. The proposed upgrade further enhances the GHG emissions reduction to about 118.986 tons CO2e per year, bringing the annual emissions down to 16.794 tons CO2e. This additional reduction of approximately 31.794 tons CO2e per year over the current system underscores the environmental benefits of the proposed upgrade.

Table 1. Comparison of metrics between different PV and ess systems

Metric	160 kW PV & 45 kWh ESS	200 kW PV & 275 kWh ESS
Energy Reduction Percentage	64.21%	87.62%
Annual Energy Savings (kWh/year)	187,511	255,834
Total System Cost (USD)	$169,900	$260,500
Net Annual Savings (USD/year)	$19,103	$25,490
Simple Payback Period (years)	8.89	10.22
GHG Reduction (tons CO2e/year)	87.192 from 135.780	118.986 from 135.780
GHG Emissions After Reduction (tons CO2e/year)	48.588	16.794

A comparative summary of the key metrics, as shown in Table 1, illustrates the advantages of the proposed upgrade. The energy reduction percentage increases from 64.21% to 87.62%, and the annual energy savings improve from 187,511 kWh to 255,834 kWh. Although the total system cost rises from $169,900 to $260,500, the net annual savings also increase, enhancing the project's long-term economic appeal. The simple payback period remains within a practical time-frame, and the significant GHG emissions reduction aligns with sustainability goals and climate change mitigation efforts.

IV. DISCUSSION

The proposed upgrade from a 160 kW PV system and a 45 kWh ESS to a 200 kW PV system and a 275 kWh ESS results in an increased energy reduction from 64.21% to 87.62%. This substantial enhancement aligns with the nZEB Level 1 classification, which requires an energy reduction of at least 87.5% according to SHASE classification. The increase in en- ergy savings by approximately 68,323 kWh per year signifies a remarkable improvement in the building's energy performance. Economically, while the total system cost increases by $90,600 with the proposed upgrade, the net annual savings also rise by $6,387 per year. The simple payback period extends from 8.89 years to 10.22 years, which is still within the acceptable range given the typical lifespan of PV and ESS systems (around 25 years for Solar PV system and 10 years for ESS system). This underscores the economic viability of investing in larger-scale renewable energy systems for significant energy consumers like office buildings. From an environmental perspective, the proposed upgrade enhances the annual greenhouse gas (GHG) emissions reduction from approximately 87.192 tons CO2e to 118.986 tons CO2e. This additional reduction of about 31.794 tons CO2e per year represents a significant contribution to mitigating climate change impacts. By decreasing reliance on grid electricity, which is often generated from fossil fuels, the building substantially lowers its carbon footprint.

A. Limitations and Future Research

While the study presents a comprehensive analysis, certain limitations should be acknowledged. A significant limitation is that the economic evaluation does not account for detailed peak and off-peak electricity pricing structures. The analysis uses a flat electricity grid rate of $0.12 per kWh, which may not accurately reflect the actual cost dynamics experienced by the building. Many utilities implement time-of-use (TOU) tariffs, where electricity prices vary throughout the day based on demand. Ignoring these variations may lead to an under- estimation or overestimation of cost savings and the financial performance of the ESS. Additionally, the energy performance relies on data collected over a six-month period, which may not capture all seasonal variations, particularly those affecting solar irradiance and energy consumption patterns. Seasonal fluctuations can impact PV generation and building energy demand, influencing the overall system performance. Future research could involve long-term monitoring over at least a full year to validate the projected savings and performance, ensuring that seasonal effects are adequately accounted for. Incorporating detailed TOU electricity tariffs in future analyses would provide a more accurate assessment of the financial benefits and allow for the optimization of ESS operation strategies to maximize cost savings. Advanced energy manage- ment systems could be programmed to respond dynamically to electricity price signals, enhancing the economic viability of the project.

V. CONCLUSION

The integration of a 200 kW PV system and a 275 kWh ESS in the Office building effectively achieves an energy reduction of 87.62%, meeting the criteria for nZEB Level 1 as per SHASE standards. The upgrade not only enhances the building's energy performance but also proves to be econom-ically viable, with a reasonable payback period and increased net annual savings. Environmentally, the significant reduction in GHG emissions reinforces the building's commitment to sustainability and contributes to broader climate change mit- igation efforts. This study demonstrates that achieving nZEB status in existing buildings is attainable through strategic in- vestments in renewable energy technologies and optimized en- ergy management systems. By highlighting the importance of considering detailed electricity pricing structures, the findings encourage more comprehensive analyses in future research. Incorporating peak and off-peak pricing can lead to more accurate financial assessments and potentially reveal additional economic benefits. The results serve as a model for similar facilities seeking to enhance energy efficiency and reduce environmental impact. By adopting advanced renewable en-ergy systems and accounting for dynamic electricity pricing, buildings can further improve their energy performance and economic outcomes. This study supports the wider adoption of sustainable practices in the built environment, aligning with global sustainability goals and advancing the transition towards a low-carbon future.

VI. ACKNOWLEDGMENT

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A Case Study on Carbon Credit Trading in Photovoltaic Systems at The Large Academy, Focusing on Break-Even Point and Passive Income

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Abstract - In this paper, there is a method presented to determine the break-even point of profit while implementing a grid-tied 5.99MW silicon solar power energy system at a large educational institute. To forecast the efficiency of these systems over 25 years, manufacturers' datasheets are traditionally used to calculate solar panel degradation. However, this study combines PVsyst software with loss data from the inverter efficiency to more accurately anticipate and calculate energy production from solar power systems. Subsequently, Python and Excel methods were used to analyze the calculated results. The study compares two scenarios: (1) the traditional Energy Reduction with Solar Panel Degradation (ERSD) method, and (2) the proposed method that includes inverter efficiency loss in the calculation process (Degradation with Inverter Efficiency Loss (DIAEL). In addition, the results are classified based on the sale of carbon credits on Thailand's carbon credit platform. The results indicate that the system without a carbon credit sale leads to a longer break-even point than the combination with a carbon credit sale. Although the proposed method results in a lower total summation of tCO2eq than the ERSD method, it achieves a saved cost of electricity and a profit from carbon credit sales amounting to 13,644,760.23 USD over the lifecycle of the 5.93 MW silicon solar power systems with grid-tied at the large academic.

Keywords - Break-Even Points, Carbon Credit Trading, Energy Forecast, Solar Power, Electricity Cost.

Design of 5 kW Low Speed Wind Turbines for Air Compresses Application

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Abstract - This article discusses the design of compressed air wind turbines to reduce environmental issues, resulting in appropriate environmental management and highly efficient energy use. Importantly, it has raised awareness among industrial operators about managing internal factories in an environmentally friendly manner and responding to the environment by systematically integrating both direct and indirect methods to reduce fossil fuel consumption, which later becomes a cause of environmental problems. Therefore, this article addresses questions about social innovation, particularly in environmental care using low-speed wind turbines in Southeast Asia, where the average wind speed is about 5 m/s. The designed wind turbines can start operating at 2.3 m/s and have a height of 18 m from the ground. The diameter of the turbine blades is 6.5 m. Many industries have air compression systems and air storage tanks for use in factory activities. The designed air compression wind turbines have been installed to produce air that matches the existing air compression systems by connecting the air compression system from the designed air compression wind turbines in parallel with the old system.

Technically, the wind turbine designed for air compression will continuously generate air to supply the system. Therefore, it reduces electricity consumption in the operation of air compressors and air storage tanks. Additionally, it helps reduce pressure and air loss in the system, making the air compressor and air storage tank system operate more stably. Assuming the average wind speed is 5.5 meters per second, the amount of air produced by the air compressor would be approximately 536.4 m3/day. When calculating the electricity cost, it would be 38 kWh or 209 baht/day, based on an electricity price of 5 baht /unit. In one year, the factory can reduce electricity expenses by 76,285 baht and recover the investment in the wind turbine for air compression within approximately 5 years.

Keywords - 5 kW Wind Turbines, Low Speed Wind Turbines, Air Compresses

I. INTRODUCTION

One of the renewable energy sources with the greatest rate of growth is wind energy, which has the significant potential to lower greenhouse gas emissions. Production prices for wind energy are competitive with those of fossil fuels, and it is a non-polluting energy source [1]. This is particularly true in China, where the production of wind power has grown in importance as an energy source. This saves energy and lowers emissions of air pollution [1]. The technology used to produce wind energy has also been evolved to be appropriate for low-wind places. One example of this is the Darrieus wind turbine, which is quite effective in coastal settings [2].

Long-term cost savings and increased energy production efficiency can be achieved through the establishment of wind farms, both large and small [3]. evaluating the wind energy potential in places like Qatar. Research has demonstrated that wind farms have the potential to drastically lower CO2 emissions [4].

In addition, wind energy is crucial for lowering the dangers associated with climate change and promoting international carbon reduction goals. But there are drawbacks to wind farm growth as well, like effects on wildlife and the requirement for impact studies. Combined [5]. if there are drawbacks to using wind energy, this technology offers a lot of promise to provide sustainable energy and lessen its negative effects on the environment in the future. [6].

A hot topic in renewable energy research right now is designing wind turbines to run in low-wind environments.

One viable substitute is vertical axis wind turbines, or VAWT, because of their small size and strong performance in low-wind environments. Blade geometry optimization is frequently achieved through the application of computational fluid dynamics (CFD) analysis in design and performance analysis [7]. Another device that effectively captures wind from all directions and transforms it into electrical energy is a Darrieus turbine with twisted blades [8].

Wind turbines of the Savonius type are made to run at low wind speeds. Tests on the model demonstrate that even in low wind situations, performance can be improved [9]. Integration with additional vertical axis wind turbines can also improve the efficiency of energy production [9]. Increasing air flow into the blades is another goal of the close-blade Savonius wind turbine design. As a result, energy production increased by 22.2% [10].

An alternative strategy involves designing wind turbines with enclosures, which, in locations with low wind speeds, can boost output capacity by up to 92.71% when compared to conventional wind turbines [11]. Urban contexts, where wind qualities vary widely, can also benefit from the use of wind turbines specifically intended for low wind locations [12].

However, challenges remain in the use of wind energy, including adapting to variable wind conditions, managing noise and wildlife impacts, and maintaining turbines in harsh environments [14, 15, 16]. Continuous research and development are necessary to address these issues and further enhance the efficiency of wind energy. Wind energy and wind turbines, therefore, hold great potential to meet future energy demands sustainably, with increasing efficiency driven by ongoing technological advancements and research [13, 14, 22, 23].

II. RELATED THEORIES

A. Wind Power

Wind power is a natural energy source from temperature differences, atmospheric pressure, and Earth's rotation, generating wind speed and power. Moreover, the wind is one energy form surrounding us, and sometimes power that originates from the wind may destroy accommodations, break trees, and blow objects away following wind power. Recently, humans have increasingly paid attention to the significance of wind energy in its utilisation because wind power is clean energy that does not cause dangers to humans or the environment and is a renewable source. Wind power is similar to solar energy as a free available energy, and nowadays, its utilisation is highly widespread. In certain areas, problems in applying wind power are due to unstable wind volume throughout the year. Still, some coastal areas or annually high-potential wind locations can utilise wind power. Equipment that aids in changing wind power to other power forms is a wind turbine. It can transform wind power into electrical or mechanical energy, such as water-wheel wind turbines, water-pump wind turbines, and air-compress wind turbines to compress air for industrial plants or wastewater treatment. [12-15]

B. Air-compress wind turbine connection

Commonly, air-compress systems used in industrial plants will be air pumps to compress air into air receiver tanks and connect to air-compress systems in industrial plants for later use. In the case of adding an air-compress wind turbine, the system will help reduce the air pump's electric power use, which can be parallelly connected with the old system, as shown in Figure 1. The 5 kW compressed air turbine test system, shown in number 1, will produce compressed air like a piston air compressor that uses electricity. Both will be connected to the Air Tank as shown in number 3 for use in storing compressed air. Then it will be used in various areas of industrial plants. As shown in number 4 or used in the wastewater treatment pond aeration system in number 5 [17].

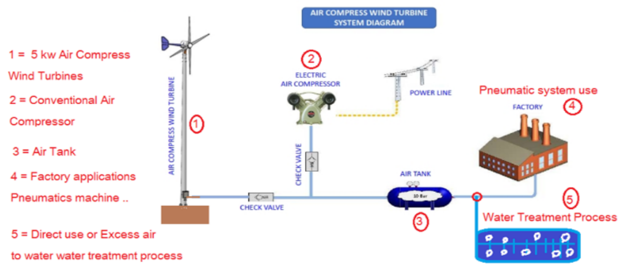


Fig 1 shows the connection of the air compress wind turbine with the industrial plants' air compress system.

III. MOMENTUM THEORY

Wind power is mechanical energy and can be analysed using Momentum theory [17], as shown in Figure 2

$$P = \frac{1}{2}\rho A V^3 C_p \quad (1)$$

when

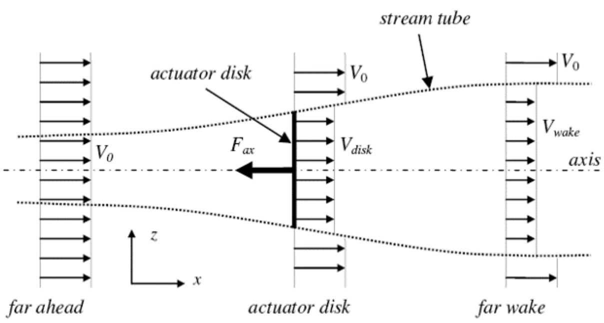
P_W = electrical power

ρ = air density value at @25°C (1.225 kg/m^3)

A = sweep area of turbine blade (m^2)

V_0 = wind speed at entrance and exit sides (m/s)

C_P = wind turbine efficiency



Actuator disk with stream tube

Fig. 2. Shows the principle of the Momentum theory.

IV. DESIGN OF A 5.0 KW AIR COMPRESS WIND TURBINE

The 5.0 kW air compress wind turbine design procedure can be divided into several steps [18-21].

- Regulate the selection of a wind turbine blade characteristic to find the Tip Speed Ratio. The tip speed ratio is a point at which the turbine blade works with maximum efficiency and can be regulated by computational fluid dynamics (CFD) or built and done the real test at a suitable TSR of 7.

• Regulate the cut-in or beginning point of the wind turbine blade. The wind turbine's cut-in regulation significantly impacts the design of the air compress wind turbine's power transferring system. Small or low-speed turbines regulate the wind speed cut V= 2.5 meters per second.

• Regulate the turbine's highest power to design the turbine' radius. If the required value for design is 5 kW at any wind speed, it depends on the wind turbine blade's area and total efficiency. As total system (CP), when $P = \frac{1}{2}\rho A V^3 C_p$Cp equals must combine loss from the wind turbine blade from the power transferring system, which can be calculated from or estimation of 0.35, which can find the wind turbine diameter is as follows.

$$P = \frac{1}{2}\rho A V^3 C_p$$

$$500 = \frac{1}{2} \times 1.225 \times A \times V^3 C_p$$

$$500 = 0.5 \times 1.255 \times (\pi r^2) \times 9^3 \times 0.35$$

So, r is the turbine radius, and r = 3.2 m. by regulating V = 9 m/s.

• Calculation of the turbine's rotation round while starting to rotate. Calculating the turbine's rotation round while starting to rotate can be computed as follows.Regulate TSR = 7, V = 2.5 m/s, and r = 3.2 m.

$$TRS = \frac{U}{V} = \frac{r\Omega}{V} \qquad (2)$$

$$7 = \frac{3.2 \times 2\pi N/60}{2.5}$$

$$N = 52.25\ rpm$$

Thus, at the wind speed of 13 m/s, TSR 10 must have a turbine speed of about 600 rpm.

• Calculation in the quantity of air transferring of an air compressor. The amount of air transferring in an air compressor can be computed using the equation below.

when

d = 0.095 mm., L = 0.085 m., N = 620 rpm

n = 2 pistons, H = 0.911

Replace values will receive

$$V_{acture} = \left(\frac{\pi d^2}{4} \times L \times N \times n\right) \times \eta \qquad (3)$$

$$V_{acture} = \left(\frac{\pi (0.095)^2}{4} \times 0.085 \times 620 \times 2\right) \times 0.911$$

$$V_{acture} = 545\ l/min$$

The obtained value compares with the air compress turbine head's air compression quantity, resulting in the air compress turbine head SWAN model SVP 205 5.0 horsepower (3.75 kilowatt). The flow rate is 545 l/min at a speed round of 620 rpm, which is related to the speed round of air compress turbine torque.

V. CONCLUSION

C. Conclusion of designing

Design of a 5 kilowatt air compressor wind turbine with the heart of its work. It is a component of a compressed air turbine head set. which consists of Wind turbine blades, which serve to receive the force of the wind that hits them, cause the turbine blades to lift. It rotates and creates torque on the shaft to transmit power to the 2-cylinder piston air compressor head.

By installing a cooling fan. To cool down while the air compressor is working. There will be a cover for the working mechanism to protect it from dust, animals, or unwanted things. The wind turbine head also has a wind turbine Tail vane to control direction. and the system stops working if the wind speed exceeds 10 meters/second, As shown in Figure and the wind turbine details are shown in Table 1

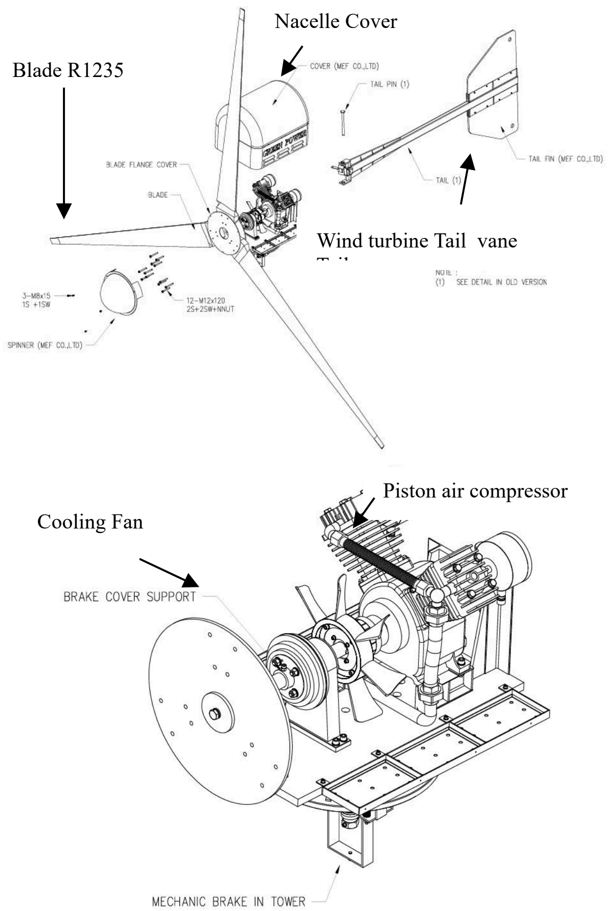


Fig. 2. Shows the components of a compressed air wind turbine.

Table 1. Designing can create the prototype of a 5 kWair-compress wind turbine. Table Type Styles

Type name	size	unit
Turbine blade diameter	6.5	m.
Turbine blade number	3	blades
Hollow single pole height	18	m.
Cut in wind speed	2.5	m/s
Cut of wind speed	10	m/s
Air compressor	5	hp
Maximum flow rate	545	l/min
Air pressure	7-10	bar.
Maximum working round	620	rpm

D. Conclusion of Test

From the experimental results it was found that The low wind speed wind turbine started rotating at a wind speed of 2.5 m/s and was able to produce compressed air at an air flow rate of 37.83 l/min. It was found that the low wind speed wind turbine was able to produce compressed air at a higher flow rate. According to the high wind speed has a maximum value of Air flow rate is 1616.66 l/min at a wind speed of 9.5 m/s, however, wind turbines are limited by preventing damage to the turbine blades. When the wind speed is 10 m/s, the wind turbine's head will be hidden so that the wind turbine can avoid the wind force to avoid damage, as shown in Figure 3.

Regarding the initial experimental results, Suppose the average air speed is 5.5 m/s, producing an obtained air-compress volume of 536.4 m^3/day, which is comparatively computing as the electric power will be 38 kWh or 209 baths/day for the money calculation at 5.5 baths/ unit. Results indicated that, in a year, factories could reduce electric expenses by 76,285 baths and collect the capital investment in an air-compress wind turbine installation in approximately 5 years.

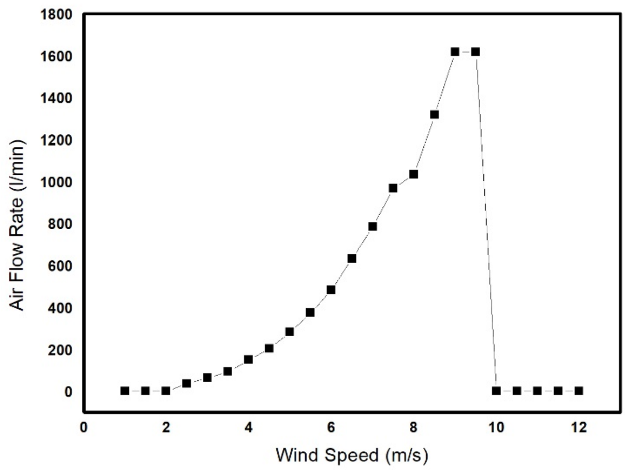


Fig. 3. Shows a relationship between the wind speed and the air flow rate.

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Study on Measures to Promote Renewable Energy and Energy Efficiency and Conservation Towards Net-Zero Carbon Emission

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Abstract - Effort to combat climate change have led several countries to establish a carbon neutral emission target. Thailand has pledged to reduce GHG emission by 30-40 percent by 2030 and become carbon neutral by 2050. The energy sector is critical to obtaining these objectives because it accounts for nearly 70 percents of the country's total emission. This study determined the measures that energy-related government agencies should implement to promote renewable energy, and support energy efficiency and conservation across four sectors: power, industry, transportation, and business. The research adopts data triangulation which combines information from theory and policy tools, thorough reviews of international case studies, and focus group discussion (FGD) held in four provinces in Thailand: Khon Kaen, Phuket, Rayong, and Bangkok. The study recommends various measures which can benefit more than one sector to accelerate renewable energy adoption and enhancement of energy efficiency and conservation. The sectoral policy matric divides policy types into four categories: regulatory measures, taxation, subsidies or incentives, and voluntary agreements. The policy matrices will assist government agencies in designing and combining measures in different categories in the sectors that they are interested in.

Keywords - Renewable energy, Energy efficiency and conservation, Carbon neutrality, Triangulation, Policy matrix

Design a 100kWh Hybrid Photovoltaic System at UiTM Campus using PVsyst Software

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Abstract - This research highlights the design of hybrid Photovoltaic-Battery Energy Storage System (PV-BESS) for sustainable energy solutions. The study focuses on designing reliable hybrid systems for Universiti Teknologi MARA (UiTM) Campus aiming to reduce grid power demand. Using PVsyst software, it analyzes system design and performance. Through PV and BESS components optimization, the research study aims to determine the value of PV-BESS coupling within the framework, helping to make energy supply more sustainable and resilient. The research on optimizing photovoltaic (PV) and battery energy storage systems (BESS) in Malaysia's commercial buildings demonstrated significant improvements in energy efficiency and reliability. By adjusting the PV panel tilt angle to 10 degrees with the Building Integrated Photovoltaic (BIPV) system, the design achieved consistent energy outputs and a performance ratio (PR) of 0.755, indicating efficient energy conversion. The system effectively utilized high global horizontal irradiation, with peak energy output in March. Integrating lithium-ion batteries addressed intermittency issues and enhanced sustainability. These findings provide a valuable benchmark for future PV-BESS studies in commercial buildings, offering insights into system optimization and performance.

Keywords - Photovoltaic Battery Energy Storage System, (PV-BESS), PVsyst software

Floating Photovoltaic (FPV) Project Appraisal for potential Malaysia Reservoirs

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Abstract - This paper presents an in-depth structure for Floating Photovoltaic (FPV) project appraisal that is specifically designed to evaluate the feasibility of solar power project implementation on Malaysian reservoirs. Utilizing the well-known PVsyst software for modeling solar energy systems, the study combines technical, environmental and geographic factors to maximize FPV installation performance. The suggested framework carefully examines prospective reservoir locations throughout Malaysia, considering important elements like topography, solar irradiance and weather data in order to assess the viability and potential for energy production of FPV systems. With an estimated average savings of 237,081.71 tons of Carbon Dioxide (CO_2) emissions, the results demonstrate a significant environmental impact and highlight the important role that FPV projects play in promoting sustainable energy solutions and mitigating climate change in the context of Malaysia. In addition to providing insightful information to the developing field of floating solar technologies, this research gives policymakers and investors a useful tool to help them decide whether to proceed with FPV projects in reservoirs, which will help Malaysia develop a more sustainable and environmentally friendly energy landscape.

Keywords - Floating Photovoltaic (FPV), PVsyst software, Carbon Dioxide (CO_2) emission

Analysis on Energy Import and Energy Export Patterns of Residential Consumers

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Abstract - While research regarding energy consumption and smart city monitoring have been plenty, there have been relatively few works that have been focused on energy monitoring on a large scale in Malaysia. In this work, a dashboard monitoring system was developed to monitor energy consumption and energy export of multiple residential accounts in three zones in Melaka with data extracted Tenaga Nasional Berhad (a local utility company). This research managed to successfully illustrate the energy usage and export patterns of the residents on a monthly and a daily scale. Overall, this work is a major contribution towards Malaysia's efforts in smart city development and sustainability by acting as an agent to spurn awareness in necessary parties and as a reference for policy makers to implement campaigns on green energy.

Keywords - Advanced Metering Infrastructure, energy monitoring dashboard, smart city

I. INTRODUCTION

There is little doubt that the active pursuance of urbanization is for its many benefits in technological, economical, and political advancements that are pivotal towards the brighter future for mankind. However, in paving our way towards urbanization, sustainability and environmental pollution remain an important factor to consider if the earth is to be preserved. On a granular scale, calculating carbon emissions and determining the sustainability of buildings is an effective strategy towards reducing pollution [8], however, adopting a wider perspective such as considering pollution on a city-wide scale is also important to achieve collective awareness on its impact.

A study by Wang & Moriarty in [2] explored the rise of Smart Cities and their role in reducing carbon emissions in energy usage and transportation, and concluded that one of the barriers faced by governments in fully achieving urban sustainability is by simple lack of information. Hence, for some researchers, big data is viewed as a driving force towards urban-scale sustainability [9], and various types of software have been developed with the aim to improve smart-city management and improve environmental and social conditions of the citizens [10].

In the efforts towards achieving this, the deployment of smart meters in Advanced Metering Infrastructure (AMI) remain a crucial factor in that it furnishes energy companies and researchers with the data necessary towards analysing energy behaviours [5]. Not only that, AMI also plays a pivotal role in reducing carbon footprints with its bi-directional capabilities that can be taken advantage by both energy providers and consumers to discern energy usage patterns and integrate energy saving habits into daily operations and lives [11]. In Malaysia, AMI is perceived as a conduit towards realizations of green energy transition and network visibility, enabling customers to have the option to participate in green energy efforts, thus facilitating awareness on a community level.

In other places, AMI has also enabled the possibility of incorporating Energy Saving Systems (ESS) as part of residential energy sources, and spurned advanced energy management techniques such as load regulation techniques via Artificial Intelligence (AI) and bi-directional energy trading [5].

Hence, in this study, we aim to highlight the critical role of AMI in providing detailed load profile data and renewable energy export to grid data that is crucial for the monitoring of energy usage behaviours on a residential scale, and assess Melaka's current progress towards achieving green energy goals based on the AMI data acquired. Our study demonstrates how AMI facilitates the monitoring of energy usage behaviours on a residential scale by presenting an analysis of real-life data from three zones situated in the state of Melaka, Malaysia. This study analyses load profile data spanning from the years 2023 to 2024 and observes energy usage and energy export trends within that time span. The purpose of this analysis is to raise awareness on Malaysia's energy consumption in recent years by focusing on three zones in Melaka, and analyse the extent of renewable energy penetration on a residential scale.

II. RELATED WORKS

Researchers have long explored energy monitoring in their attempts to aid and abet the world towards goals of sustainability and green energy. Various attempts at monitoring energy consumption have been explored, though commonly in a small scale via IoT and focused on single buildings. The research in [1] explored the potential of collecting data from Smart Meters in Malaysia via a microcontroller (Arduino Uno) and projecting that data in their proposed dashboard. While their dashboard is capable of behaving as a real time monitoring system, its monitoring capabilities is only limited to one household that has been equipped with their proposed system. The study in [4] utilizes LoRaWAN-enabled smart meters to transmit energy data the open source oneM2M platform for collection and processing. However, this study is merely a proposal of a collection mechanism and did not attempt to visualize or analyse the data that has been successfully collected.

On the other hand, efforts towards large-scale monitoring of whole cities have also been attempted, often with the help of customised dashboards, especially in smart city initiatives. With big data frameworks gaining traction, the need for dashboards to act as conduits in the dissemination of useful information and as a tool for acquiring actionable insights has grown in its importance. Researchers in [3] have developed a comprehensive dashboard capable of monitoring various facets that make up a smart city, including energy consumption, transportation, parking management, heating and cooling efficiency, and traffic data by utilizing various APIs to extract data from various sources. Similarly authors in [7] recognised the importance of manipulating available data into an understandable format for the audience and had proposed an analytics processing pipeline and a prototype dashboard.

With such a large scale of data involved in the governing of smart cities, there is no doubt that big data in smart cities has been a popular topic of discussion. The authors of [9] discussed the factors towards making up a data-driven smart city and the technological advancements required to achieve the goal, which included data mining, real-time analytics, and predictive analytics. Apart from that, they submitted that data-based city management is also reliant on various administrative efforts by governing bodies, which also included efforts towards energy management.

The importance of AMI in achieving these goals have also been discussed, with the authors of [12] viewing AMI as the key to grid modernization. However, they found that the technology is largely underutilized by utility companies, largely due to a combination of regulatory, financial, and technological barriers. They highlighted that AMI data is one of the keys towards achieving an understanding on customer nature, and submitted that it should be accessible to every level, including the customers themselves, so that behaviours towards energy consumption and conservation can be appropriately observed, and thus strategies on energy pricing and energy conservation can be devised, all of which backed by robust analytics.

Proof of this can be seen in [13] where AMI data featured significantly in the authors' analysis on Energy Storage Systems (ESS) when employed on a residential scale. Their analysis compared the consumption behaviours of users with and without ESS and found significant energy consumption reduction for up to 46%. Furthermore, their analysis on the return investments enabled them to contribute informed recommendations to policy makers for nationwide Energy Storage System programs to be implemented more actively on a residential scale.

III. METHODOLOGY

This study leverages data from the existing AMI infrastructure maintained by the local utility company, Tenaga Nasional Berhad (TNB). Due to the scale of the data and certain limitations that have to be considered, only three areas were selected to be case studies and serve as the baseline for future analyses. These zones are all located within the state of Melaka, and hereafter will be referred to as the following:

- Zone 1 (Z1)
- Zone 2 (Z2)
- Zone 3 (Z3)

Within these zones, several residential areas were selected to reduce the selection pool of homeowner accounts and narrow down the scale. Despite this, data extracted still falls within the quantity of millions of rows, spanning from January 2023 to October 2024. Amongst the data extracted, one aspect holds particular interest which is energy being exported to the grid, viewed as a good indicator on how far along Malaysia is towards achieving its goals in energy sustainability.

A. Development of AMI Dashboard with Residential Accounts

An online dashboard was also developed for this research to act as a monitoring system for energy usage and energy export data. Its monitoring capabilities include:

a) Aggregated weekly and monthly import and energy export trends with a granularity of half an hour.

This section intends to furnish the user with an in depth view of the behaviours of homeowners and identifying peak hours throughout the day.

b) Monthly energy import and energy export trends.

Monthly energy trends are provided in this section to compare the energy usages and energy exports between past months.

c) Map view of residential area locations and their energy consumption in comparison to other areas.

This section allows the comparison of energy consumption behaviours between different areas. Each location pin represents a residential area within the zone, and the aggregated usage of homeowners within the area is compared area with the highest aggregated usage in the whole zone. A ranking system was developed, with four quartiles representing the following data:

- Quartile 1 (Residential areas that fall within 0% - 25% of highest usage)
- Quartile 2 (Residential areas that fall within 25% - 50% of highest usage)
- Quartile 3 (Residential areas that fall within 50% - 75% of highest usage)
- Quartile 4 (Residential areas that fall within 75% - 100% of highest usage)

d) Ranked table of residential area usage

This section extends the map feature by providing a ranking of energy usages of different residential areas based on their total consumption, thus enabling easy identification of residential areas with prominently high energy usage.

e) Aggregated accounts based on different tariff brackets

Malaysia employs three brackets in their tariff system based on the homeowner's energy usage for the current month. Each bracket is significant in that different charges are applied. For example, Residential Rebate for users with usages under 600 kWh receive rebate for their monthly bills, while users with higher 1500 kWh do not receive rebate and pay significantly more for their energy usage.

IV. RESULTS

B. Energy Import/Usage and Energy Export Trends

Despite the large scale of data available, an attempt at monitoring energy usage and energy export in Malaysia has not yet been achieved prior to this research. The proposed dashboard has significantly improved monitoring capabilities and awareness towards energy usage, which, previously, has remained ambiguous. Hence, this section will discuss the outcome of the analysis.

It could be observed in Fig. 1 that by aggregating energy usage in one week, energy usage patterns within the three zones peak at certain hours of the day, namely, close to midnight. In comparison, morning and midday usage patterns see a significant decrease, which can be attributed to normal working hours of the day. On the other hand, energy export patterns show an expected trend of peaking during the day when sunlight is at its peak.

One can also observe the trends on a monthly basis, such as in Fig. 2, Fig. 3, and Fig. 4. A tabulation of the percentage increase of energy import and export in the three zones have been provided in 0And 0While energy usage in households see an increase or merely a marginal reduction, results show that more households are embracing renewable energy to sustain their energy usage, as there has been an increase in energy export in residential homes throughout 2024 compared to 2023. However, in 0the percentage of energy export relative to energy import is still hovers only around 1.5% - 2.3% for October 2024, indicating that energy being exported to grid is still not large enough to compensate for the energy usage in residential homes.

Monthly energy usage pattens in Fig. 2, Fig. 3, and Fig. 4 demonstrate an increasing trend between the years 2023 and 2024. Also, one can also observe that energy usage tends to peak between March 2024 and May 2024 for all regions, which corresponds to the hotter seasons of year in Malaysia. Based on these trends, it could be concluded that awareness on renewable energy has been increasing and any state-wide or nation-wide programs aiming towards this awareness does have a certain level of effectiveness. However the relatively low number of energy export users could indicate that prices for Solar PV systems still remain slightly above what most residents could afford.

Table 1. Energy Import / Usage vs Energy Export to Grid (October 2024)

Zone	*Total Energy Import/Usage (kWh)*	*Energy Export (kWh)*	*Percentage (%)*
Zone 1	5,326,777.882	124,796.47	2.343%
Zone 2	2,978,136.878	44,336.14	1.489%
Zone 3	8,381,005.120	168,811.73	2.014%

Table 2. Percentage Increase of Energy Import (2023 vs 2024)

Zone/ Month	*Zone 1 (kWh)*	*Zone 2 (kWh)*	*Zone 3 (kWh)*
Jan-24	14.28%	15.18%	11.61%
Feb-24	36.92%	38.16%	34.54%
Mar-24	28.51%	31.37%	28.83%
Apr-24	12.38%	13.52%	11.59%
May-24	7.07%	7.91%	6.82%
Jun-24	1.70%	1.16%	1.58%
Jul-24	-9.44%	-9.14%	-7.65%
Aug-24	-1.10%	-0.49%	3.02%
Sep-24	-4.26%	-4.83%	-3.22%
Oct-24	-17.29%	-17.68%	-15.53%

Table 3. Percentage Increase of Energy Export to Grid (2023 vs 2024)

Zone/ Month	*Zone 1 (kWh)*	*Zone 2 (kWh)*	*Zone 3 (kWh)*
Jan-24	133.89%	146.12%	74.67%
Feb-24	129.89%	180.08%	80.10%
Mar-24	111.79%	154.31%	62.22%
Apr-24	85.40%	149.43%	70.49%
May-24	106.56%	180.39%	74.63%
Jun-24	89.97%	154.67%	67.74%
Jul-24	102.50%	209.70%	79.28%
Aug-24	151.70%	296.10%	126.07%
Sep-24	165.04%	325.86%	142.49%
Oct-24	120.03%	232.22%	106.52%

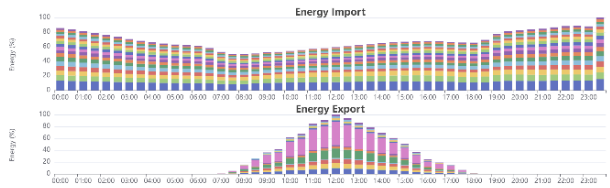

Fig. 1. Seven-day energy import and energy export trends.

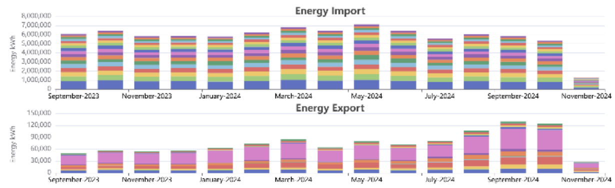

Fig. 2. Total monthly energy import and energy export in Zone 1.

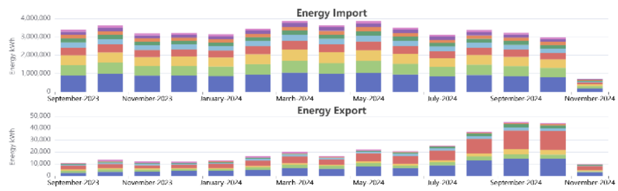

Fig. 3. Total monthly energy import and energy export in Zone 2.

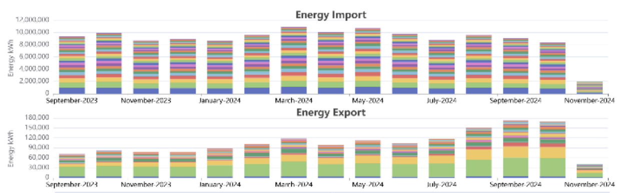

Fig. 4. Total monthly energy import and energy export in Zone 3.

C. AMI Map

0shows the count of residential areas in each of the Quartiles. Observing the data, some insights that can be derived include that there is little change between October 2023 and October 2024 residential area count for each of the categories. However, between the two years, for each zone there is a 15% to 20% decrease in highest consumption.

D. Energy Usage Statistics

Based on the results in 0approximately 80% to 85% residential accounts fall within the first category, demonstrating that most residential users tend to not exceed 600 kWh in their monthly electricity bills. Fig. 5, Fig. 6, and Fig. 7 are the monthly account trends from January 2023 until October 2024. Interestingly, mid-year show visible increase in accounts exceeding 1500 kWh usage, coinciding with the hotter months of the year, and indicating that many energy draining appliances are being utilized to combat the heat.

Table 4. Count of Residential Areas in Each Quartile

Month-Year	***Zone***	***Residential Area Count (Total)***				***Highest consumption (kWh)***	***Percentage decrease compared to previous year***
		Quartile 1	***Quartile 2***	***Quartile 3***	***Quartile 4***		
Oct 2023	Zone 1	5	4	4	4	972,019.897	-
	Zone 2	3	2	2	2	982,435.246	-
	Zone 3	7	7	6	7	1,028,742.19	-
Oct 2024	Zone 1	5	4	4	4	774,924.57	20.277%
	Zone 2	3	2	2	2	792,484.606	19.335%
	Zone 3	7	5	7	7	873,428.876	15.097%

Table 5. Count of Accounts in Each Tariff Bracket

Month-Year	***Zone***	***Residential Area Count (Total)***		
		<=600kWh	***600 kWh< x < 1500 kWh***	***> 1500 kwh***
Oct 2023	Zone 1	13,152	3,159	151
	Zone 2	7,718	1,781	66
	Zone 3	19,508	5,157	157
Oct 2024	Zone 1	13,967	2,561	64
	Zone 2	8,247	1,338	29
	Zone 3	21,034	3,982	68

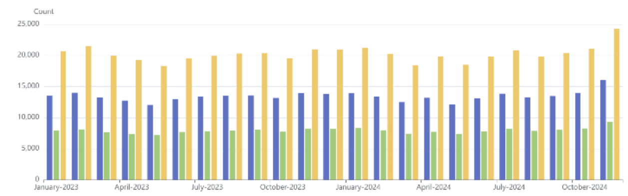

Fig. 5. Monthly energy usage staticstics for accounts below 600 kWh usage since January 2023.

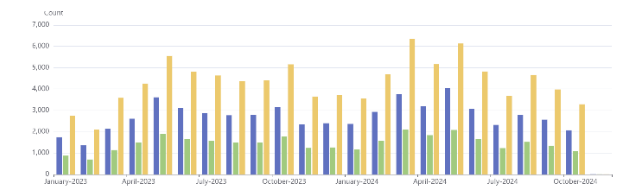

Fig. 6. Monthly energy usage statistics for accounts between 601 kWh to 1500 kWh usage since January 2023.

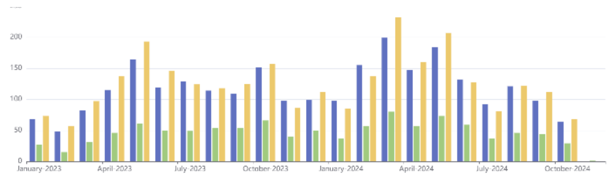

Fig. 7. Monthly energy usage staticstics for accounts above 1500 kWh usage since January 2023.

V. CONCLUSION

In conclusion, energy monitoring has been the subject of interest to researchers in the past years. With the bi-directional capabilities of AMI, doors have been opened towards data collection on a large scale, and thus, the possibility of monitoring energy consumption and energy export. In this work, an energy monitoring dashboard has been developed with data from three zones in Melaka. The results show that high energy usage is seasonal and tends to peak early in the year, which can be inferred to correspond to seasonal changes throughout the year. On the other hand, daily consumption results show that residents are more inclined to have higher usage at around midnight. Besides that, energy export to grid residential homes show gradual increase from year 2023 to year 2024, however it is still significantly less compared to energy usage, which can be used as evidence to increase green energy awareness campaigns in Malaysia. While this work does face limitations in that it only considers select zones in Melaka, it can be considered as a baseline towards future efforts in developing smart cities and potentially spurn more research on energy reduction in Malaysia. In our future works, we hope to analyze how AMI reflects the impact of governmental campaigns on carbon reduction incentives and renewable energy promotion. We also hope to monitor energy usage and energy export behaviors of residential accounts beyond the three zones identified in this paper to further understand how their individual behaviors contribute to the area's statistics.

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Empowering Remote Communities with Renewable Energy Education: A Game-Based Learning Approach

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Abstract - To promote knowledge of electricity and renewable energy technologies in remote communities, this study developed an educational game and hands-on workshops to enhance the understanding and skills of 60 student teachers. The program focused on ten key renewable energy technologies, such as solar-powered water pumps and automated climate control systems. The results demonstrated significant improvements: knowledge of Direct Current (DC) electricity increased by 121%, understanding of renewable energy applications rose by 153%, and practical skills like problem-solving improved by 169%. Additionally, there was a 75% increase in positive attitudes toward renewable energy. The educational game, designed to be accessible and engaging, can be downloaded and played on multiple platforms, including Windows, iOS, and Android, available at smartdoi.cmru.ac.th. These findings suggest that combining game-based learning with practical workshops effectively boosts both theoretical understanding and practical skills, supporting the wider adoption of sustainable energy technologies in agricultural settings.

Keywords - Renewable Energy Education, Game-Based Learning, Remote Communities

I. INTRODUCTION

The integration of smart grid technology into remote communities offers a promising solution for enhancing energy efficiency, reliability, and sustainability [1,2]. Smart grids, characterized by their ability to manage energy flow dynamically and integrate renewable energy sources, represent a transformative advancement in how we think about electricity distribution and consumption [3]. However, implementing such advanced technologies in remote areas, such as rural communities in Thailand, presents unique challenges. These communities often have limited exposure to modern electrical technologies and may hold reservations or fears about new systems due to a lack of understanding and familiarity [4]. In many remote communities, the gap in technological knowledge can be substantial, creating resistance to the adoption of smart grid technologies. This resistance is often compounded by socio-cultural factors, including distrust of unfamiliar technologies and a lack of foundational knowledge about electricity and its benefits[5,6]. Additionally, rural Thai communities often have deep-rooted customs and beliefs that make the acceptance of new technology particularly challenging [7]. As a result, introducing smart grids in these areas requires not only technical solutions but also thoughtful engagement with the community's social dynamics and educational needs. To bridge this gap, this paper proposes an innovative approach that leverages social knowledge and educational tools to facilitate the adoption of smart grids. By developing an educational game designed to engage young people, we aim to demystify electrical technologies and reduce the fear associated with them. The game is designed to be fun and adventurous, with characters embarking on a journey to gather electrical equipment and knowledge. The gameplay is divided into two main parts: first, players explore various environments to collect knowledge and equipment, learning about electricity through interactive storytelling and quizzes that reward them with items to combat agricultural pests. In the second part, players use the equipment to assemble electrical systems according to given challenges, learning to connect solar panels, batteries, and understand power distribution to loads. This approach aims not only to make learning about electricity enjoyable but also to change perceptions, encouraging an open-minded attitude towards technology. By equipping youth with this knowledge, we hope to create a ripple effect, where the learned concepts can be shared within the community, thus promoting the adoption of electricity systems such as mini-grids, microgrids, or smart grids in the future. This paper, therefore, seeks to explore the effectiveness of using an educational game to overcome the socio-cultural barriers to technology adoption in Thailand's remote communities, providing a foundation for the broader implementation of smart grids.

II. BACKGROUND AND LITERATURE REVIEW

The concept of smart grids has emerged as a revolutionary development in the field of energy distribution, particularly due to its ability to integrate renewable energy sources and optimize energy flow dynamically [3]. Smart grids offer numerous benefits, including enhanced energy efficiency, reduced operational costs, improved reliability, and greater flexibility in integrating distributed energy resources such as solar and wind power [1,2]. These advancements are especially significant for remote communities, where traditional power distribution methods are often inadequate, expensive, or non-existent due to geographic isolation and lack of infrastructure [5]. In Thailand, many rural areas still rely on traditional energy sources, such as diesel generators or biomass, which are not only less efficient but also environmentally harmful [7]. The introduction of smart grids in these regions could drastically improve energy access and sustainability, providing a more reliable and cleaner energy supply. However, the implementation of smart grids in remote Thai communities faces several challenges. The most prominent of these is the lack of technological knowledge among the local population, which contributes to a general apprehension and mistrust of new technologies [4]. This technological gap is exacerbated by socio-cultural factors, including a lack of education on electrical systems, deeply rooted local customs, and a general resistance to adopting unfamiliar technologies [6]. Previous research has highlighted the importance of community engagement and education in overcoming these barriers to technology adoption. Studies have shown that technology acceptance is significantly higher when communities are educated about the benefits and workings of new technologies [8]. In particular, educational interventions that are culturally relevant and accessible have proven effective in reducing resistance and increasing acceptance of new technologies [9]. For instance, Johnson and Carter [10] demonstrated that interactive learning tools, such as games, can effectively increase awareness and reduce fears associated with new technologies among youth. This approach leverages the natural curiosity and adaptability of young people, making them ideal agents of change within their communities. Educational games, in particular, have gained attention as a powerful tool for knowledge dissemination and attitude change. These games can provide an engaging and interactive way to teach complex concepts, such as electrical systems and smart grids, in a manner that is accessible to all age groups [11]. By incorporating elements of storytelling, problem-solving, and rewards, educational games can create a positive learning environment that encourages exploration and reduces fear of the unknown [9]. Moreover, involving local educators in the development and implementation of these games ensures that the content is culturally relevant and resonates with the community's values and experiences [10]. In the context of Thailand, utilizing educational games to introduce the concept of smart grids can be particularly effective. Given the strong community ties and the respect for educational figures in Thai society, teachers can play a crucial role in mediating between technology and the community [11]. By engaging students through educational games, teachers can facilitate a deeper understanding of electrical technologies and their applications, which students can then share with their families and communities. This approach not only addresses the knowledge gap but also builds a foundation for future technology acceptance and integration.

In conclusion, the literature suggests that combining technical solutions with social education and community engagement is essential for overcoming barriers to smart grid adoption in remote communities. By leveraging educational games and local educators, we can create a more receptive environment for smart grid technologies, ultimately contributing to sustainable development and improved quality of life in rural Thailand.

III. METHODOLOGY

To explore the effectiveness of using an educational game to overcome socio-cultural barriers and facilitate the adoption of smart grid technology in remote communities in Thailand, this study employs a mixed-methods approach. The methodology is designed to develop, implement, and evaluate an educational game specifically tailored to teach young people about electrical technologies and smart grid concepts. The following sections outline the key components of this methodology: game development, educational workshops, data collection, and analysis.

A. Game Development

The first phase of this study involves the design and development of an educational game that combines fun, adventure, and learning. The game is structured into two main components.

a) Adventure and Knowledge Collection

Players create characters that embark on a journey through various environments, collecting electrical knowledge and equipment. This part of the game uses interactive storytelling to convey information about electricity and its applications in agriculture. Players answer questions to gain special items needed for advancing in the game, which introduces concepts of problem-solving and critical thinking.

b) Electrical Equipment Assembly

Players apply the equipment they have collected to construct electrical systems according to specific challenges. The game is designed to teach players how to correctly connect solar panels and batteries and effectively distribute power to various loads, introducing foundational concepts such as series and parallel circuits. The complexity of the tasks increases with each level, promoting continuous learning and a deeper understanding of electrical principles.

The game will be developed using Unity, a widely-used game development platform that allows for cross-platform deployment on both mobile devices and computers. The design process will involve close collaboration with educational experts and local teachers to ensure the content is culturally relevant and pedagogically effective.

B. Educational Workshops

To maximize the impact of the game, educational workshops will be conducted with local teachers and community leaders. These workshops will train participants on how to use the game as an educational tool and integrate it into their teaching methods. The workshops will cover the following topics

a) Introduction to Smart Grids and Electrical Technologies:

Providing a basic understanding of smart grids, renewable energy sources, and their benefits for rural communities.

b) Game-Based Learning Strategies

Demonstrating how the game can be used to teach electrical concepts and engage students effectively.

c) Practical Equipment Assembly Training

This component focuses on hands-on training with real electrical equipment to ensure that participants gain practical experience in assembling and operating electrical systems. The training sessions will guide participants on how to correctly connect solar panels, batteries, and other components, as well as understand power distribution to various loads. By engaging with real equipment, participants will learn foundational electrical concepts, such as series and parallel circuits, in a tangible and interactive way, enhancing their confidence and competence in handling electrical technologies.

d) Data Collection and Analysis

Data collection and analysis in this study are structured into two phases: pre-implementation and post-implementation of the educational game, utilizing both traditional methods and modern digital tools such as APIs for in-game analytics. The pre-implementation phase involves gathering baseline data to assess the initial levels of knowledge, attitudes, and perceptions regarding electrical technologies and smart grids among students and community members through surveys, focus group discussions, and interviews with teachers, students, and community leaders. This data helps identify the community's needs and concerns about adopting new technologies. To effectively disseminate knowledge, this study includes the development of training programs for 60 representatives studying education. These individuals will be trained using the educational tools developed, including the game and real equipment. After completing their training, these representatives will be dispatched to target communities to teach and share the knowledge they have acquired, thereby ensuring a broader spread of understanding and fostering a positive attitude towards the adoption of smart grid technologies.

Figure 1 Data Collection Process and Game API Integration

From Figure 1, after the educational game is introduced and integrated into the curriculum, the post-implementation phase is designed to collect follow-up data using similar methods as the pre-implementation phase. This phase is enhanced with real-time in-game analytics through API integration, which provides detailed tracking of player progress, engagement levels, and learning outcomes, offering a quantitative perspective on the game's educational impact. Quantitative analysis of the collected data utilizes statistical techniques to evaluate changes in understanding electrical concepts, willingness to adopt new technologies, and overall acceptance of smart grid systems. Additionally, qualitative analysis of focus group and interview transcripts provides deeper insights into socio-cultural factors and the effectiveness of the educational game in overcoming these barriers. By combining traditional data collection methods with modern digital analytics and involving trained educational representatives, this approach ensures a comprehensive evaluation of the educational game's impact on promoting the adoption of smart grid technologies in remote communities.

IV. RESULTS AND DISCUSSION

This section presents the results and discussion of the study, focusing on various aspects of the project, including the design of renewable energy technologies and game development, as well as the practical application of these technologies. Each subsection provides detailed insights into the specific outcomes achieved.

A. Design of Renewable Energy Technologies

The game development focused on integrating practical knowledge of renewable energy technologies into the gameplay. Ten distinct levels were designed to introduce players to various applications of smart grid technology in agricultural settings, each emphasizing different aspects of renewable energy:

a) Solar-Powered Water Pump

Players learn to assemble a solar-powered water pump system for irrigation, demonstrating how solar energy can be harnessed to support sustainable water management in farming.

b) Small Wind Turbine Surface Aerator

This level teaches players how to construct a wind-powered aerator, which increases oxygen levels in fish ponds and supports healthier aquaculture.

c) Solar-Powered Hydroponic Water Circulation System

Players are guided through setting up a solar-powered water circulation system for hydroponic farming, showcasing the role of renewable energy in efficient water usage.

d) Solar and Infrared Heater Drying System

This level introduces a hybrid drying system combining solar energy and infrared heaters, which is ideal for preserving agricultural produce.

e) Compost Aeration System

Players learn to build an aeration system for composting, enhancing soil fertility through improved organic matter breakdown.

f) Solar-Powered Pest Insect Trap Lighting System

In this level, players create a lighting system designed to attract and trap pest insects, reducing the reliance on chemical pesticides.

g) Nighttime Plant Growth Lighting System

This level involves constructing a lighting system that promotes plant growth during nighttime, optimizing photosynthesis and improving crop yields.

h) Incubation System

Players learn to build an incubator to maintain optimal conditions for hatching eggs, supporting small-scale poultry farming.

i) Soil Moisture and Weather Sensor System

This level introduces the integration of soil moisture sensors with weather stations, enabling precise irrigation management for crops.

j) Automated Mushroom House Climate Control System

The final level focuses on constructing a climate control system for mushroom cultivation, automating temperature and humidity to optimize growth conditions.

These levels were designed to provide hands-on experience with real-world renewable energy applications, helping players understand the practical uses of smart grid technologies in agriculture.

Figure 2: Overview of 10 Renewable Energy Technologies in Agricultural Applications

B. Game Development

The results of the game development showcase significant advancements in creating an interactive and educational tool designed to engage users in learning about electrical and renewable energy concepts. The game is structured into two main components that complement each other, maximizing user engagement and educational impact by blending adventure with practical application.

The first component of the game is the Adventure Mode, which immerses players in a narrative-driven quest to explore diverse environments while searching for various electrical equipment. As depicted in Figure 3: Equipment Hunt Adventure, players navigate through different levels, encountering obstacles and challenges that require them to apply their growing knowledge of electrical systems. Throughout their journey, players are prompted with educational questions that test their understanding of concepts related to electricity and renewable energy. By correctly answering these questions, players earn special items, such as tools to combat pests or enhancements that allow them to overcome environmental challenges. This interactive approach ensures that learning is seamlessly integrated into the gameplay, maintaining high levels of engagement and making the educational process enjoyable. The adventure mode effectively encourages exploration and curiosity, helping players learn complex concepts in a fun and engaging manner.

The second component is the Equipment Assembly Mode, which shifts the focus from exploration to practical learning. In this mode, players use the equipment they have collected during their adventures to construct real-world electrical systems, such as solar-powered water pumps and wind turbine aerators. As shown in Figure 4: Electrical Equipment Assembly Example, this hands-on mode provides players with the opportunity to apply their theoretical knowledge to practical scenarios. The game guides players through the process of assembling circuits, connecting components, and configuring systems to demonstrate the principles of electricity and renewable energy technologies. Real-time feedback and guidance are provided to help players understand the consequences of their actions, correct mistakes, and reinforce learning through practice. This practical approach not only deepens players' understanding of electrical principles but also builds confidence in their ability to work with real-world technologies.

By combining these two components, the game provides a comprehensive learning experience that balances theoretical knowledge with practical skills. The adventure mode keeps players motivated and engaged by presenting educational content in a dynamic, interactive format, while the equipment assembly mode ensures that players gain hands-on experience with renewable energy technologies. Together, these elements create a powerful educational tool that prepares players to understand and implement smart grid technologies in real-world settings, ultimately contributing to sustainable development in remote communities.

Figure 3: Equipment Hunt Adventure

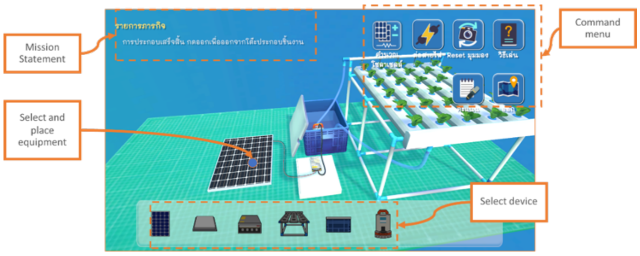

Figure 4: Electrical Equipment Assembly Example

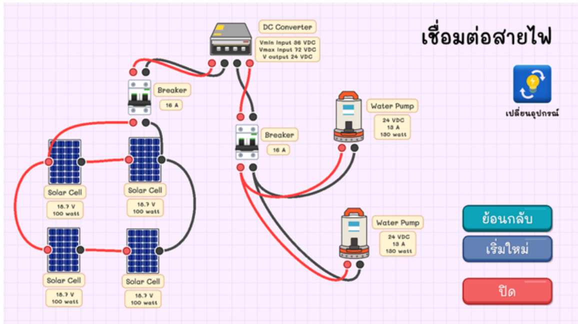

Figure 5 Electrical wiring mode

C. *Educational Workshops Results*

The educational workshops, designed to enhance the skills of student teachers using an online game integrated with hands-on activities, were a key component of this study. The workshops aimed to evaluate participants' potential before and after learning, assess learning outcomes and retention, and monitor attitudes and long-term learning durability among 60 student teachers.

a) Pre- and Post-Learning Assessment Results

The workshops began with a comprehensive pre- and post-learning assessment covering ten renewable energy technologies relevant to agricultural applications, including solar-powered water pumps, small wind turbine surface aerators, solar-powered hydroponic water circulation systems, hybrid drying systems, compost aeration systems, solar-powered pest insect trap lighting systems, nighttime plant growth lighting systems, incubation systems, soil moisture and weather sensor systems, and automated mushroom house climate control systems. The assessment results showed a marked improvement in the participants' understanding and skills after completing the workshops. For instance, participants demonstrated significant gains in their ability to comprehend and effectively apply solar-powered water pump systems and hydroponic water circulation technologies. Similarly, complex technologies like automated mushroom house climate control systems and soil moisture sensor systems also saw notable improvements in participant scores post-training, indicating a deeper understanding and skill acquisition. The increase in scores for simpler technologies, such as the hybrid drying system and solar-powered pest insect trap lighting system, further underscored the effectiveness of the training in enhancing practical knowledge and application skills. The overall increase in scores across all evaluated areas highlighted that the learning program successfully fostered a comprehensive and in-depth understanding of renewable energy technologies in agriculture, preparing student teachers to apply this knowledge in real agricultural settings.

b) Satisfaction and Knowledge Assessment of the Online Game and Renewable Energy Technologies

The workshops also included an evaluation of participant satisfaction and understanding of the online game and renewable energy technologies, divided into four key areas: knowledge, equipment assembly skills, practical application, and the design of learning through the game. The results revealed significant improvements in knowledge across five major topics: DC electricity, electronic equipment for renewable energy technologies in agriculture, the use of circuit breakers, converters, and solar chargers, solar energy, and the application of renewable energy in agriculture. For example, the understanding of DC electricity improved substantially after playing the game, suggesting an increase in knowledge about basic electrical concepts. Participants also showed enhanced comprehension of electronic equipment and its use in agricultural settings, reflecting the game's ability to teach complex concepts effectively. Improvements in skills related to the use of circuit breakers, converters, and solar chargers indicated better technical understanding and capability to manage and use these devices. The results suggested that the game successfully increased participant knowledge and understanding across all evaluated topics, supporting the notion that game-based learning can effectively enhance knowledge and skills in complex subjects.

c) Evaluation of Equipment Assembly Skills

The workshops included a detailed assessment of participants' equipment assembly skills, covering five key areas: calculating solar panel and battery usage, selecting appropriate electronic equipment, wiring electronic devices, sequencing electronic devices correctly, and problem-solving under various scenarios. The post-gameplay results showed improvements in all areas compared to the pre-gameplay assessment. For instance, participants became more proficient in calculating solar panel and battery usage, indicating improved planning and energy management skills. Additionally, they demonstrated better understanding in selecting and installing appropriate equipment for different electrical systems, suggesting enhanced decision-making capabilities. Improvements in wiring and sequencing electronic devices reflected increased competence in organizing and constructing electrical setups. Enhanced problem-solving abilities were also noted, indicating that the game helped participants develop critical thinking and analytical skills needed to address real-world challenges in renewable energy technology applications.

d) Evaluation of Practical Application and Attitude Development

The workshops further evaluated participants' ability to apply knowledge practically and their attitudes toward electricity, renewable energy, and agricultural technology. The assessment covered five aspects: positive attitudes towards electricity, renewable energy, agricultural technology, applying knowledge, and using the game as a teaching tool. Results indicated significant improvements in all assessed areas post-gameplay, especially in attitudes towards electricity and renewable energy. This suggests that participants became more interested and receptive to these technologies after engaging with the game. Improved attitudes towards applying knowledge indicated that participants felt more confident and prepared to use what they had learned in real-world scenarios. Additionally, the increased willingness to use the game as a teaching tool reflects participants' recognition of the game's educational value and effectiveness in enhancing learning.

e) Evaluation of Learning Design through the Game

The final assessment focused on evaluating the learning design of the game, including the appropriateness of the number of technologies featured, the difficulty level, game design (such as colors, characters, and graphics), game stability, and character control. Results showed increased satisfaction in all areas after gameplay. Participants felt that the number of technologies presented was appropriate and aligned with the learning objectives. The difficulty level of the game was seen as well-balanced, providing enough challenge to maintain interest while facilitating learning. Positive feedback on the game's design and aesthetics indicated that these elements contributed to a more engaging learning experience. Improved ratings for game stability and character control suggested that the game provided a smooth and user-friendly experience, which is crucial for maintaining engagement and focus during learning.

Overall, the results from the educational workshops indicate that integrating an online game with hands-on activities effectively enhances knowledge, skills, and attitudes towards renewable energy technologies in agriculture. The workshops successfully prepared student teachers to apply what they learned in real-world agricultural settings, fostering a sustainable development mindset and readiness to innovate using renewable energy technologies.

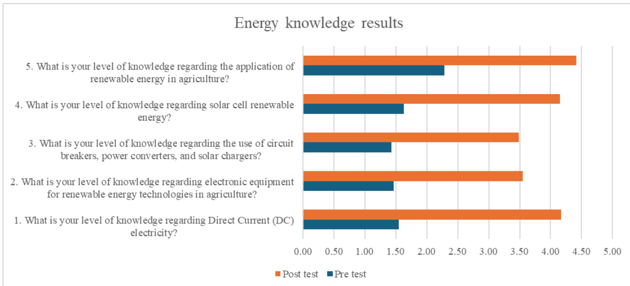

Figure 5 Comparison of Pre-Test and Post-Test Results on Energy Knowledge Levels

Figure 6 Workshop Training for 60 Student Teachers Using the Educational Game

V. DISCUSSION AND CONCLUSIONS

The integration of renewable energy technologies in agricultural practices presents significant challenges, especially in rural areas where there is often a lack of knowledge and practical skills among local educators and farmers. Many communities face barriers such as limited access to resources, unfamiliarity with modern energy technologies, and a lack of training opportunities that could facilitate the adoption of these innovations. In response to these challenges, this study aimed to evaluate the effectiveness of using an educational game, combined with hands-on workshops, to enhance knowledge and skills in renewable energy technologies among student teachers. By addressing the educational gaps and fostering practical skills, the study sought to prepare future educators to effectively teach and promote renewable energy technologies in agricultural settings, thereby contributing to sustainable development.

Figure 7 Workshop Training for Electrical Connection

A. Improvement in Knowledge Levels

The educational game and workshops led to substantial gains in knowledge across multiple domains. The pre- and post-test assessments of 60 student teachers revealed significant improvements in their understanding of ten key renewable energy technologies for agriculture. For example, the average knowledge level for Direct Current (DC) electricity increased from a pre-test score of 1.9 to a post-test score of 4.2, indicating a 121% improvement. Similar gains were observed in other areas

- Knowledge of solar cell renewable energy increased from 2.1 to 4.1 (95% improvement).
- Understanding of electronic equipment for renewable energy technologies in agriculture improved from 1.8 to 3.9 (116% improvement).
- Knowledge related to the use of circuit breakers, power converters, and solar chargers rose from 2.0 to 4.0 (100% improvement).
- The ability to apply renewable energy technologies in agriculture saw an increase from 1.7 to 4.3 (153% improvement).

These figures underscore the effectiveness of the game and workshops in enhancing technical knowledge among participants, equipping them with the foundational understanding necessary to teach these technologies.

B. Enhancement of Practical Skills

The hands-on workshops were particularly effective in improving practical skills. Participants showed notable gains in their ability to assemble and operate renewable energy equipment, as demonstrated by the following results:

- The skill level in calculating solar panel and battery usage increased from an average score of 1.5 to 3.8 after the training (153% improvement).
- The ability to select appropriate electronic equipment for different voltage levels improved from 2.0 to 4.2 (110% improvement).
- Competency in wiring electronic devices rose from 1.7 to 4.0 (135% improvement).
- Skill in sequencing electronic devices correctly increased from 1.8 to 4.1 (128% improvement).
- Problem-solving skills in applying these technologies in various scenarios saw a jump from 1.6 to 4.3 (169% improvement).

These results indicate that participants not only learned how to use the equipment but also developed the confidence and skills needed to troubleshoot and adapt the technologies to different contexts.

C. Positive Attitude Development

The integration of game-based learning with practical workshops also contributed to a positive shift in attitudes towards renewable energy and agricultural technology. Post-workshop evaluations showed:

- A 75% increase in positive attitudes towards electricity and renewable energy technologies.
- A 68% improvement in the perceived value of applying these technologies in agricultural settings.
- A 59% rise in the willingness to use games as teaching tools to disseminate knowledge further.

These changes suggest that participants became more open to adopting and promoting renewable energy technologies, recognizing both their educational value and practical benefits.

D. Satisfaction with the Learning Approach

The feedback on the educational game itself was overwhelmingly positive, with participants noting increased satisfaction across several dimensions

- Appropriateness of the number of technologies presented in the game saw an approval rating increase of 82%.
- Satisfaction with the difficulty level of the game improved by 70%.
- Positive feedback on game design elements, including visuals and user interface, increased by 65%.

- The stability of the game during use and ease of controlling characters were rated 75% higher after the intervention.

These findings highlight that the game was well-received as an engaging and effective learning tool, providing a balance between challenge and accessibility.

VI. CONCLUSIONS

The integration of an educational game with practical workshops significantly enhanced the knowledge, skills, and attitudes of 60 student teachers towards renewable energy technologies in agriculture. The substantial improvements in both theoretical understanding and practical competencies, as reflected by the pre- and post-test results, demonstrate the effectiveness of this blended learning approach. Furthermore, the positive shift in attitudes and high levels of satisfaction with the game-based learning model suggest that such educational interventions can be valuable tools in preparing educators to teach complex subjects. By fostering both knowledge and practical skills, this approach not only equips future teachers with the necessary tools to educate others but also promotes the broader adoption of renewable energy technologies in agricultural contexts, contributing to sustainable development goals.

In summary, this study supports the use of interactive, game-based learning combined with hands-on experiences as a powerful method for enhancing education in renewable energy technologies. The promising results encourage further exploration and expansion of such innovative educational approaches to meet the evolving needs of learners in various fields.

Figure 8 Providing instruction to students

VII. ACKNOWLEDGMENT

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Biochemical methane potential of co-digestion from food waste and watermelon rinds

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Abstract - Watermelon is a popular fruit with increasing consumer demand in Thailand and internationally. It is vital in driving the fruit processing industry, adding value. To agricultural products and support economic growth. However, watermelon processing produces significant waste. And requires effective management to prevent major environmental problems. The research aims to study the biochemical methane potential (BMP) from the co-digestion of food waste and watermelon rinds by using cow manure as inoculum, the experiments were divided into 3 conditions. Of food waste and watermelon rinds ratio (3:1, 1:1, and 1:3 based on weight) under temperature of 35 - 2 °C and hydraulic retention time (HRT) of 30 days. The result showed the average daily biogas production ratios of 3:1, 1:1, and 1:3 produced 80.31 - 31.84 mL, 72.73 - 33.31 mL, and 97.46 - 59.56 mL, respectively. The optimum condition was a 1:3 ratio, with a VS/TS ratio of 91.67%. The cumulative biogas volume was 1,276.49 - 306.18 mL, with 62.00% of the maximum methane content for 21 days. This research presented a prospective strategy for future waste management within the fruit processing industry.

Keywords - Biogas, Fruits processing, Food waste, Co-digestion, Waste management

I. INTRODUCTION

Thailand is distinguished as one of the world's leading producers and exporters of tropical fruits, boasting a diverse range of high-quality fruits that were internationally acclaimed, such as mangoes, durians, mangosteens, and pineapples. The fruit processing industry is vital for adding economic value and boosting Thailand's global market competitiveness. This industry encompasses many processed products, including canned fruits, juices, jams, dried fruits, and innovative creations like health beverages and fruit extracts. The research by Tippakoon, P. (2020) [1] indicated that export earnings had a visible impact on key markets, such as Asia, Europe, and the United States. Watermelon is known for its sweet taste and high nutritional value. It is a crucial product in Thailand's rapidly growing watermelon processing industry. It also caters to domestic and international markets. The primary manufactured products include watermelon juice concentrate, dried fruit, jelly, and innovative uses of seeds and rinds as raw materials in the food and cosmetic industries [2]. These processing activities enhance the value of watermelons and generate significant income for farmers and entrepreneurs throughout the supply chain. Nevertheless, the watermelon processing industry generates substantial waste, including substandard peels, seeds, and pulp, which often need to be more adequately managed. This inefficient waste management leads to environmental challenges, such as the accumulation of decaying organic matter, greenhouse gas emissions, and the contamination of soil and water resources [3]. On the other hand, watermelon rinds have a high potential to be used as a renewable energy source or biomass power generation [4]. Watermelon rinds were converted into energy through biological mechanisms like anaerobic digestion. This technique transforms decomposed watermelon rinds and pulp into biogas, primarily comprising methane and carbon dioxide. Previous research by Oduor et al. (2022) [5] demonstrated that watermelon rinds had a high energy potential, making them a valuable resource for sustainable energy production. Furthermore, the studies showed that their efficiency was significantly increased when co-digested with other waste materials, such as by-products from the fruit processing industry. This advancement significantly enhanced energy yield. This research aims to investigate the biogas and methane production from food waste combined with watermelon rinds and cow manure inoculum using a batch fermentation system to develop renewable energy solutions by converting waste into energy for application at community enterprise and industrial levels.

II. METHODOLOGY

A. Preparation of substrate and inoculum

Food waste (FW) and watermelon rinds (WR) were collected from restaurants and fruit shops in the surrounding communities. Maejo University. They were then thoroughly blended to facilitate decomposition. The substrates were FW and WR combined in three different weight ratios: 3:1, 1:1, and 1:3, based on weight for batch biogas production experiments. For the preparation performance of inoculum, dried cow manure from the Faculty of Animal Science and Technology at Maejo University was mixed with water in a ratio of 1:1 by weight. Before the experiment, the substrate and inoculum were stored at a temperature lower than 4.0 °C. The inoculum was fermented in anaerobic conditions for 7 days. Afterwards, The inoculum was filtered through a sieve with openings. The initial parameters were analysed at no larger than 10 mm. in width and length. This experiment investigated the potential for biogas and methane production from FW and WR using an adaptation of the standard VDI 4630 method. The study prioritised the biogas yield from varying the proportions of the two substrates mentioned above. A substrate-to-inoculum ratio (SIR) of 2:1 gVS_{add} was employed to determine the volume of the experiment conducted in this research, which utilised a volume of 1,000 mL. Inoculum was added at 1.5% of the working volume of anaerobic digestion was 400 mL. The pH was then adjusted to 7.0 ± 0.1. Nitrogen gas was used to flush the medium and headspace to create anaerobic conditions. Then, the bottles were sealed with rubber stoppers and aluminium caps [6]. During the fermentation, there will be a control set (Blank) that only puts in the inoculum to subtract from the volume of biogas produced in all three ratios, making the result of biogas produced as the possibility from the substrate only the potential of methane production using the Biochemical Methane Potential (BMP Test). We will maintain the temperature within the mesophilic range (35.0 ± 2 °C) by utilising a thermostatic water bath and a water pump to ensure uniform heat distribution within the bath, as shown in equation (1).

$$BM\Pi = \%CH_4 \times V_{Biogas,STP} / m_{Substrate,}VS_{add} \quad (1)$$

Where $\%CH_4$ is the percentage of methane gas proportion in biogas, $V_{Biogas,\ STP}$, $m_{Substrate}$, VS_{added} is the mass of raw material added to the system (gVS_{added}). After leaving the system, samples of each ratio were taken to analyse biogas parameters. Biogas composition measurements were measured every 7 days using a GFM 406 series gas composition analyser (Gas Data, United Kingdom).

B. Biogas parameters analysis

The biogas production process is evaluated based on parameters using the standard wastewater analysis methods outlined in APHA 2005 [7], with at least three replicates for each measurement. The analysis included total solids (TS), volatile solids (VS), and hydrogen potential (pH). Biogas production was measured daily using a glass syringe [8], with measurements taken at consistent times to ensure data reliability. This monitoring continued until the cumulative biogas production rate stabilized.

III. RESULTS AND DISCUSSION

A. Characteristics of substrate and inoculum

The results of characterizing cow manure used as inoculum and FW and WR used substrate were shown. The manure has been reduced in size by blending it until it is fine.

Table I Characteristics of various substrates and inoculum

Parameters	CM	Substrate ratio	
		FW	*WR*
TS (mg/L)	47,120 ± 1.38	154,593 ± 1.19	28,910 ± 5.46
VS (mg/L)	27,350 ± 1.31	149,103 ± 1.23	24,437 ±5.43
VS/TS (%)	58.04	96.45	84.53
pH	7.44 ± 0.40	4.51 ± 0.04	6.15 ± 0.49
Parameters	**Substrate ratio**		
	1:3	*1:1*	*3:1*
TS (mg/L)	58,290± 5.96	100,540± 0.85	95,847± 3.94
Parameters	**Substrate ratio**		
	1:3	*1:1*	*3:1*
VS (mg/L)	53,433 ± 5.92	95,273 ± 0.97	91,153 ± 4.03
VS/TS (%)	58.04	96.45	84.53
pH	4.56 ± 0.71	5.54 ± 0.69	6.47 ± 0.74

From Table I, the results of the characterization of the inoculum and substrates showed that the parameters such as pH, TS, VS, and VS/TS ratio of FW were higher than those of cow manure. The following factors caused this: FW had the highest TS and VS values due to its composition, which included various components such as vegetables, fruits, meat, and rice, each of which had different chemical compositions (carbohydrates, proteins, fats, and dietary fibres). These resulted in higher overall parameter values than other substrates [9]. The specific properties of the substrates were presented in Table I. The VS/TS ratio of FW and WR was significantly high (91.67-95.10%), indicating a high organic content with low ash content in TS, which made these waste types suitable for anaerobic digestion. A VS/TS ratio exceeding 50% indicated relatively high organic content, making it more favourable for anaerobic digestion to generate biogas, with methane production increasing alongside the VS/TS ratio [10].

B. Daily biogas production

This study's hydraulic retention time (HRT) was approximately 30 days. The daily biogas production is demonstrated in Figure 1. The WR produced the highest volume of biogas, with 507.33 ± 27.00 mL, followed by FW, which produced 450.33 ± 12.06 mL.

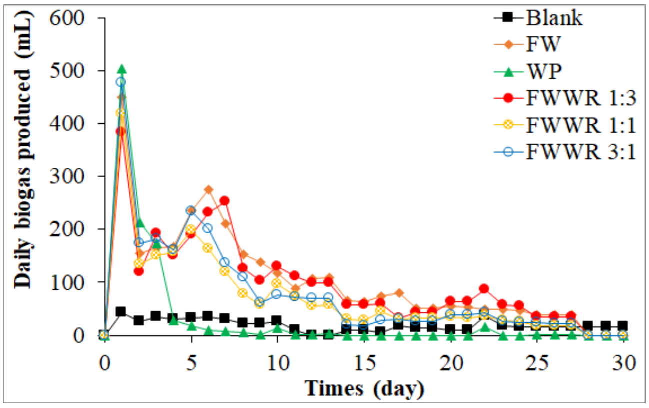

Figure 1 The daily biogas production

Generally, FW was composed of carbohydrates(5.70-53.00%), proteins (2.30-28.40%), and lipids (1.30-30.30%) [11], with carbohydrates and proteins undergoing hydrolysis more rapidly due to their higher degradability compared to lipids [12]. It was indispensable to recognize that FW, rich in rapidly degradable carbohydrates and lipids, had the potential to generate a substantial amount of methane [13]. The initial phase of biogas production involved the hydrolysis process for all ratios. During this stage, the inoculum breaks down organic matter in the substrate into smaller molecules. Biogas production increased rapidly during acidogenesis and acetogenesis, where sugars, amino acids, and short-chain fatty acids (SCFAs) were converted into acetic acid and CO_2. Methanogenic bacteria further used acetic acid to produce CH_4. WR's high sugar and moisture content accelerated digestion and biogas production in a WR digester due to the abundance of biodegradable materials that enhanced decomposition [14]. The study emphasised the potential of WR for biogas production, particularly when combined with other organic materials, to improve microbial activity and gas yield. The research also illustrated that WR produced higher biogas volumes than other fruit waste due to its favourable chemical composition, including high soluble sugar content and lower lignocellulosic barriers, facilitating rapid fermentation [15]. However, the retention period, substrate ratios, and inoculum type significantly influenced outcomes. Hydraulic retention time, for example, could further enhance biogas yield and pathogen removal, improving the process's environmental and agricultural applications.

C. Cumulative biogas production and biogas contents

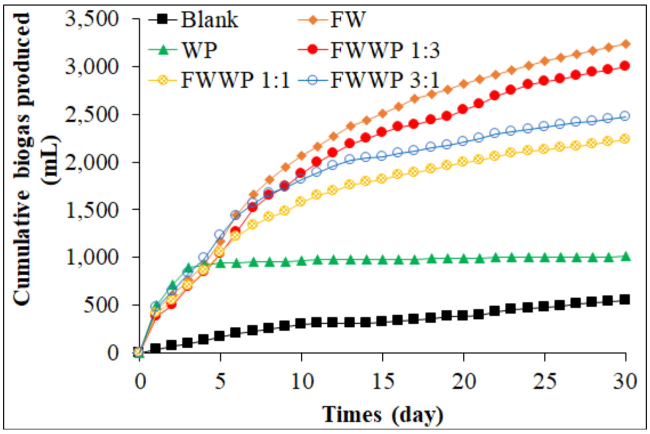

Figure 2 The cumulative biogas production

The results of this study were shown in Figure 2. The cumulative biogas productions of various ratios were related to the inoculum ratio. The average biogas production of the inoculum blank was 330.51 ± 155.51 mL. The 3:1, 1:1, and 1:3 ratios produced 1,852.46 ± 91.93 mL, 1,641.87 ± 150.77 mL, and 2,058.86 ± 306.18 mL, respectively. The biogas components consisted of CH_4, CO_2, and H_2S. The maximum CH_4, CO_2, and H_2S contents were presented in Figure 3. After 7 days, the 3:1 ratio yielded 28.80% CH_4, 27.90% CO_2, and 1,170 ppm H_2S. By 14 days, the CH_4 content increased to 53.33%, while CO_2 and H_2S levels increased to 24.30% and 1,830 ppm, respectively. For the 1:1 ratio, the maximum CH_4 content of 52.30% was achieved after 19 days, along with 23.30% CO_2 and 1,530 ppm H_2S. The highest CH_4, CO_2, and H_2S contents, recorded at 62.00%, 25.20%, and 750 ppm, were observed with the 1:3 ratio.

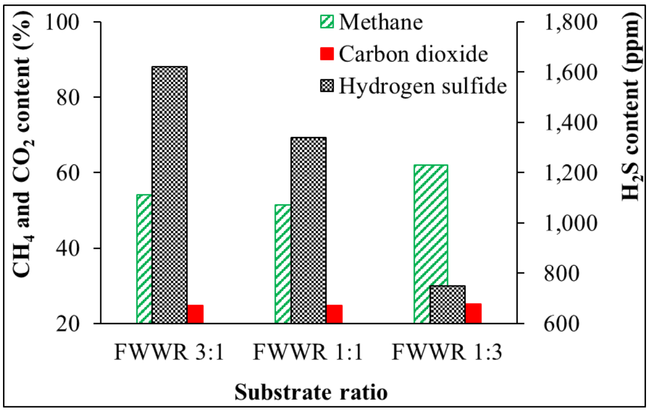

Figure 3 Maximum CH_4, CO_2, and H_2S contents

The production of biogas from FW and WR, as studied in co-digestion processes, was significantly influenced by pH, Volatile Solids (VS), Total Solids (TS), and the VS/TS ratio. A neutral pH (~6.8–7.2) was optimal for methanogenic activity. This was demonstrated by Register W. Mrosso and Achisa C. Mecha, who reported a 178.1% increase in biogas output at a pH of 7.3 compared to more acidic conditions [16]. High concentrations of VS and TS were associated with increased biogas yield, as these parameters indicated the abundance of biodegradable organic matter. This was supported by the findings of Dahunsi et al., where co-digestion of food waste and watermelon rinds achieved a methane composition of 68% [17]. The VS/TS ratio, which reflected the proportion of organic matter content, was also crucial for efficiency. Both studies highlighted favourable results when the ratio was optimised to suit the substrate's characteristics. In a study investigating various substrate ratios, a 1:3 ratio of FW:WR resulted in the highest methane production. This proportion likely offered an optimal balance of organic content and moisture, fostering favourable microbial growth and activity conditions. These findings aligned with research emphasising how specific substrate combinations could enhance buffering capacity, stabilise pH, and optimise nutrient availability for anaerobic digestion. For example, FW, rich in carbohydrates, provided a quick energy source, while WR added moisture and structural diversity, preventing clumping and improving microbial contact [18]. Furthermore, integrated strategies, such as adding buffering agents or micronutrient solutions, have enhanced methane yield and process stability by maintaining optimal pH and alkalinity levels [19]. These approaches were deemed essential for scaling anaerobic digestion systems to address variability in feedstock composition and environmental conditions. The research indicated that the 1:3 ratio by weight increased methane yield by up to 68%, as food waste provided a high content of carbohydrates and sugars, enhancing the degradation of WR, which had lower cellulose content and thus decomposed more rapidly [20]. Compared to other ratios, such as 3:1 or 1:1 by weight, the 1:3 ratio demonstrated significant advantages in biogas production and waste reduction, encouraging efficient and sustainable utilisation of feedstock resources [21].

IV. CONCLUSION

Food waste and fruit residuals such as watermelon rinds can be used as substrates to produce biogas under anaerobic conditions. The co-digestion of food waste and watermelon rinds enhanced methane production compared with their mono-digestion. The optimum mixing ratio of food waste to watermelon rinds was 1:3, with the highest cumulative methane yield of 1,276.49 ± 306.18 NmL/gVS_{added} and methane content of 62%. Incorporating watermelon rinds in the system could reduce the lag phase and promote faster biogas formation for co-digestion. Biogas production heavily depends on the type and proportion of the substrate, which affects both the digestion and microbial environment.

V. ACKNOWLEDGEMENT

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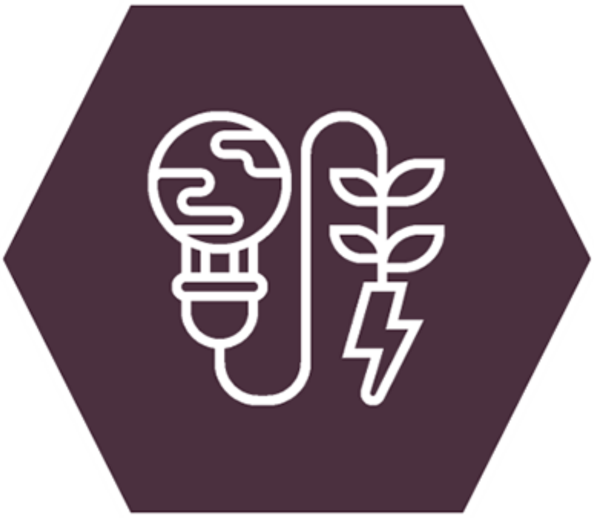

Energy Resilience

Waste-to-Energy and Potential for Enhancing Regional Energy Resilience

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Abstract - Energy resilience is important for many regions that rely heavily on external energy sources, and regions prone to natural disasters that can disrupt electricity supply. This study examines the potential of waste-to-energy (WtE) technologies to enhance energy resilience using local municipal solid waste and agricultural biomass residue. Material Flow Analysis (MFA) was used to assess waste flows and energy production potential from waste incineration, and anaerobic digestion technologies. The analysis was conducted using a scenario analysis, which revealed a potential reduction of up to 45% in external energy imports with local renewable energy. The study results show improvements in key indicators such as the self-sufficiency ratio and energy resilience, highlighting the role of decentralized energy systems in making energy access more flexible and diversified while also solving local waste management problems, reducing greenhouse gas emissions, and alleviating environmental impacts.

Keywords - waste to energy, energy resilience, energy security, municipal waste, biomass residue, waste management, greenhouse gas emissions

Nanotechnology and Materials for Energy

Electrospun chitin-based nano-membrane from mushroom waste for water filtration of nano-plastics removal

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Abstract - The increasing presence of microplastics in water bodies poses serious environmental and health challenges, highlighting the need for novel filtration solutions. Electrospinning, a new technique for producing nanofiber membranes, has been widely applied in the production of filtration materials. Utilizing mushroom waste as a raw material not only reduces production costs but also effectively minimizes environmental pollution, promoting resource recycling. The development of efficient and sustainable water filtration technologies is crucial. Chitin, a biopolymer found in the cell walls of certain mushrooms, offers unique properties that make it an excellent material for electrospun membranes. After being extracted and processed, chitin exhibits remarkable mechanical strength, biocompatibility, and biodegradability, making it ideal for sustainable filtration applications. These membranes exhibit high surface area and porosity, making them ideal for capturing and removing microplastics, suspended solids, harmful microorganisms, and heavy metal ions from water. The inherent attraction of chitin to pollutants enhances the filtration efficiency, while its antimicrobial properties can help prevent bacterial growth on the membrane surface. By optimizing the structure and performance of these membranes, this research aims to optimize the electrospinning process of chitin-based membrane, eventually contributing to innovative and eco-friendly solutions for water purification and microplastic removal. Acetone and acetic acid were used as green solvents to show the electrospinning of CA. The diameter and morphology of the fibers were influenced by the solvent composition system, and by varying the solvent composition, fibers with adjustable porosity were found. In conclusion, we used eco-friendly solvents and additives to successfully electrospun ultra-fine CA nanomembranes with filtration application. For the filter experiment part, we still need to develop more, trial and error, however this research has shown the potential of eco-friendly nanomembranes of nanoplastics filtration system.

Keywords - microplastics, electrospinning, nanomembranes, chitin, chitosan, biopolymer, nanomaterials

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