AI Digital Twin Technology for Forecasting Solar Generation

By

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Thesis
Submitted to Flinders University
for the degree of

Bachelor of Engineering (Software)(Honours)
College of Science and Engineering
20/10/2025

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ABSTRACT

By integrating digital twin technology with artificial intelligence (AI) and machine learning (ML), solar energy management systems have the potential to accurately predict future energy generation. This project investigates the design and implementation of an AI-powered digital twin model for solar panel arrays located around Flinders University's Bedford Park and Sturt Campuses. This model is designed to forecast the power output based on historical generation and irradiance data taken from sensors located on the arrays, and weather forecast variables both current and historical such as temperature, daylight hours, and weather conditions. Several AI and ML algorithms were proposed for the model to test if the model can capture the complex, nonlinear relationships between environmental factors and solar generation. By data processing and simulation, the model provides predictive insights that can assist with operational planning, energy optimisation, and grid integration enhancement. This study evaluates the accuracy and reliability of the digital twin forecasts through the comparison of different AI and ML models, different locations of the arrays, and comparison with predictions on different days with historical solar data. This study demonstrates the potential of AI-powered digital twins to improve the reliability and efficiency of solar energy systems. These findings contribute to the increase knowledge of predictive digital twin applications in renewable energy management systems and highlight opportunities for future development of intelligent energy forecasting systems.

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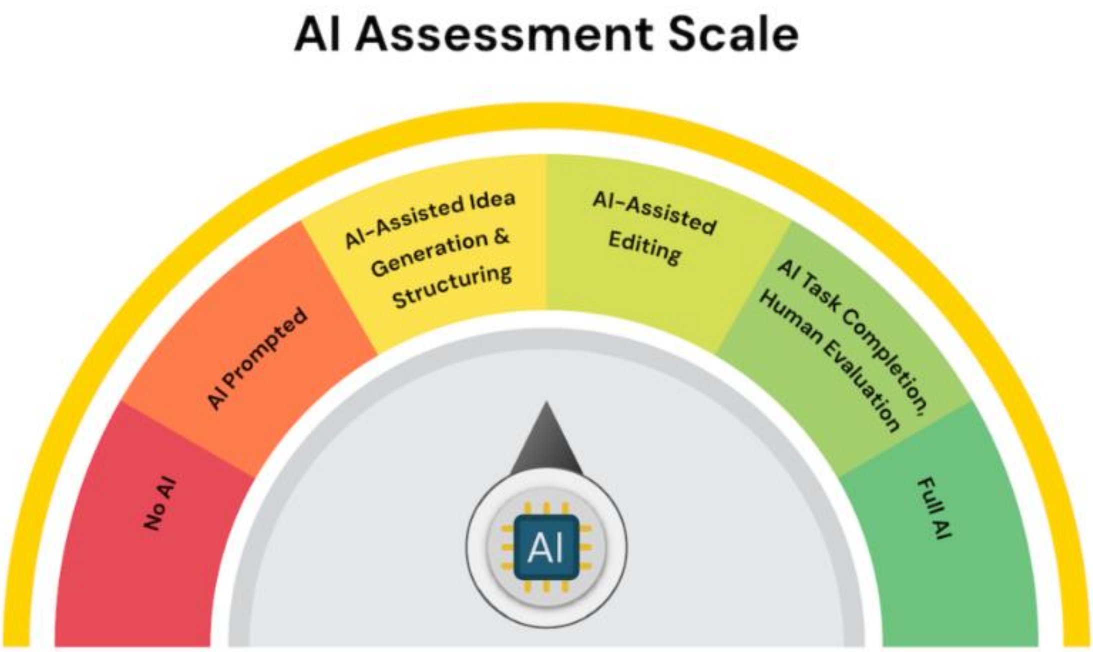

Adapted from the AI Assessment Scale Perkins, M., Furze, L., Roe, J., & MacVaugh, J. (2023). Navigating the generative AI era: Introducing the AI assessment scale for ethical GenAI assessment. arXiv preprint arXiv:2312.07086.
https://leonfurze.com/2023/12/18/the-ai-assessment-scale-version-2/

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I certify that this Thesis:

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Date: 21/10/2025

Artificial Intelligence

In accordance with Item 3. of the above declaration and the assessment specification in the Topic Information guide on how Artificial Intelligence can be used, Artificial Intelligence has been used in this Thesis for the following purposes:

Sections	**Role of AI** – specify how AI was used
N/A	There is no use of AI in this document.

ACKNOWLEDGEMENTS

A special thank you to Dr. Matthew Stephenson for your supervision, and support throughout this project.

LIST OF SYMBOLS

Symbol	Definition
^{o}C	Degrees Celsius
km/h	Kilometres per Hour
kW	Kilowatts
mm	Millimetres
W/m^2	Watts per Metre Squared

LIST OF ABREVIATIONS

Abbreviation	Definition
ACDT	Australia Central Daylight Time
ACST	Australia Central Standard Time
AI	Artificial Intelligence
AI-DT	AI Digital Twin (AI-powered digital twin)
AI-DTS	AI for Digital Twin Systems
API	Application Programming Interface
ASI	All-Sky Imagers
BMS	Building Management System
CSV	Comma-Separated Value
DL	Deep Learning
DRAMA	Drama
DT	Digital Twins

DTS	Digital Twin System
EMS	Energy Management Systems
IoT	Internet of Things
IST	Information Science and Technology
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron
MPC	Model Predictive Control
NN	Neural Network
NWP	Numerical Weather Prediction
PV	Photovoltaic
RES	Renewable Energy Sources
RF	Random Forest
RegEx	Regular Expression
RL	Reinforcement Learning
SCADA	Supervisory Control and Data Acquisition
STE	Sturt East
XGBoost	Extreme Gradient Booster (also spelt eXtreme Gradient Booster)

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1. INTRODUCTION

1.1. Overview

With the global transition from fossil fuels to renewable energy sources (RESs), solar has become one of the fastest growing energy sources (Arafet & Berlanga, 2021). However, solar is inherently intermittent at generating power, and requires robust understanding of energy patterns, forecasts, demand, and grid management. Traditional energy management systems (EMS) such as rule-based controls, data loggers, and Supervisory Control and Data Acquisition (SCADA) lack the intelligence and adaptability required for modern decentralised energy systems. This has seen growing research in intelligent systems that assist with predictions, responsiveness, monitoring and decision-making.

In response, there is an increasing interest in integrating artificial intelligence (AI) and machine learning (ML) with digital twin (DT) technology to create an AI powered Digital Twin System (DTS). AI-enhanced DTs are powerful tools that can assist with predictive maintenance, energy output predictions, forecasting, diagnostics, control, and decision-making.

This thesis explores how combining AI and ML with DT technology can address these challenges in forecasting by developing a dynamic data-driven model capable of predicting solar generation performance.

1.2. Background and Significance

A Digital Twin (DT) is a powerful tool that virtually represents a physical asset, system or process, by continuously synchronising with real-world data to enable forecasting, optimisation and monitoring. In the renewable energy sector, a DT can model the operational behaviour and environmental influences of an array of solar panels, by acting as intelligent cyber-physical systems.

In parallel, AI and ML algorithms such as Random Forest (RF), Neural Networks (NN), and Long Short-Term Memory (LSTM) have proven their capability of learning complex nonlinear relationships between weather patterns and solar energy output, making them powerful tools for forecasting. Operational efficiency and energy management could be improved by integrating these models into a DT framework to create a predictive and adaptive system.

The significance of this project is to provide an insight into the spatial reliability of an AI-based solar forecasting framework. This project forms part of a larger DT ecosystem for managing solar arrays located around Flinders University’s Bedford Park and Sturt campuses, by developing a forecasting layer that predicts the solar generation for three different sites. By comparing the performance across these sites with topographical differences, this project follows a practical and scalable approach.

1.3. Key Definitions

- Artificial Intelligence (AI): Computational methods that enable computer systems to perform tasks like decision-making, and problem solving.
- Digital Twin (DT): A virtual replica of a physical asset that mirrors the state, behaviour, and behaviour of that particular asset in real time.
- Machine Learning (ML): A field of study in AI where systems learn and improve from data without being explicitly programmed.
- Solar Forecasting: Using meteorological and operational data to predict the solar power generation over a specified horizon (e.g., hours or days ahead).

1.4. Problem Statement

Due to variability of weather and environmental conditions, accurately forecasting solar energy generation is challenging. Traditional methods often fail to capture complex weather and environmental dynamics leading to inefficient energy management and poor planning. With the growing interest in AI-powered DTs, efficient energy management, improved forecast accuracy, and grid stability can be achieved by integrating real-time data with predictive ML techniques. While current literature highlights the concept of DTs and their potential, limited studies have implemented and validated DTs for forecasting solar energy generation, particularly across multiple solar arrays.

This project investigates how AI and ML techniques can enhance solar energy generation predictions to provide a more reliable and efficient prediction for renewable energy management by addressing the research question: *How can AI Digital Twin Technology improve the accuracy of solar energy generation forecasting?*

1.5. Project Aim and Objectives

1.5.1. Project Aim

To design and implement a solar forecasting framework that forms the predictive core of a digital twin capable of managing solar energy systems.

1.5.2. Project Objectives

- To collect and preprocess historical solar and irradiance data from three sites around Flinders University's Bedford Park and Sturt campuses: Information, Science and Technology (IST), Drama, and Sturt East Buildings.
- To collect and preprocess historical and real-world weather data from WeatherAPI.

- To develop four AI/ML algorithms: Random Forest (RF), Extreme Gradient Boosting (XGBoost), Multilayer Perceptron Neural Network (MLPNN), and Long Short-Term Memory (LSTM).
- To train and validate these four algorithms for seven-day solar generation forecasting.
- To compare the performance of each model using RMSE, R^2, and MAE metrics.
- To identify the impact of environmental and topographical influences across the three sites.
- To outline integration pathways for future work and embedding this framework into the larger digital twin system (DTS).

1.6. Thesis Statement

This thesis provides the groundwork for providing an effective and scalable approach for short-term solar energy prediction, by integrating AI/ML algorithms into a DT framework. Using a combination of ML techniques and synchronised weather and solar data, the proposed system enhances forecasting accuracy and establishes a foundation for future real-time, intelligent energy management across distributed solar networks.

1.7. Thesis Structure

This thesis is structured into six chapters beginning with Chapter 1 introducing the research context, motivations, and objectives. Chapter 2 is a review on the existing literature on the concept of DTs, the role AI acts in DT technology, and DT applications in renewable energy forecasting. Chapter 3 outlines the methodology and system design followed to complete this project, including data collection, processing, model selection, training and validation, evaluating results, and outputting results. Chapter 4 presents the experiment setup, evaluation metrics, and results achieved from the four algorithms across the models developed for all three sites. Chapter 5 discusses the results comparing them to existing studies, highlighting key finding and limitations. Chapter 6 concludes this project and lists some suggested directions for future research and work.

2. LITERATURE REVIEW

2.1. Overview

Recently there has been growing interest in intelligent energy management systems (EMS) to assist with predictions, responsiveness, monitoring, and decision-making. In response, there is an increasing interest in integrating artificial intelligence (AI) with digital twin (DT) technology to create an AI-enhanced digital twin system (DTS). AI-enhanced DTs are powerful tools that assist with predictive maintenance, energy output predictions, forecasting, diagnostics, control, and decision-making.

This literature review examines the theoretical foundations and recent developments in DT technology specifically focussing on implementing AI and ML with this technology, and why DTs can be used for solar forecasting. The objective is to identify what is a DT, identify the strengths and limitations of existing forecasting approaches, and outline the current research gaps and challenges, establishing the conceptual basis for present DT models.

2.2. Concept of Digital Twins

Although DT technology has gained popularity over the past decade, the concept of DTs is a lot older with Micheal Grieves proposing a three-component DT for Product Lifecycle Management at the University of Michigan in 2002 (Grieves, 2016). A similar concept known as 'Mirror Worlds' was mentioned earlier in 1991 by David Gelernter, where the physical world inputs information to a software model to mimic reality (Gelernter, 1993). Rasheed et. al. (2020), defines DTs as "a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimisation, monitoring, controlling and improved decision making". Initially emerging from the aerospace industry, DTs have evolved to be deployed in a wide range of disciplines such as, agriculture, healthcare, manufacturing, construction, energy, and sustainability.

DTs consist of five components: physical assets, virtual counterpart, data streams, bidirectional communication framework, and analytic services (Jiang et al., 2021). They are typically powered by either multi-physics, multi-scale or hybrid-system models (Jiang et al., 2021). DTs continuously update the virtual model by collecting real-time data from Internet of Things (IoT) sensors embedded on the physical asset. The virtual model uses this data to mirror the behaviour, performance and state of the physical asset.

Recent studies have indicated DTs improve the performance conditions, optimise physical assets, increase the life of RESs, lower repair costs, and decrease downtime (Attaran & Celik, 2023; Sharma et al., 2024). These benefits make them especially useful for solar panel forecasting and energy management. For example, a DT for solar panels can use irradiance and weather data to adjust the performance and energy generation.

2.3. The Role of Artificial Intelligence in Digital Twins

In a digital twin system (DTS), AI can contribute to many roles including the six broader roles known as AI-DTS (AI for Digital Twin Systems) as indicated in the DTS Architecture (figure 1).

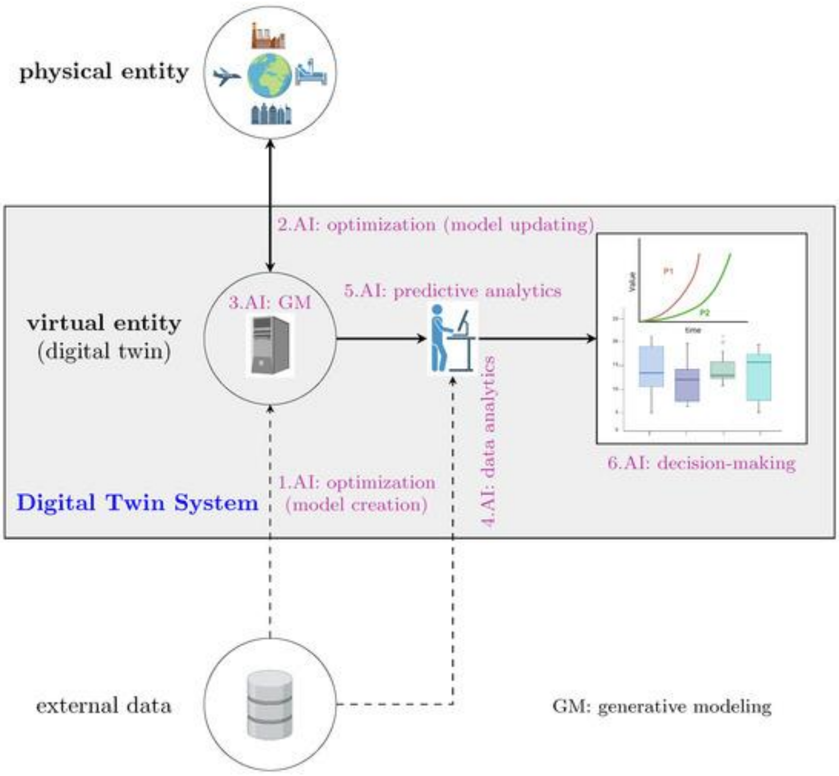

Figure 1 – Digital twin System Structural Architecture showcasing different AI roles (Emmet-Streib, 2023).

Table 1 – The six different AI-DTS techniques and their roles in the DTS (Emmet-Streib, 2023).

AI-DTS Techniques	Role in the DTS	Significance to the DTS
1. AI: Optimization (Model Creation)	A process that involves the digital twin using data and parameters to estimate and assist with creating the model.	Allows the simulation to capture the essential features of the physical entity to help create the model.
2. AI: Optimization (Model Updating)	Ensures the DT is synchronised with its physical counterpart whilst in operation.	Involves regularly updating the data and assets of the DT.
3. AI: Generative Modelling	Uses ML models like generative adversarial	Contributes to the simulation model by learning underlying

	networks (GANs) to generate data containing characteristics from large-scale data.	patterns and distribution of data to help generate new or similar data from the DT.
4. AI: Data Analytics	Examines datasets to identify any patterns and trends.	Allows the model to make appropriate decisions and solve problems.
5. AI: Predictive Analytics	Using statistical algorithms and ML to predict future outcomes.	Allows for future predictions by identifying patterns in historical data.
6. AI: Decision Making	Making decisions and summarises all results achieved up to this point.	Can integrate everything together and produce quantitative or qualitative summaries of the DTS.

In solar forecasting, integrating these six AI-DTS techniques can enhance the capabilities of DT models, enabling advanced analytics, intelligent forecasting and real-time decision-making. For instance, in solar energy systems AI algorithms can assist with processing diverse data sources such as irradiance, and weather forecasts to predict future PV output.

Many machine learning (ML), and deep learning (DL) techniques can be used to assist with forecasting in energy management. Researchers have had successful performance in using ensemble methods such as Random Forest (RF), and Extreme Gradient Booster (XGBoost) in forecasting energy output in photovoltaic systems (Abdou & Memon, 2023; Didavi et al., 2021). RF is easy to use and offers robustness against overfitting, whereas XGBoost offers higher accuracy and efficiency in handling large datasets. Choi et. al. (2018 as cited in Wang et. al., 2023) suggests LSTM to assist with power load forecasting like predicting the power load data. LSTM also has the benefit of capturing long-term dependencies in data, enabling more accurate predictions. Huang et al. (2020) demonstrated success in achieving good performance with Multilayer Perceptron (MLP) compared to LSTM.

Integrating AI with DT technology enables the model to continuously learn and adapt based on new data streams. This adaptive intelligence transforms the twin from static to a self-updating predictive system, allowing dynamic optimisation in energy management, and improve reliability and resilience against environmental fluctuations.

2.4. Solar Forecasting Techniques

2.4.1. Current Solar Forecasting Techniques

Current solar forecasting techniques include satellite images, all-sky imagers (ASIs), and Numerical Weather Prediction (NWP) models. Satellite images determine cloud pattern using visible and infrared images taken from satellite-based sensors flying overhead (Sobri et al., 2018). ASIs are digital cameras that capture images with a 180-degree field of view, enabling the entire sky from one horizon to the other to be captured (Barhmi et al., 2024). ASIs detect clouds in the pictures using image-processing techniques and determining the Cloud Motion Vectors by lliking the clouds within consecutive images. Using these vectors, future cloud positions are determined, and future irradiance is estimated accordingly. Historically, NWP models have been the primary technique for forecasting applications to predict variables such as surface solar irradiance, temperature, humidity, wind, and probability of precipitation (Sobri et al., 2018). However, for solar forecasting they require statistical methods to correct errors and blend the output for multiple models (Sobri et al., 2018).

2.4.2. Current Techniques vs Digital Twins

Although current forecasting techniques and DTs can be used in energy management for monitoring, controlling, and optimising power generation and distributions, DTs offer the following advantages compared to techniques like satellite images or NWP:

1. **Real-Time Adaptability:** AI DTs have dynamic response time to constant changing environmental and operational conditions.
2. **Predictive Maintenance:** DTs detect early signs of faults and send recommendations to the virtual machine to complete regular maintenance or repairs, reducing system downtime and costs.
3. **System-Level Optimisation:** DTs optimise and can communicate through interconnected components (e.g., generation, loads, wind speed, solar irradiance, and storage).
4. **Simulation and Decision-Making:** DTs simulate future predictions by using what-if scenarios to enable proactive energy management.

Soori et. al. (2023) mentions DTs have the capability to help maximise the value of renewable energy systems, reduce costs, and minimise downtime.

2.4.3. Applications of Digital Twins in Solar Systems

Due to their ability to model, optimise and simulate a physical entity in real-time, AI DTs can be deployed in many fields including solar and wind turbine energy systems. DT technology can allow considerable planning and designing, energy forecasting, reliability analysis, fault detection, predictive monitoring, and intelligent maintenance transforming EMSs. These application areas allow for EMSs to be more reliable and efficient. Table 2 outlines some of the potential uses for DTs in managing solar systems.

Table 2 – Various applications of DT technology in Solar EMS (Fahim et al., 2022).

Application	Potential Uses
Plan and Design	• Solar system design (Massel et. al., 2021). • Develop plans and assist with operations. • Plan and predict energy consumptions and supply (Kavousi-Fard et. al., 2024)
Energy Forecasting	• Use of optimal planning and operating, real-time control and remote monitoring to power output (Fahim et. al., 2022).
Reliability Analysis	• Improve performance using real-time data monitoring for reliable analysis. (Wang et. al., 2021).
Management and Monitoring	• Optimal management of solar panels.
Fault Detection	• Improve stability and reliability of solar panels using fault detection.
Security and Resiliency	• Real-time security protection (Danilczyk et. al., 2019) • Enhance security. • Detect cyber-attacks (Danilczyk et. al., 2019) • Protect the grid from natural outages (Danilczyk et. al., 2019)
Predictive Maintenance and Condition Monitoring	• Enhance reliability • Predict faults and failures • Decrease maintenance costs • Remote monitoring and control • Optimise performance

2.5. Integration Strategies

Integrating AI-enhanced DTS into existing EMS shifts the systems from a conventional rule-based management system to a predictive, self-optimising system. This integration assists with solar forecasting by using real-time data from sensors and management systems to create a dynamic, evolving simulation that predicts future outcomes more accurately than traditional methods. The primary layers common across all integrations of DTS into EMS include:

1. **Physical Asset:** The physical object used to generate the DT (e.g., solar panels).
2. **Data Extraction Layer:** Using IoT enabled sensors embedded onto the solar panel arrays to capture parameters important for energy management such as irradiance, temperature, conditions, cloud cover. There parameters are then transmitted to the virtual entity (DT) for analysis and decision making.

3. **Intelligent Modelling Layer:** Using AI, ML, and DL algorithms such as LSTM to assist with power load forecasting and predict power load data (Choi et. al., 2018 as cited in Wang et. al., 2023). This layer is where the data is interpreted by AI for predictive accuracy and adaptability for decisions made.
4. **Design, Control and Execution Layer:** Using the output of the virtual model, real-time decisions are made, and strategies are executed autonomously. Some decisions that the DT can make include dynamic load balancing, dispatch energy storage, predictive maintenance, recommend maintenance schedules, and synchronise assets connected to the grid. Model Predictive Control (MPC) and Reinforcement Learning (RL) can be embedded into the DTS to assist with system-level optimisation.

2.6. Research Gaps and Challenges

Although DTs have the potential to transform EMS and forecasting using AI algorithms, ML, DL, and optimisation frameworks there are still some current research gaps and technical challenges with this technology:

1. **Real-Time AI Inference:** Current literature use DT models that combine SCADA and AI-DT technology or offline batch-trained models. This often means that real-time inference using live sponsors are unexplored. This lack of inference is mostly due to DTs in the energy sector using non-standard frameworks and architecture as most developers use their own architecture models.
2. **Data Quality and Availability:** DTS rely on real-time data from sensors and IoT devices, which can produce low quality data if coverage is inconsistent or if there’s environmental noise. This can lead to missing data, and limitations in data quality and availability impacting the performance of the AI techniques in the virtual entity.
3. **Complex Computational Functions:** Any AI DTs using deep learning models and real-time forecasting are intense and demand robust computational resources. These systems often require efficient architecture like physics-models or hybrid cloud-edge configurations that are not standardised.
4. **Tool-Specific Implementations:** There is a lack of academic works that evaluate the use of DT platforms like XMPro for AI-powered DTs in the renewable energy sector.

These gaps highlight the need for robust, adaptive, and explainable DTS for the renewable energy sector. Given these gaps, this project develops and evaluates the capability of AI-enhanced DTs by creating forecasting models designed to be the core function of a broader DT project. These models are designed to use real solar generation and irradiance data collected from distinct sites at Flinders University via the university’s Building Management System (BMS).

2.7. Summary

This chapter analysed the concept of DTs from its origin to the current state of implementing AI with DT technology in solar energy systems. This review highlighted the significant potential of combining these two paradigms for improved forecasting. The literature indicates strong progress in individual domains such as DTs for power load forecasting but showed limited work outside of the scope.

The next chapter outlines the methodology adopted for this project, which is based on some concepts outlined in this chapter.

3. METHODS

3.1. Overview

This chapter outlines the methodology followed to design and implement a model to predict the solar generation for the next seven days as part of a broader digital twin project for managing the solar system at Flinders University's Bedford Park and Sturt Campuses. This model follows data-driven design principles like ones that appear in Amasyali et al. (2018) and Seyedzadeh et al. (2020). Historical solar generation, irradiance and weather data, and collecting real-time weather inputs via an Application Programming Interface (API) were used to train and evaluate four predictive machine learning (ML) algorithms: Random Forest (RF), Extreme Gradient Booster (XGBoost), Multilayer Perceptron Neural Network (MLPNN), and Long Short-Term Memory (LSTM).

Each step was performed to ensure the methodology and results are reproducible and the derived from existing digital twin (DT) system architectures. Figure 2 shows the final experimental procedure workflow followed in the project to make sure the model can serve as a practical forecasting and decision-making support tool.

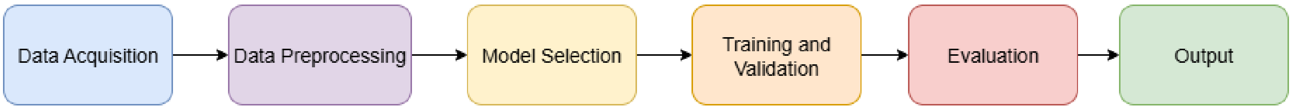

Figure 2 – Experimental Procedure workflow.

1. **Data Acquisition:**
   Solar and weather data collected and updated daily to ensure predictions were made using the most recent information.
2. **Data Preprocessing:**
   Datasets prepared for training with times aligned, interpolated, and resampled. Outliers corrected and normalised features.
3. **Model Selection:**
   Chose the three most appropriate models for initial training purposes with plans to expand into LSTM at a future stage.
4. **Training and Validation:**
   Datasets split chronologically into training and testing sets. Performed hyperparameter tuning to balance bias, variance, and computational efficiency.
5. **Evaluation:**
   a) RMSE (Root Mean Square Error) – quantify average error magnitude.
   b) R^2 (Coefficient of Determination) – how well predictions explain variance in observed data.

6. **Output:**
   Each model produced 24-hour rolling forecast of predicted solar generation at 15-minute intervals, 7-day rolling forecasts at hourly intervals, and pick two random days to compare predicted generation vs actual to evaluate model's accuracy.

3.2. System Architecture and Design

3.2.1. Architecture

Loosely based on architecture designs proposed by Emmet-Streib (2023) and essential components listed by Khajavi et al. (2019), the system architecture for this project comprised of a physical layer, data and integration layer, and virtual layer. This architecture was chosen due to its seamless interaction between real-world data, AI analytics, and virtual forecasting modules, creating a continuously updating framework. Figure 3 shows the general system architecture created for this project, demonstrating how it integrates data to generate future predictions.

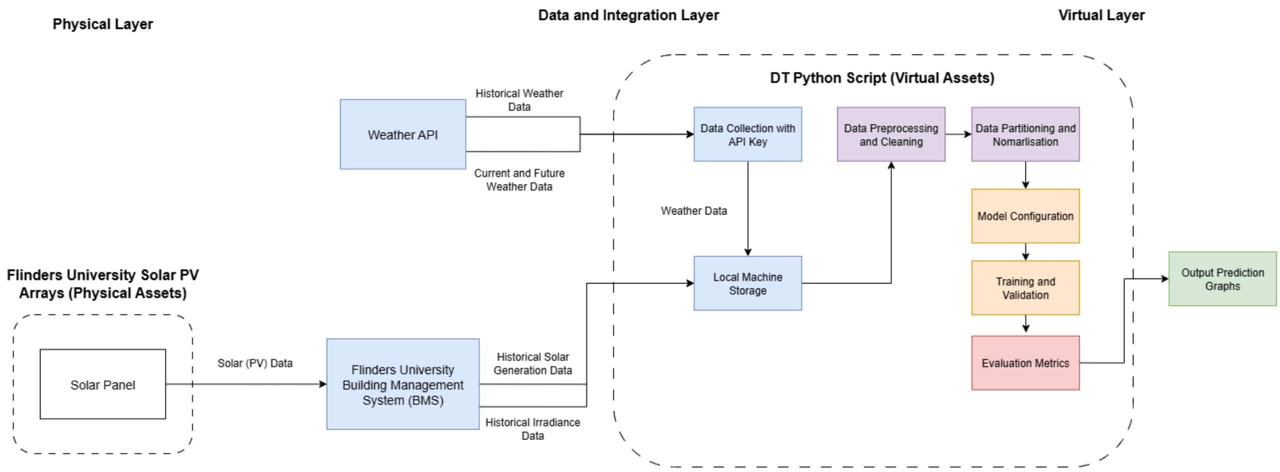

Figure 3 – System Architecture Diagram

3.2.2. Physical Layer

The physical layer represents the physical assets of the solar system, which in this case is the solar photovoltaic (PV) panels (figure 4) and their corresponding inverters, which convert generated DC power to AC output. Sensors are installed at each site to measure solar irradiance, panel temperature, and send generation data to the university's Building Management System (BMS) (figure 5). This layer is responsible for the continuous collection of operational and environment data fed into the DT if there are any faults or failures the DT detects that no data is collected and send the user a warning during updates.

Figure 4 – Solar panels at Flinders University Bedford Park campus (News Desk Flinders University, 2018).

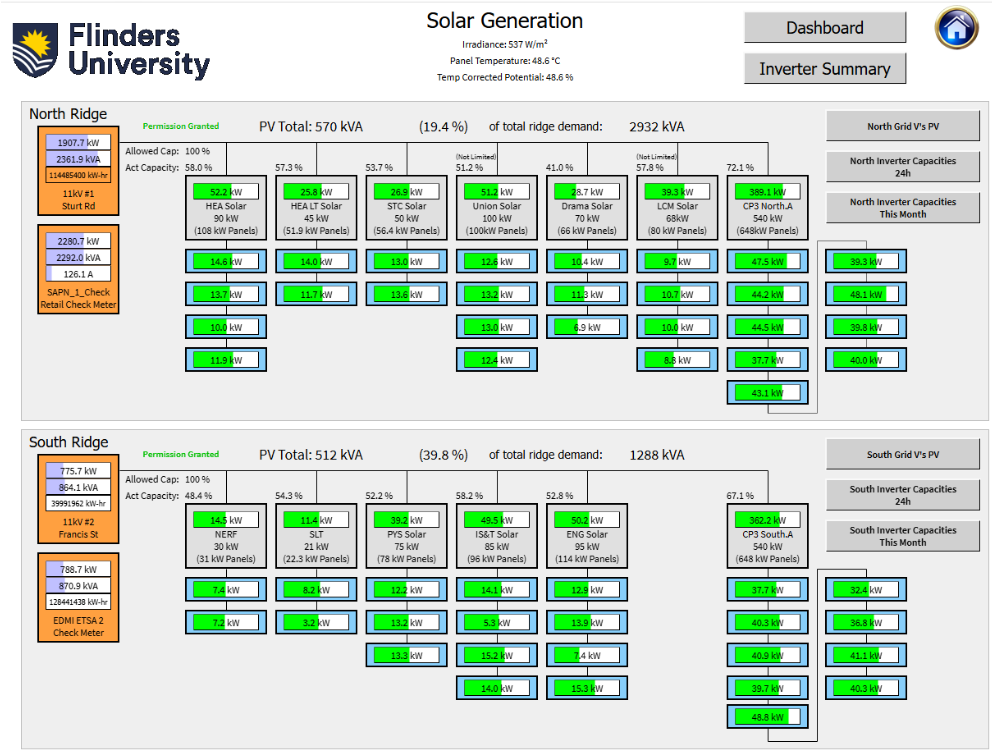

Figure 5 – The campus buildings solar generation page of the BMS

3.2.3. Data and Integration Layer

This layer is where the data is collected from the primary sources for historical and real-time data. Although data acquisition and preprocessing are part of the virtual assets, it is performed as part of this layer to make sure data is synchronised and features are extracted. Due to the datasets using different timestamps and Adelaide having two time zones throughout the year (i.e., Australia Central Standard Time (ACST) and Australia Central Daylight Time (ACDT)) the model handles timestamp standardisation, as well as missing value imputation. The scripts also merge the datasets using “asof” temporal alignment, to find any matches in times and dates between the three datasets. Each dataset is passed in as a comma-separated value (CSV) file.

3.2.4. Virtual Layer

This layer represents the forecasting engine, where the AI-driven model simulates and predicts solar generation for the next seven days. In this layer ML algorithms are tested to produce short term (up to seven days) generation forecasts. The virtual model acts as most of the virtual asset and the core component that makes the DT functional. This asset allows for the expansion into what-if analysis and predictive management of energy flow for future development stages.

3.3. Data Acquisition

3.3.1. Data Sources

Three structured datasets were acquired for this project (table 3):

Table 3 – Data sources and relevant inputs.

Dataset	Feature Name	Value Type	Unit/Format	Reporting Frequency	Description	Modelling Use	Data Type
IST_DB_PV_kW.csv	Timestamp	Datetime	DD-MMM-YY HH:MM:SS AM/PM ACDT/ACST	15 minutes	Local timestamp for PV generation data from IST site.	Time index for IST readings. Synchronisation key for feature merging.	Historical (Used only in IST model)
	IST_DB_PV_kW	Numeric (float)	kW (Kilowatts)	15 minutes	PV output from IST (Information Science and Technology) building arrays.	Target variable for model training and prediction for IST building.	Historical (Used only in IST model)
DRAMA_DB_PV_kW.csv	Timestamp	Datetime	DD-MMM-YY HH:MM:SS AM/PM ACDT/ACST	15 minutes	PV output from DRAMA (Drama) building arrays.	Time index for DRAMA readings. Synchronisation key for feature merging.	Historical (Used only in DRAMA model)
	DRAMA_DB_PV_kW	Numeric (float)	kW (Kilowatts)	15 minutes	Target variable for model training and prediction for DRAMA building.	Target variable for model training and prediction for DRAMA building.	Historical (Used only in DRAMA model)
STE_DB_PV_kW.csv	Timestamp	Datetime	DD-MMM-YY HH:MM:SS AM/PM ACDT/ACST	15 minutes	PV output from STE (Sturt East) building arrays.	Time index for STE readings. Synchronisation key for feature merging.	Historical (Used only in STE model)
	STE_DB_PV_kW	Numeric (float)	kW (Kilowatts)	15 minutes	Target variable for model training and prediction for STE building.	Target variable for model training and prediction for STE building.	Historical (Used only in STE model)
Bedfordpark_hourly_weather.csv	datetime	Datetime	DD/MM/YY HH:MM	Hourly	Local timestamp of	Temporal feature key for	Historical/Current

					weather record.	feature alignment with PV data.	
	temp_c	Numeric (float)	°C (Degrees Celsius)	Hourly	Current temperature at time of recording.	Predictor feature – affects PV generation efficiency.	Historical/Current
	humidity	Numeric (integer)	% (Percent)	Hourly	Relative humidity level.	Predictor feature – affects irradiance and panel efficiency.	Historical/Current
	precip_mm	Numeric (float)	mm (Millimetres)	Hourly	Rainfall.	Predictor feature – reduces irradiance and PV generation.	Historical/Current
	wind_kph	Numeric (float)	Km/h (Kilometres per hour)	Hourly	Average wind speed.	Predictor feature – influences panel performance and cooling.	Historical/Current
	cloud	Numeric (integer)	% (Percent)	Hourly	Estimated cloud cover.	Primary predictor – affects PV generation and key variable for generation forecasting.	Historical/Current
	condition	Text (string)	String (e.g., Sunny)	Hourly	Weather condition label (e.g., Partly Cloudy, Clear).	Descriptive feature – used for categorical encoding.	Historical/Current
	dewpoint_c	Numeric (float)	°C (Degrees Celsius)	Hourly	Dew point temperature.	Secondary predictor – measurement of atmospheric moisture.	Historical/Current
	is_sun_up	Boolean (0/1)	0/1	Hourly	Daylight indicator.	Masking feature – separates daylight and nighttime hours (zero output periods).	Historical/Current
	mintemp_c	Numeric (float)	°C (Degrees Celsius)	Daily	Daily minimum temperature.	Auxiliary trend variable for the day – assist with level forecasting.	Historical/Current
	maxtemp_c	Numeric (float)	°C (Degrees Celsius)	Daily	Daily maximum temperature.	Auxiliary predictor – Used for daily generation range estimating.	Historical/Current
	sunrise	Datetime (string)	HH:MM AM/PM	Daily	Time of sunrise.	Feature to calculate daylight duration.	Historical/Current
	sunset	Datetime (string)	HH:MM AM/PM	Daily	Time of sunset.	Feature to calculate daylight duration and solar window estimation.	Historical/Current
PV_MET_75_Irradiance.csv	Timestamp	Datetime	DD-MMM-YY HH:MM:SS AM/PM ACDT/ACST	Daily	Timestamp of irradiance reading.	Temporal feature key for feature alignment with PV data.	Historical
	PV_MET_75_Irradiance	Numeric (float)	W/m^2 (Watts per metre squared)	Daily	Measured daily irradiance.	Core predictor variable – baseline for PV generation potential.	Historical

3.3.2. Location and Duration

The data corresponds to three sites located at Flinders University's Bedford Park and Sturt campuses all located in the suburb of Bedford Park, South Australia. Relevant weather data and time zones were gathered by coding the latitude and longitude coordinates for Bedford Park when collecting from WeatherAPI. Historical records span September 2024 – October 2025, with the model testing performed using a January 2025 – October 2025 holdout period for validation. Data handling and analysis was conducted between August 2025 and October 2025.

3.3.3. Software Tools and Python Libraries

All initial preprocessing, training, and evaluation were conducted in Python 3.13 using Google Collab. These codes were initially run manually, before being automated to run autonomously and converted to Python Scripts and ran using Python shells (IDLE). The following libraries were used in the codes:

- **NumPy, pandas:** For data preprocessing, feature engineering, manipulation and transformation.
- **XGBoost, scikit-learn and TensorFlow/Keras:** For implementing ML and DL algorithms.
- **Matplotlib and Seaborn:** For performance visualisation, correlation analysis and presentation of results.

Reproducibility was maintained keeping duplicates of codes on different machines and a USB with a Readme.txt file created with instructions on setting up the experiment and running the code.

3.4. Data Preprocessing

3.4.1. Timestamp Standardisation

Due to variation in timestamps in the CSV files, and South Australia using two different time zones throughout the year because of daylight savings, timestamps were cleaned using Regular Expression (RegEx). RegEx extracts and matches the timestamp formats to standardise the timestamps into DD-MMM-YY HH:MM:SS AM/PM ACDT/ACST format. This ensured temporal alignment across data sources and the timestamp formats in the output are aligned with the data.

3.4.2. Data Cleaning and Resampling

Any records with a missing timestamp were dropped, with forward fill interpolation being used to fill time gaps. Forward fill fills in any missing values by propagating the last known values forward. All data was resampled to hourly intervals to match the weather data frequency. All duplicates were removed to prevent sampling bias.

3.4.3. Merging Datasets

The three datasets used for the model (irradiance data, weather data, and generation data) were merged using the pandas merge_asof function. This function performs as "asof" merge, which matches to the nearest key compared to standard left join which requires exact keys, this is particularly handy for time series data and other ordered datasets. This merge created a unified dataset for model training.

3.5. Feature Engineering

3.5.1. Temporal Features

Pyton's datetime module was used to extract time-based features such as hour of day, day of year, and weekday for timestamp data and capture diurnal and seasonal variability in solar irradiance. These features enabled the model to learn cyclical generation patterns linked to solar positions.

3.5.2. Seasonal Encoding

Using one-hot encoding via pandas.get_dummies(), each observation was categorised into one of four seasons (summer, autumn, winter, and spring) based on the month recorded. This allowed for the model to detect season-dependent changes such as temperature and precipitation that impact energy generation without imposing ordinal relationships.

3.5.3. Sunrise and Sunset Conversion

To maintain consistency with all other temporal features, the times recorded for sunrise and sunset were converted into numerical formats (minutes since midnight). Roughly less than 2% of missing entries were found, so these were imputed using the column mean to preserve statistical integrity and prevent model bias.

3.5.4. Feature Selection

Following correlation and mutual information analysis against the targe variable (solar generation non-numeric and low importance columns (e.g., weather conditions) were removed. The final features were selected based on relevance, noise reduction, and improved training efficiency.

3.6. Predictive Model Configuration

3.6.1. Algorithms Selected

Four algorithms were selected based on demonstrating different algorithmic paradigms for regressions and reflecting similar works by Yalçin et al. (2023), Sehrawat et al. (2023), and Al-Isawi et al. (2023). These models enable comparative evaluation to be conducted between classical and deep learning methods:

- **Random Forest (RF):** An ensemble tree-based learner combining multiple decision trees to produce an accurate and stable model. RF is common in tasks like classification and regression as it offers interpretability and robustness.

- **XGBoost:** An open-source ML library that uses a parallelised, regularised gradient-boosted framework commonly used for tabular data. XGBoost as the benefit of superior error reduction.
- **MLPNN:** A feedforward neural network (NN) that consists of three layers commonly used for nonlinear relationships.
- **LSTM:** A recurrent NN suited for temporal dependencies in time-series forecasting.

3.6.2. Data Partitioning and Normalisation

After the datasets were merged the data was split into 80% training and 20% testing subsets using random seed of 42 for reproducibility. StandardScaler was used to standardised features and ensure equal weighting and stable gradient descent.

In the LSTM framework, a sliding window approach was used to preserve temporal dependencies, and the data was reshaped into 3D arrays (samples, timesteps, features). This allowed the model to learn from historical sequences of generation and weather data.

3.6.3. Model Configuration

- **RF:** 100 estimators, random_state = 42
- **XGBoost:** 100 trees, max_depth = 6, learning rate = 0.1, subsample = 0.8
- **MLPNN:** Two hidden layers (128 and 64 neurons) with ReLU activation Adam optimiser (lr = 0.001), dropout = 0.2, 100 epochs.
- **LSTM:** One LSTM layer with 50 units followed by a dense output layer, Adam optimiser, 50 epochs, batch size = 32.

3.6.4. Training and Validation

Models were trained using RMSE (Root Mean Square Error), R^2 (Coefficient of Determination), and Mean Squared Error (MSE) loss with training and validation being conducted on the designated subsets, ensuring no data were leaked. Training curves were monitored to detect overfitting, while ensemble algorithms used internal cross-validation. Outputs were stored for comparative evaluation based on consistent error metrics.

3.6.5. Forecasting and Visualisation

Two forecasts were produced for each model:

1. **Accuracy Validation:** Random samples of two past weeks were selected from the dataset to validate the accuracy of the algorithms be comparing the predicted vs the actual PV generation.
2. **Future Forecasting:** Using the current data as the starting point, a seven-day hourly forecast was generated based on historical solar trends and average diurnal weather

patterns. The Astral library assisted with computing the sunrise and sunset times taken from the weather data, allowing the model to automatically nullify predictions during nighttime hours.

For the manual test versions interactive Plotly visualisations were developed to display the next seven-day forecast, and the predicted vs actual generation graphs. This allowed for evaluations to be more dynamic when looking into model accuracy and trends. However, this was changed to Matplotlib plots in the Automated versions due to limitations with the local machine where the automated scripts are run from.

3.7. Evaluation Metrics

Performance logs were kept assessing forecasting accuracy and logging:

- **RMSE (Root Mean Square Error):** Measures the magnitude of large prediction errors.
- **MAE (Mean Absolute Error):** Captures the average absolute deviation.
- **R^2 (Coefficient of Determination):** Indicates how well the model predictions explain the observed variance.

These metrics evaluate the stability, precision, and explanatory strength.

3.8. Planning Items

3.8.1. Safety Considerations

Table 4 – Safety Considerations Assessment.

No.	Consideration	Risk	Mitigation
1	Data and Privacy	Unauthorised access could compromise infrastructure.	Secure communication protocols, data encryption, authentication mechanisms and access control policies were implemented to protect data and prevent breaches.
2	System Malfunction or False Recommendations	Inaccurate predictions could lead to incorrect operational decisions (e.g., underutilised solar input, battery overcharging)	Fail-safe mechanisms, and continuous model validation were implemented. A human also verified critical decision pathways.

3.8.2. Project Risk Assessment

Table 5 – Project Risk Assessment.

Risk	Likelihood	Impact	Mitigation
Forecast API Failure	Medium	High	Cach recent data or fallback to historical data.
AI Model Under Performance	Medium	Medium	Iterative training, tune the model, introduce other neural network models if required.
Sensor Malfunction	Medium	Medium	Calibrate protocols and replace/remove malfunctioned sensor and declare panel redundant.

3.8.3. Project Timeline

The project was structured over a 10-month period, table 3 outlines the key milestones.

Table 6 – Key Milestones throughout the project.

Weeks	Milestone(s)
1-8	Literature Review, Proposal Seminal, XMPro Academy, Software Familiarisation.
8-15	Methodology, XMPro Academy Course Completion, Retrieve Solar Data, Begin Designing and Implementing Data Stream with Solar Data
16-30	Setup Final Python Scripts, Setup AI Algorithms, Collect Weather Data, Analyse Results, Produce Results.
31-40	Test Scripts, Complete Final Scripts, Log Issues and Bugs, Resolve Issues and Bugs.

To manage progress, dependencies and indicate milestones a Gantt chart was developed (Appendix A).

3.8.4. Quality Management

To ensure model reliability and consistent data:

- Performance logs were kept to detect any drift in performance.
- Model outputs plotted on graphs to detect any difference as day progress.

3.9. Critical Assumptions

This project relies on several critical assumptions to properly develop and evaluate the feasibility of AI-driven DT technology for forecasting solar generation. The first assumption is that it is assumed that all sensor data collected form the solar arrays are time synchronised, accurately calibrated, and free from any major measurement bias. Another assumption is that the weather datasets, including temperature, sunrise and sunset times, cloud cover, and humidity represent on-site conditions based on the recorded conditions for Bedford Park, South Australia with a forecast accuracy within ± 5%.

It is also assumed that all data preprocessing pipelines effectively mitigate missing or noisy values, ensuring consistent input quality for training and validation. Due to all three sites being within the same geographical region. Additionally, it is assumed that the digital framework can be implemented into a streaming environment in the future with negligible data latency and near real-time performance.

These critical assumptions establish the conditions to consider when interpreting the results. Any deviation from these conditions such as sensor drift or inaccurate forecasts may impact the reliability of the predictions and limit the generalisability of the findings.

3.10. Methodology Limitations

Although the methodology was designed to be a robust framework for developing the core of a DT that can forecast solar generation, several limitations were encountered during implementation. One primary constraint was the final performance of the LSTM framework. Due to the time availability required for hyperparameter tuning, the model's complexity, and iterative nature of sequence learning, further optimisation was not fully completed within the project timeframe. This led to optimisation tasks like adjusting the learning rates, lookback windows, and hidden layer dimensions not being implemented. Consequently, the predictive accuracy of the LSTM framework may not accurately represent the achievable performance of LSTM.

Another constraint was data quality and temporal resolution. Minor gaps and varying sampling frequencies were present in some of the solar and weather data, requiring interpolation and resampling. Consequently, this may have introduced smoothing effects or minor loss of high-frequency dynamics. Standardisation of all data to hourly intervals and applying appropriate preprocessing techniques help to mitigate these limitations. But some precision loss is acknowledged.

Computational constraints restricted the ability to train model on longer historical windows and perform extensive cross-validation runs. Using the available resources, the methodology was updated to a balance thoroughness with practical feasibility.

3.11. Summary

This methodology outlined a data-driven approach for forecasting solar PV generation as part of the functional component of a broader DTS. By systematically processing data, feature engineering and comparative modelling using RF, XGBoost, MLPNN, and LSTM, this project achieved a reliable foundation for predictive energy management. Whilst limitations in time, computation and integration do exist, the methodology demonstrates scalability and adaptability for future deployment within a DT environment.

4. RESULTS

4.1. Overview

This chapter presents the results obtained from the solar forecasting models developed for the larger digital twin system (DTS) for solar energy management. These results outline the comparative analysis on the performance of four machine learning (ML) algorithms (Random Forest (RF), Extreme Gradient Boosting (XGBoost), Multilayer Perceptron Neural Network (MLPNN), and Long Short-Term Memory (LSTM)), seven-day forecasting, predicted vs actual validation, and forecasting predictions across three different locations.

All results obtained follow the methodology outlined in chapter 3, using consistent preprocessing and evaluation metrics. All models were trained using an 80/20 train-test split, with validation performed through repeated runs to confirm reproducibility.

4.2. Model Performance and Accuracy

All four models were trained and tested using the same datasets, with initial testing using historical solar generation from the Information, Science and Technology (IST) building located at South Ridge at the Bedford Park campus. The training also used irradiance, and weather attributes (e.g., temperature, cloud, humidity, precipitation, etc.). Model accuracy was assessed using Root Mean Square Error (RMSE), coefficient of determination (R^2), and Mean Absolute Error (MAE), with performance logs logged with these values. Table 7 summarises the average performance of each algorithm:

Table 7 – Model performance of algorithms using solar generation from IST building.

Algorithm	Average RMSE	Average R^2	Average MAE	Notes
Random Forest	5.676	0.926	2.878868913	Low bias with strong baseline accuracy. Tendency to average predictions.
XGBoost	6.033	0.917	2.696869911	More sensitive to hypermeters. Larger errors with lower predictive performance.
MLPNN	5.717	0.925	3.059	Minor over-smoothing, but good nonlinear fitting.
LSTM	5.702	0.925	2.831193349	Best overall performance

As shown in table 7 all the models achieved a high accuracy of 0.917 or higher. The LSTM algorithm achieved the lowest MAE and RMSE, reflecting its ability to model time series dependent patterns. RF and MLPNN performed competitively, with RF having the highest accuracy, whilst XGBoost showed slightly greater variability due to boosting sensitivity.

4.3. Seven-Day Forecasting

The trained algorithms were used to predict the hourly solar generation of the IST building for the next seven days following the current day at the time. Figures 6–9 show the results from each algorithm:

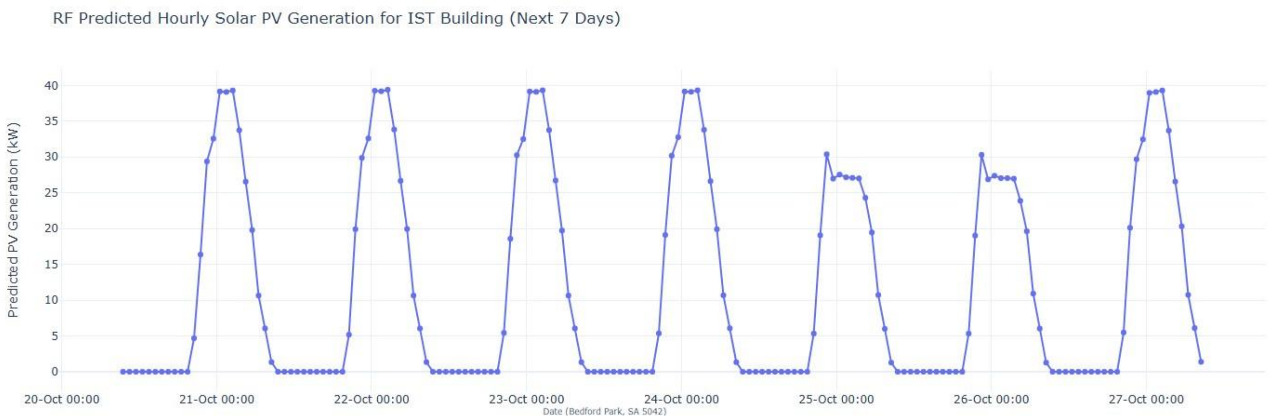

Figure 6 – Predicted 7-day forecast from Random Forest IST model.

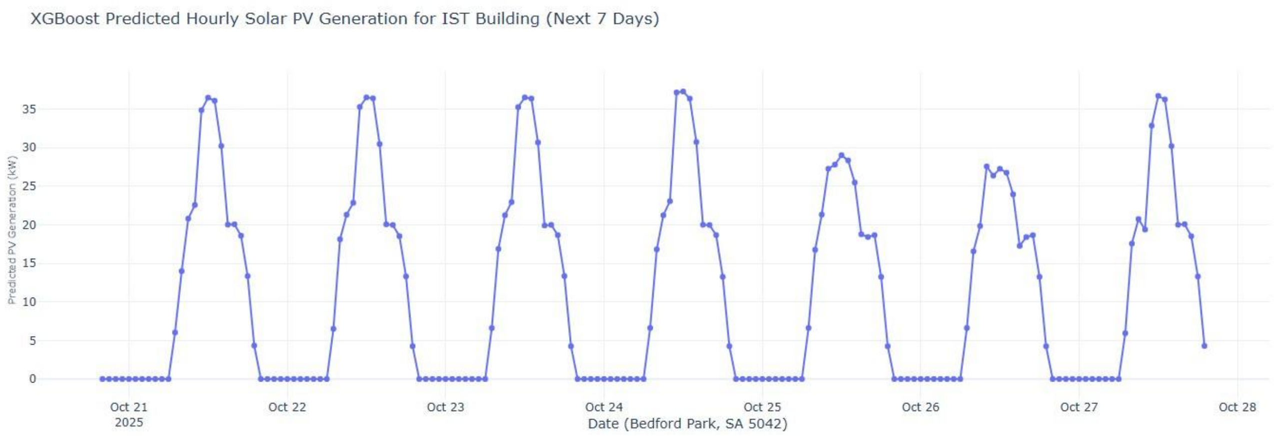

Figure 7 – Predicted 7-day forecast from XGBoost IST model.

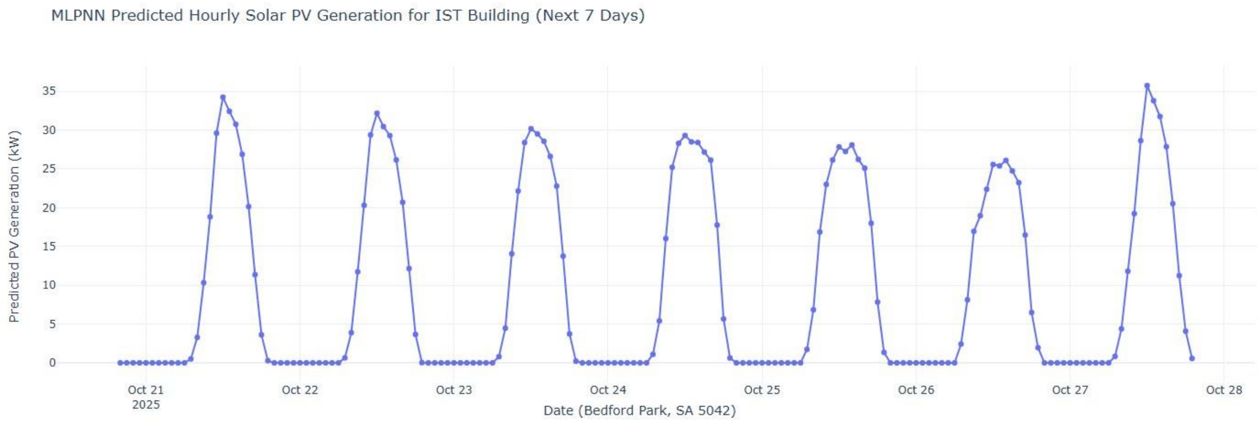

Figure 8 – Predicted 7-day forecast from MLPNN IST model.

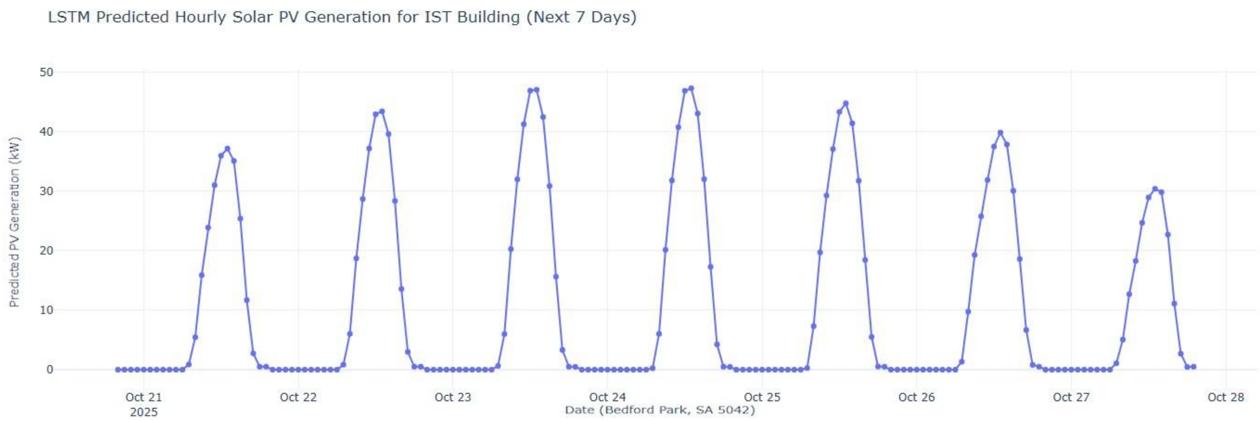

Figure 9 – Predicted 7-day forecast from LSTM IST model.

Key insight:

- Accuracy decreased in the RF and XGBoost models beyond three days, with the last four days appearing to be generalised with similar values across the days.
- The expected diurnal cycle occurred with strong midday peaks, and negligible nighttime outputs. Day-day variations particularly in the MLPNN and LSTM models correspond to recorded fluctuations in solar irradiance. This confirms the model's responsiveness to short-mid-term weather effects.

4.4. Validation Against Historical Days

To test the accuracy and generalisability of the predictions, two past weeks were randomly selected to compare the predictions against the actual solar generation reading from those weeks. All algorithms were trained and validated using the same datasets as section 4.3. The two random weeks selected were:

- Week 1: 2025-03-27 00:00 - 2025-04-02 23:00
- Week 2: 2025-07-27 00:00', 2025-08-02 23:00

Figures 10–17 show how well the algorithms performed:

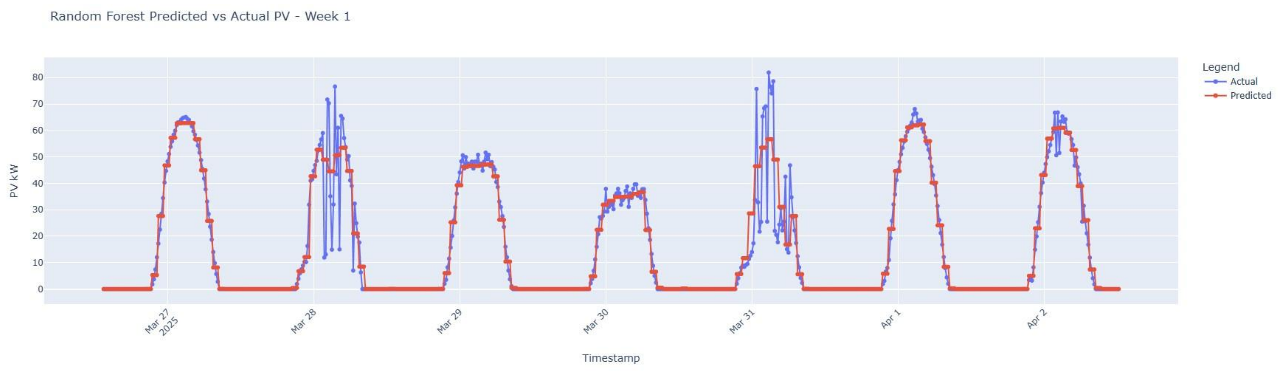

Figure 10 – Week 1 predicted vs actual for Random Forest.

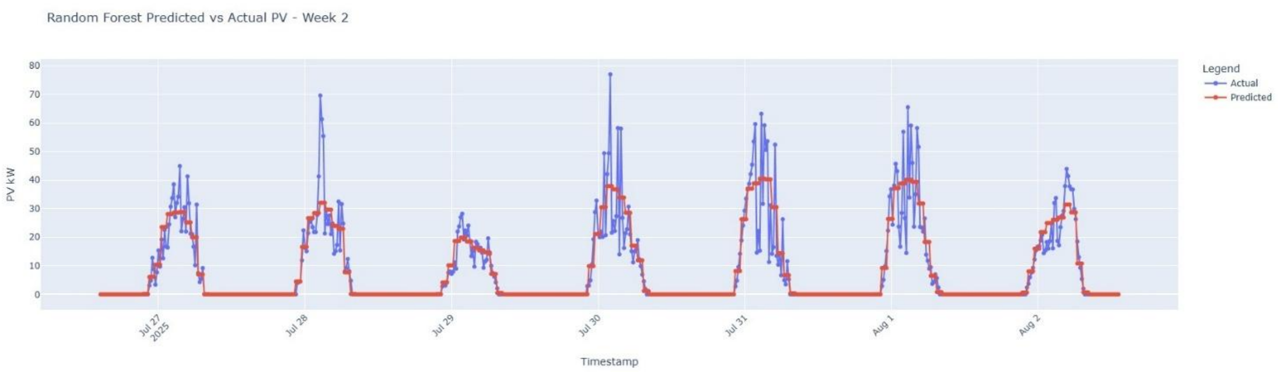

Figure 11 – Week 2 predicted vs actual for Random Forest.

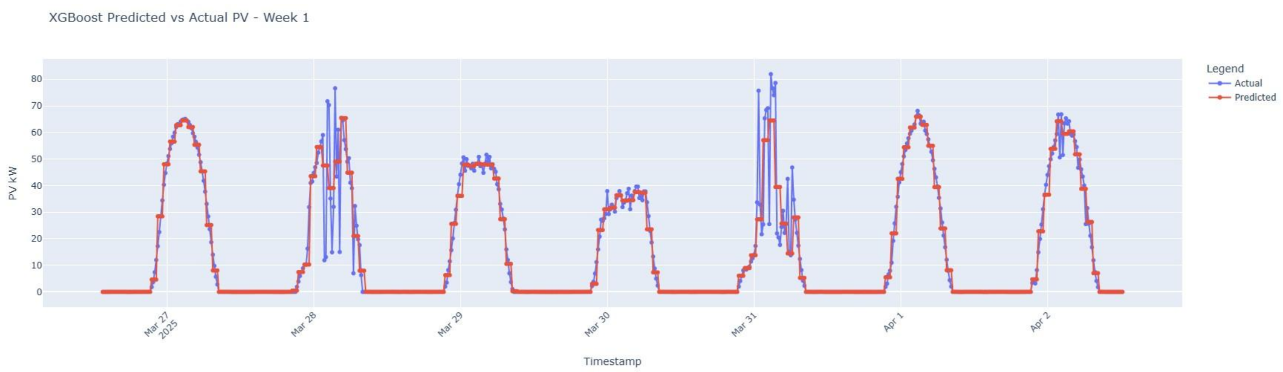

Figure 12 – Week 1 predicted vs actual for XGBoost.

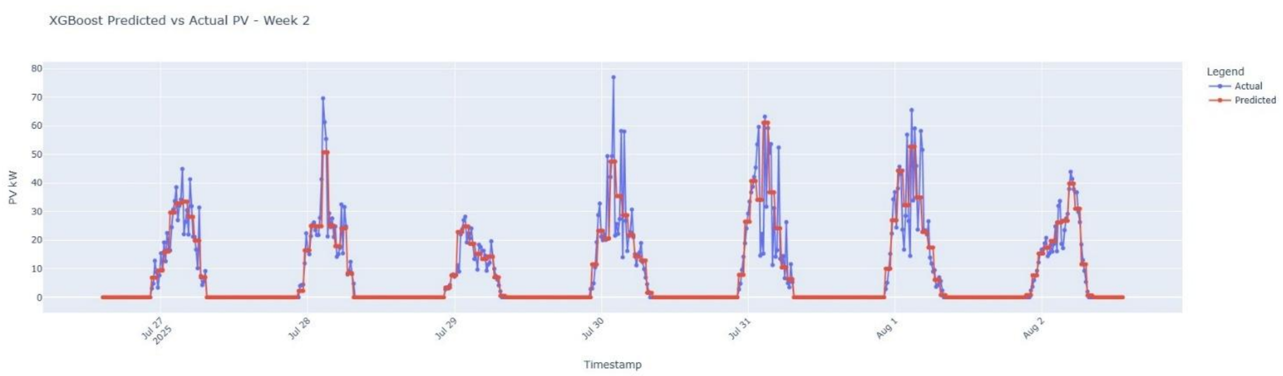

Figure 13 – Week 2 predicted vs actual for XGBoost.

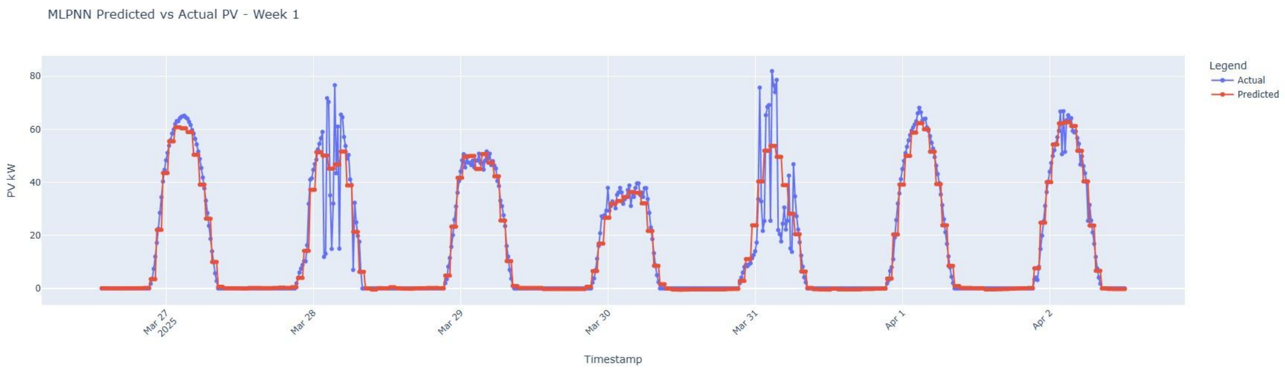

Figure 14 – Week 1 predicted vs actual for MLPNN.

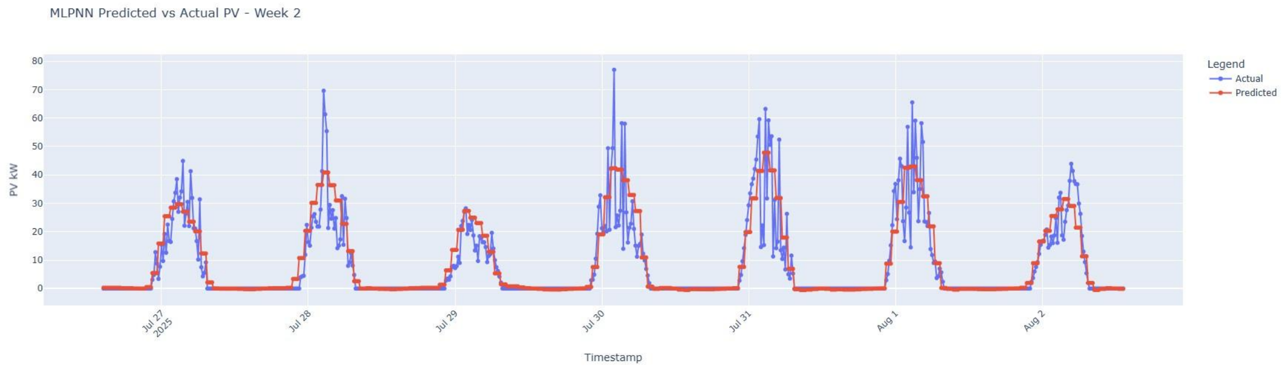

Figure 15 – Week 2 predicted vs actual for MLPNN.

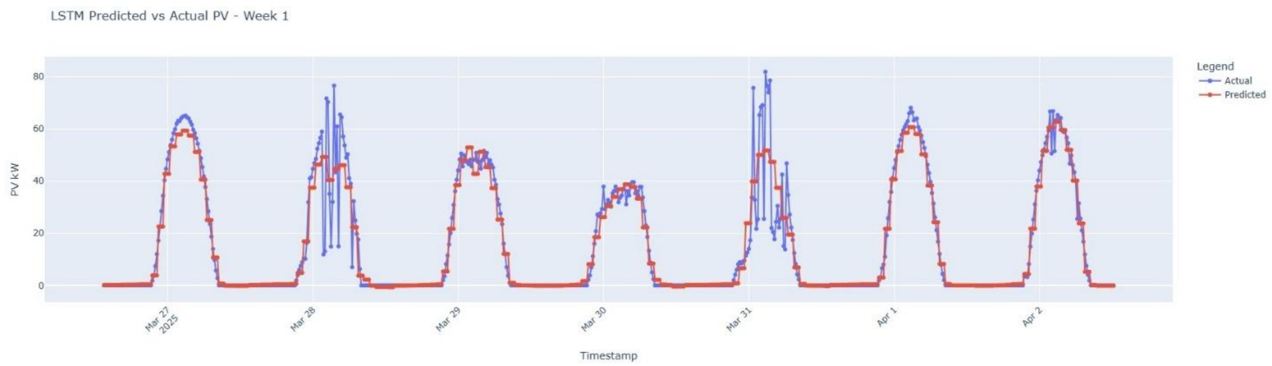

Figure 16 – Week 1 predicted vs actual for LSTM.

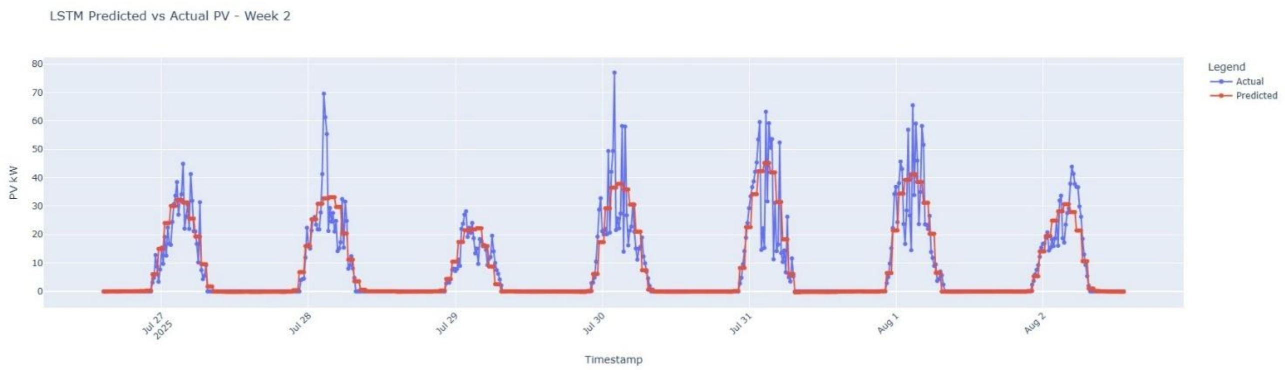

Figure 17 – Week 2 predicted vs actual for LSTM.

Key Insights:

- On clear-sky days all predictions closely followed the patterns of the actual curves.
- Slight underestimations occurred around the midday peak.
- On days with constant changing weather patterns such as cloud cover, all algorithms could not perform properly. This was expected due to unpredictable factors like cloud drifting. During these periods, errors increased and major underestimations occurred.
- RF and XGBoost captured drifting and rapid changing patterns better that MLPNN and LSTM.

4.5. Cross-Site Comparison

To evaluate generalisation and geographical impacts, the algorithms were used to test the model with three different sites all within the suburb of Bedford Park, South Australia and part of the Flinders University grounds: IST building, Drama (DRAMA) building, and Sturt East (STE) building. Each location contains its own array of solar panels as part of the Flinders University BMS but with different microclimatic and topographical conditions.

The IST building is located at South Ridge (the southern half of Bedford Park campus), which is located on top of a steep hill, providing higher exposure and stronger wind flow. These factors may influence irradiance stability and temperature. The DRAMA building is located at North Ridge (the northern half of Bedford Park campus), which is down the hill from South Ridge and roughly 365m (as the crow flies) from IST. The STE building is located at the Sturt Campus, which is the northernmost point of the Flinders University Bedford Park grounds, 1.22 km (as the crow flies) from IST, and is at a lower elevation than IST and DRAMA sites.

Although all these sites are in the same suburb, subtle variations in terrain height, slop orientation, shading patterns do impact solar generation and irradiance readings.

Table 8 contains the performance metrics of each site, and figures 18- show the predictions of the three sites recorded at the same time:

Table 8 – Cross-site comparison of algorithms performance metrics.

Site	Algorithm	Average RMSE	Average R^2	Average MAE	Notes
IST	Random Forest	5.676	0.926	2.878868913	Strong baseline.
	XGBoost	6.033	0.917	2.696869911	Sensitive to hypermeters.
	MLPNN	5.717	0.925	3.059	Minor over-smoothing.
	LSTM	5.702	0.925	2.831193349	Excellent generalisation.

DRAMA	Random Forest	3.991	0.910	1.834299	Lowest RMSE.
	XGBoost	5.862	0.914	2.601145576	Slight overprediction.
	MLPNN	4.069	0.907	2.168764	Minor bias drift.
	LSTM	4.205	0.9015	2.126342	Consistent across cycles.
STE	Random Forest	4.734	0.9048	2.200331	Stable output.
	XGBoost	5.052	0.892	2.129645	Drop in R^2.
	MLPNN	4.629	0.911	2.288212	Good error control.
	LSTM	4.813	0.9017	2.282142389	Minor lag observed.

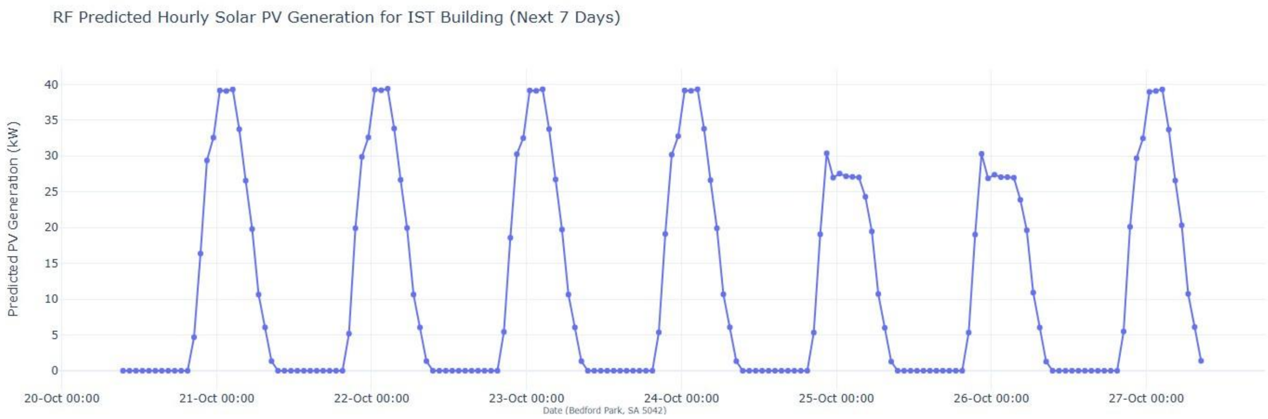

Figure 18 – RF predicted 7-day forecast for IST building.

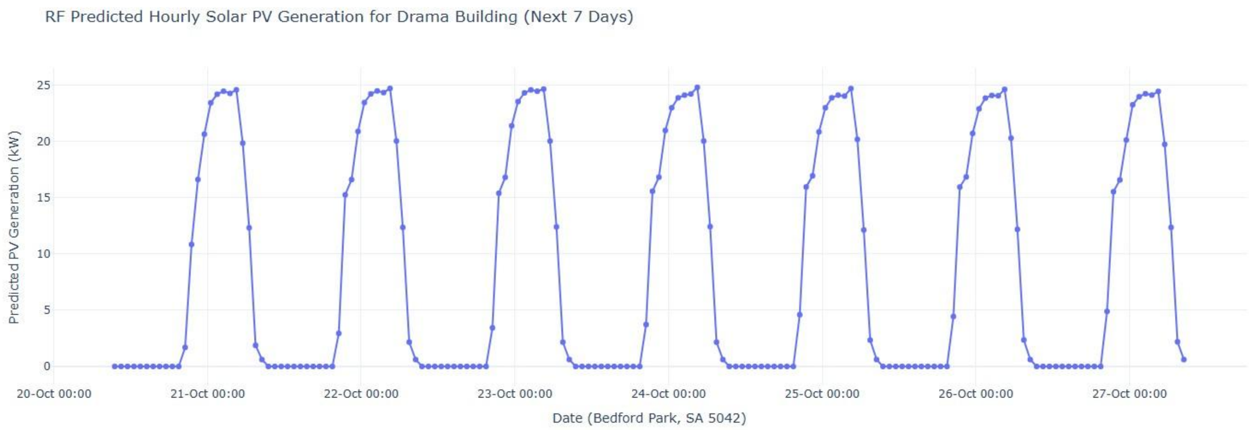

Figure 19 – RF predicted 7-day forecast for DRAMA building.

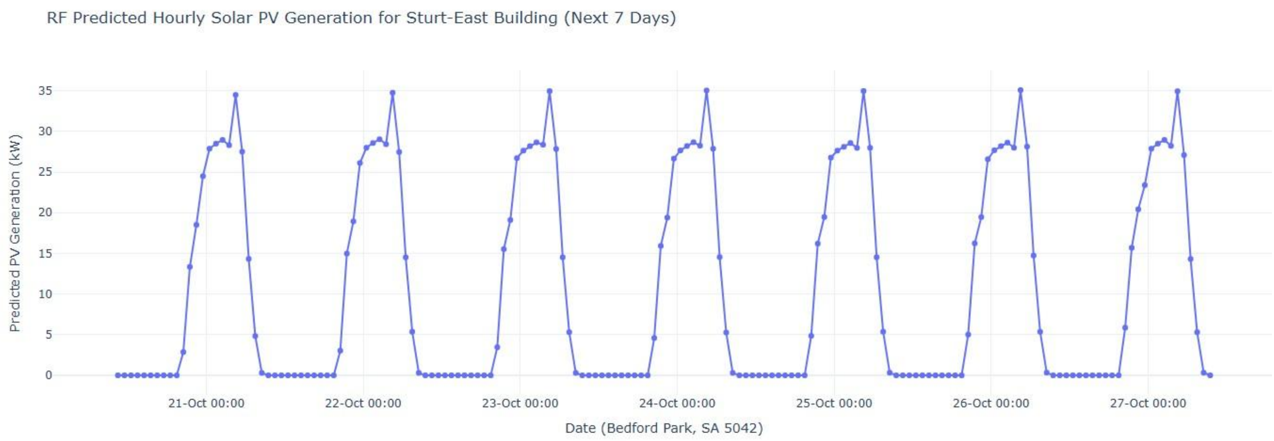

Figure 20 – RF predicted 7-day forecast for STE building.

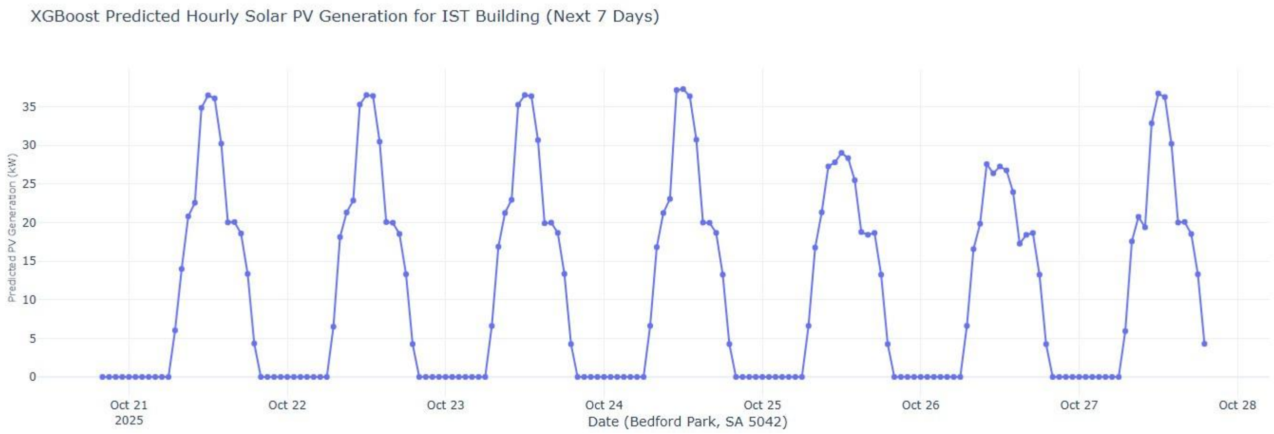

Figure 21 – XGBoost predicted 7-day forecast for IST building.

Figure 22 – XGBoost predicted 7-day forecast for DRAMA building.

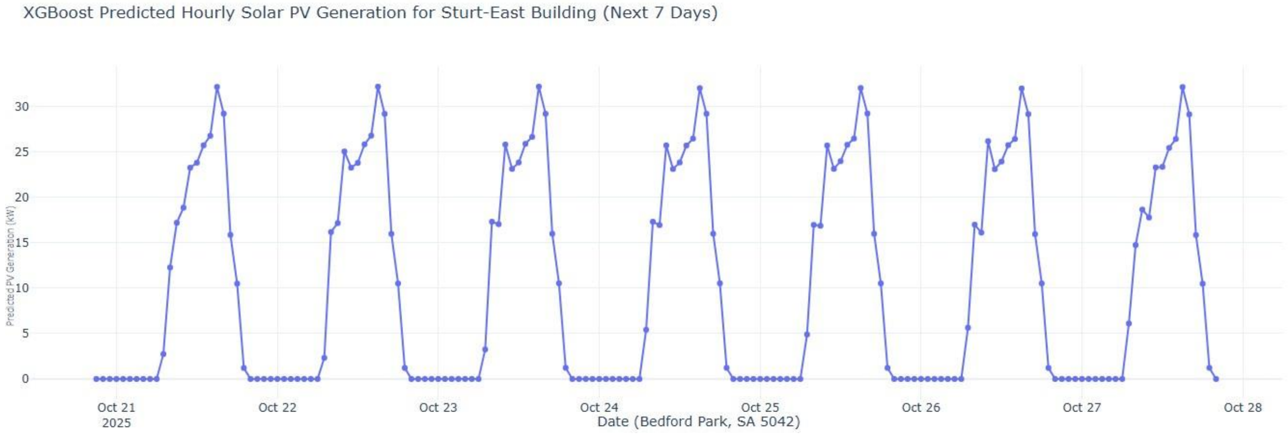

Figure 23 – XGBoost predicted 7-day forecast for STE building.

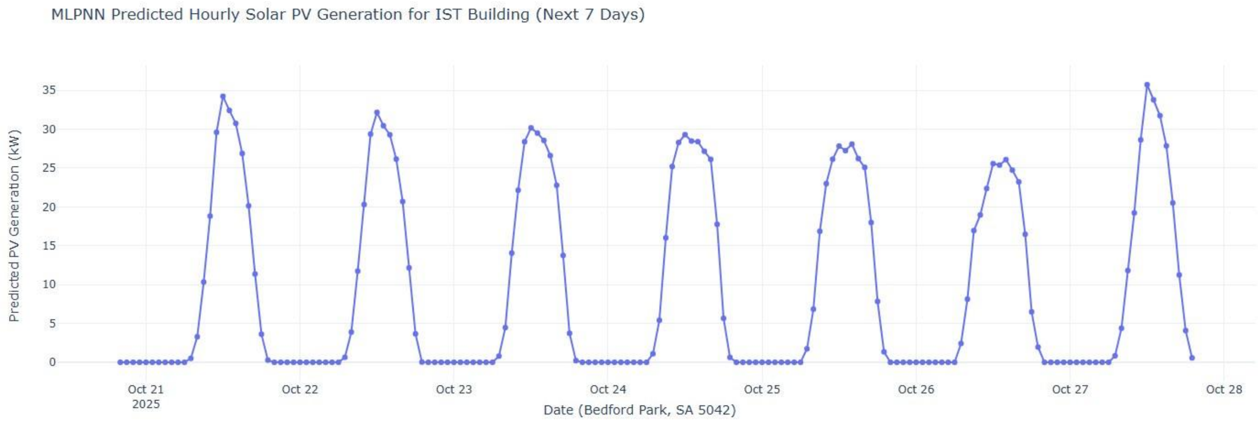

Figure 24 – MLPNN predicted 7-day forecast for IST building.

Figure 25 – MLPNN predicted 7-day forecast for DRAMA building.

Figure 26 - MLPNN predicted 7-day forecast for STE building.

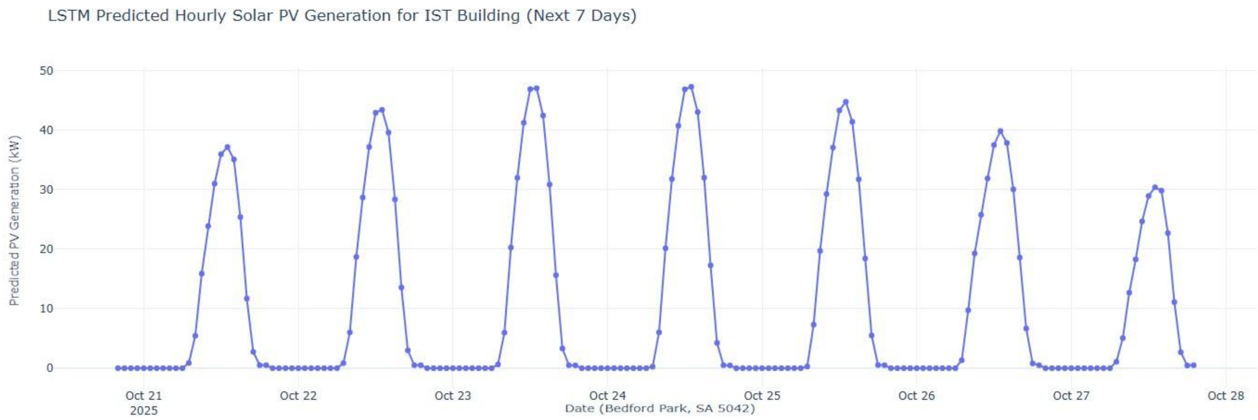

Figure 27 - LSTM predicted 7-day forecast for IST building.

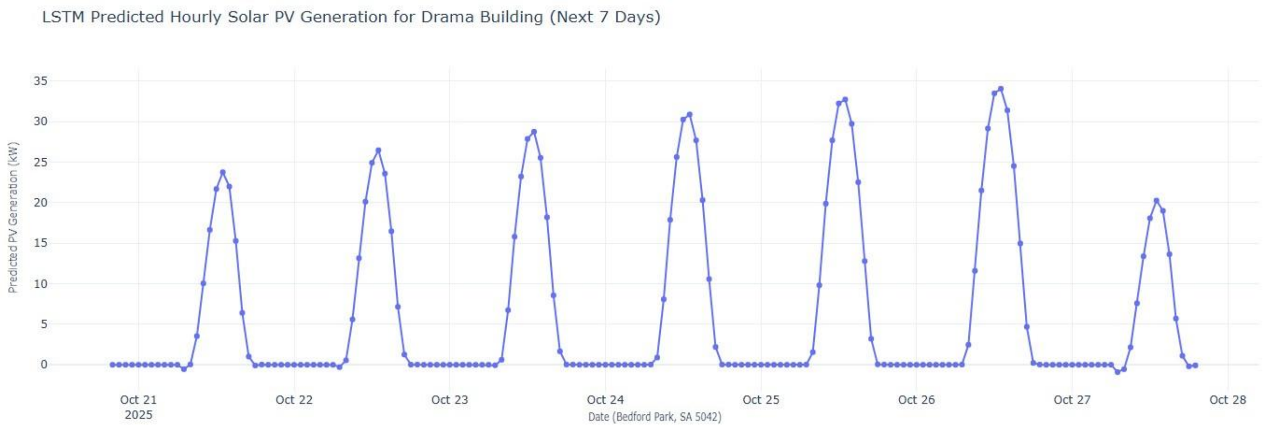

Figure 28 - LSTM predicted 7-day forecast for DRAMA building.

Figure 29 - LSTM predicted 7-day forecast for STE building.

Key insights:

- Radom Forest and LSTM offered the most reliable forecast across varying terrain conditions.
- Even minor differences in sites impact the sensitivity of predictive accuracy based on local geography and weather variability.
- High R^2 values validate the generalisability of the model architecture.
- Accuracy can be attributed to terrain elevation and microclimatic differences.
- XGBoost tended to slightly overfit.
- MLPNN displayed moderate accuracy across all three sites.

4.6. Error Analysis

Error analysis was conducted evaluating the consistency and reliability of the predictive models. Model accuracy was measured using RMSE, MAE, and R^2 as seen in Tables 7 and 8, supported by visual inspections of the output graphs to identify deviations.

XGBoost over-predicted occasional under variable cloud conditions, whereas LSTM exhibited the most stable residuals. This confirmed LSTM's capacity to learn temporal patterns.

Terrain elevation and shading contributed to systematic bias. IST suffers from hilltop irradiance variability, which saw the widest spread of errors. Drama was the most consistent with predictions.

Random Forest despite being reliable for short-term predictions it did suffer from generalisation and averaging values over periods longer than 3 days.

4.7. Summary

This chapter demonstrated the results achieved in this project by comparing four ML algorithms across varying site and terrain conditions. Although difference in sites is minor, they highlight the impact local geography and weather variability has on the sensitivity of predictive accuracy. These insights are critical for scaling the DT framework to the whole Flinders University solar network, where environmental conditions can influence performance.

5. DISCUSSION

5.1. Overview

This chapter evaluates the significance, impact, and limitations the results presented in chapter 4 relate to existing research. This discussion aligns the results with the project's aim of developing a solar forecasting framework as part of a broader DT solar energy management system. This chapter evaluates the findings discovered in the model performance across sites, interprets the observed prediction patterns, compares the findings with existing literature, identifies the practical implications for future integration, and determines how the results answer the research question: *How can AI Digital Twin Technology improve the accuracy of solar energy generation forecasting?*

5.2. Significance of Results

As seen in chapter 4, all four models (RF, XGBoost, MLPNN, and LSTM) can effectively forecast solar generation using historical solar and weather data, and real-time weather data. All four model achieved an R^2 of 0.892 or higher with RF, MLPNN and LSTM achieving the highest accuracy across all three sites ($R^2 \approx 0.912$). RF and LSTM consistently achieved the lowest RMSE and MAE values, demonstrating their capability of capturing nonlinear relationships and temporal dynamics in solar generation data. The results demonstrate strong capability in integrating these algorithms into a DT, validates the methodology, and confirms data-driven approaches can support autonomous EMS.

Compared to previous studies by Benali et al. (2019) and Yu et al. (2019), the accuracy achieved in this project aligns and sometimes exceeds R^2 values for similar datasets for similar uses. RF's high accuracy and robustness against noise along with LSTM's capacity to predict short-term forecasts and model temporal dependencies mirror other findings identified in other solar forecasting research. XGBoost showed slightly higher variance, indicating sensitivity to parameter tuning, while MLPNN performed reliably but lacks temporal awareness compared to LSTM. These results confirm the reliability of data-driven methods for DT technology.

5.3. Forecasting Behaviour

The results achieved from seven-day forecasting demonstrated that all models have the capability of accurately capturing diurnal generation patterns. However, minor deviations during cloudy conditions and sunrise/sunset transitions occurred, which was to be expected as it is difficult for the algorithms to capture these patterns. The LSTM network experienced the smoothest transitions with fewer outliers, consistent with its ability to model sequential dependencies over time.

Random Forest provided the lowest RMSE and comparable performance with the benefit of lower computational costs. Although RF is suitable for embedded or edge deployment in DT frameworks, it does tend to lose accuracy after three days, due to the ensemble's inability to extrapolate the beyond that time, and its dependency on time scaling of data.

Short-term forecasts remained accurate within a confidence interval of ± 6% suggesting that integrating these models into a hybrid approach could balance real-time performance and energy prediction accuracy within the operational layer of a DT.

5.4. Terrain and Location Impacts

Cross-site comparison revealed that topographical and microclimatic factors impact prediction accuracy. Since IST is positioned at the highest point above sea level compared to the other two sites, it experienced greater irradiance fluctuation, while Drama appeared the most stable in results due to balanced exposure. These findings support that local microclimates and terrain elevation can contribute to forecast accuracy and uncertainty. They highlight the need for site-specific model calibration with DTs to ensure predictive accuracy is maintained when scaling this framework for multiple solar arrays.

5.5. Research Question Answered

This project successfully answered the research question: *How can AI Digital Twin Technology improve the accuracy of solar energy generation forecasting?*

This project confirms the feasibility of deploying a DT to produce seven-day predictions. The models produced an error margin of less than 6% with RF and LSTM being suitable for short-term predictions, particularly three days or less for RF. For a fully functional DT, it is essential to integrate the models with real-time data streams to complete the feedback loop.

5.6. Limitations and Impact

Certain limitations throughout the project impacted the results. A full seasonal coverage couldn't be achieved due to the limited training period. Computational and time constraints impacted the LSTM model from not being fully tuned, likely impacting its performance. Some gaps in the weather and irradiance data required interpolation, introducing minor uncertainties. Despite these constraints, the outcomes remain consistent and repeatable, with each model's reliability being validated.

5.7. Summary

This project contributes to a broader solar energy management DT by providing a modular Python-based forecasting framework. This project demonstrates that AI-based forecasting models like RF and LSTM can accurately predict solar generation. The demonstrated models form the analytical core of solar energy management DT strengthening the need for DTSs in the renewable energy sector an area underdeveloped in current literature.

6. CONCLUSIONS AND FUTURE WORK

6.1. Summary of Findings from Results

This project designed and implemented an AI-DT based solar forecasting framework that train and validates four ML algorithms – RF, XGBoost, MLPNN, and LSTM – for short-term energy predictions. Using historical solar generation, weather and irradiance data with real-time weather data three sites were tested: IST, Drama, and Sturt East.

RF, MLPNN, and LSTM achieved the highest performance with average R^2 values above 0.90 and RMSE below six, demonstrating strong accuracy. These results confirm that DTs can be reliable for solar generation predictions if implemented with ML-based frameworks.

6.2. Project Significance

This project successfully met its objectives by:

1. Designing a scalable DT core for solar forecasting.
2. Training and Validating four AI/ML based predictive models in Python.
3. Demonstrating that AI/ML algorithms can be used to accurate forecast solar generation across multiple locations.

These findings contribute to the growing research in AI-powered DTs for renewable energy management. This project serves as a foundation for supporting grid stability, improved renewable energy forecasting accuracy, and autonomous decision-making.

6.3. Limitations

Several limitations were encountered in the project that impacted the results:

- LSTM requires further hyperparameter tuning for optimal performance.
- The limited data period restricted seasonal variation and long-term validations to be conducted.

Despite these limitations, the outcome remains consistent, and the methodology is structured to be repeatable and scalable for larger dataset and deployment.

6.4. Future Work

Future work should focus on optimisation, hyperparameter tuning the LSTM algorithm and extending the system into a fully functional DT. For proactive energy scheduling and fault detection, optimisation and recommendations layers should be incorporated. Using larger dataset and deeper architecture can Enhance the LSTM and hybrid AI models and capture seasonal and spatial dependencies. The model can be deployed into a DT platform like XMPro to provide real-time monitoring, and easier data integration.

6.5. Final Words

This project demonstrates that an AI-powered DT can effectively forecast future solar energy generation with strong accuracy. By bridging the gap between data collection and system virtualisation, this project establishes a practical pathway towards an intelligent, self-learning EMS. Continued refinement and expansions will further strengthen the role of the DT in renewable energy infrastructure.

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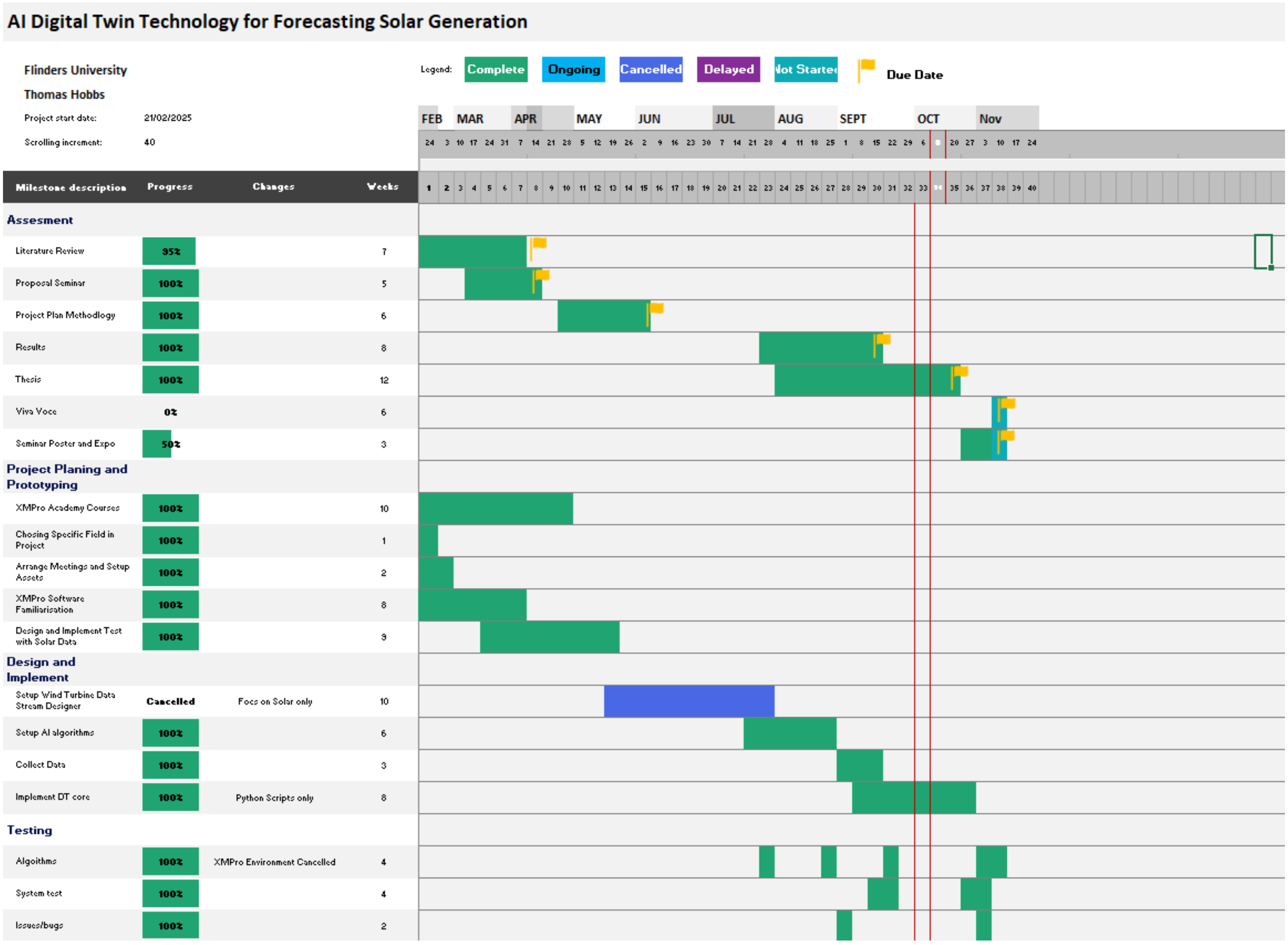
APPENDICES

Appendix A – Final Project Timeline



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