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Integrating Reflective Practice into the Self-Improvement Cycle Module for Renewable Energy Forecasting Accuracy

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Abstract. The increasing reliance on renewable energy sources such as solar and wind power necessitates the development of advanced forecasting techniques to address the inherent variability and unpredictability of these energy systems. Accurate forecasting is vital for optimising energy production, maintaining grid stability, and effectively integrating renewable energy into power systems. Traditional forecasting methods often struggle to adapt to rapidly changing environmental conditions and new data inputs, limiting their effectiveness in dynamic contexts. This study introduces the Self-Improvement Cycle (SIC) module, which is designed to enhance forecasting accuracy through continuous learning, adaptation, and feedback integration. The SIC module leverages advanced machine learning algorithms, reinforcement learning techniques, and reflective practice principles to create a self-improving framework that dynamically updates models based on real-time data and external feedback. The module's design incorporates multiple feedback loops, enabling the system to iteratively refine its performance and remain robust in the face of changing conditions. Reflective practice, a concept drawn from psychology, plays a critical role in the SIC module by facilitating ongoing evaluation and adaptation. By learning from previous predictions and continuously adjusting algorithms, the SIC module demonstrates its potential to improve forecasting accuracy across various domains, with a particular emphasis on renewable energy forecasting. The theoretical and mathematical foundations of the SIC module are explored, showcasing its capability to enhance predictive accuracy and resilience in an evolving energy landscape.
Key words: renewable energy forecasting, self-improvement cycle, adaptive algorithms, reflective practice, reinforcement learning, feedback integration.

Introduction

Renewable energy sources, such as solar and wind power, are pivotal in combating global climate change and ensuring a sustainable energy supply. The increasing reliance on these energy sources is driven by their potential to reduce greenhouse gas emissions and minimise dependence on fossil fuels. However, the inherent variability and unpredictability of renewable energy sources pose significant challenges for accurate forecasting, which is crucial for their effective integration into power grids (Gielen *et al.*, 2019; Hassan *et al.*, 2024; IRENA, 2019). Accurate forecasting enables grid operators to optimise energy production, balance supply and demand, and maintain grid stability.

Recent advancements in machine learning and artificial intelligence (AI) have shown promise in enhancing the accuracy of renewable energy forecasts. By incorporating high-resolution meteorological models and sophisticated algorithms, these technologies significantly improve forecast performance (Benti *et al.*, 2023; Liu & Fu, 2023). For instance, the Meteomatics EURO1k model demonstrated substantial improvements in renewable energy forecasting accuracy through the integration of detailed weather data, reducing forecast errors and increasing grid reliability (Pasquier *et al.*, 2024). Moreover, machine learning (ML) algorithms, such as neural networks or decision trees, have proven effective in predicting wind energy based on daily wind data, further underscoring the potential of these technologies in addressing forecasting challenges (Subramani *et al.*, 2024).

In addition to meteorological modelling, deep learning techniques, particularly neural networks,

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have been employed to provide accurate short-term load forecasts. These models have shown remarkable success in power load forecasting for smart grids, improving forecast accuracy and optimising the management of renewable energy resources (Wen *et al*., 2024). However, despite these advancements, achieving consistent and reliable forecasts remains challenging due to the complex and dynamic nature of weather patterns, the non-stationarity of data, and the limited availability of labelled data for model training.

Addressing these challenges requires adaptive and resilient forecasting models capable of learning from new data and continuously improving over time. Solutions such as domain adaptation, transfer learning, and fine-tuning techniques have been proposed to enhance model performance, enabling forecasting models to generalise better across different datasets and conditions (Gao *et al*., 2024). To manage these complexities effectively, it is essential to integrate reflective practice into forecasting models. Reflective practice enables continuous learning and adaptation by allowing models to iteratively evaluate past performance and refine their predictions. These approaches highlight the need for models that can dynamically adapt to changing environmental conditions, improve their predictions over time, and incorporate feedback to refine their performance.

In response to these needs, the Self-Improvement Cycle (SIC) module offers a novel framework designed to enhance forecasting accuracy through continuous evaluation, learning, and adaptation. Leveraging advanced reinforcement learning algorithms and reflective practices, the SIC module dynamically updates models based on real-time data, external feedback, and evolving conditions. Initially developed within the ARIREF model (Veigners & Galins, 2024), the SIC module's principles and methodologies extend across various domains, making it a valuable forecasting tool in diverse fields such as renewable energy, financial markets, and supply chain management.

The foundation of the SIC module lies in reflective practice, a concept from psychology and pedagogy that involves continuous evaluation and refinement of actions based on feedback and new insights. Reflective practice, originally conceptualised by Donald Schön, refers to the ability to reflect on one's actions in order to engage in a process of continuous learning and adaptation. In its traditional context, reflective practice is employed by individuals to critically evaluate their own practices and those of their peers, thereby facilitating continuous improvement (Leitch & Day, 2006; Schön, 2017). When applied to algorithmic models within the SIC framework, reflective practice enables forecasting algorithms to iteratively assess their past predictions, integrate real-time feedback, and adapt to new data. Within the context of AI-driven forecasting, reflective practice enables iterative learning from performance data, continuous algorithmic adjustments, and adaptation to new conditions. By integrating reflective practice into forecasting, the SIC module ensures that models remain dynamic and capable of handling evolving scenarios, improving both predictive accuracy and resilience.

The SIC module incorporates multiple feedback sources, such as internal performance metrics, external benchmarks, real-time data, and user feedback, into a continuous learning loop. Through this loop, the SIC module identifies performance gaps, adjusts its algorithms, and refines its predictions. Integrating external data sources such as global benchmarks and real-time weather information ensures that the SIC module remains responsive to external conditions, enhancing the model's long-term relevance and accuracy.

The SIC module is designed as a new system to improve forecasting accuracy through continuous evaluation, learning and adaptation. The main purpose of the paper is to show how the SIC module, which uses reinforcement learning algorithms and reflective practice, dynamically updates models based on real-time data, external feedback and changing circumstances. Specifically, this paper aims to:

- explore the theoretical foundations of the SIC module, emphasising its basis in reflective practice;
- demonstrate the SIC module's potential applications in renewable energy forecasting, supported by theoretical and initial observations;
- consider the versatility of the SIC module across other forecasting domains, such as financial forecasting and supply chain management, to highlight its broader applicability;
- outline future directions for empirical testing to validate the SIC module's effectiveness in real-world condition.

Materials and Methods

The development and implementation of the SIC module requires a combination of theoretical foundations, algorithmic structures, and the practical integration of real-time data. The SIC methodology focuses on creating an adaptive and self-learning system capable of refining its renewable energy forecasting capabilities over time. Through continuous evaluation and integration of data, the SIC module ensures that forecasting models evolve to maintain accuracy in dynamic environments.

The SIC module is grounded in machine learning and AI principles, particularly reinforcement learning and reflective practice. The module's continuous learning process is facilitated by reinforcement learning algorithms, which enable dynamic adjustments based on feedback loops. These algorithms optimise policy parameters using gradient-based methods, such as Stochastic Gradient Descent (SGD), to minimise forecasting errors. The objective function for the policy gradients in the module is defined as:

$$J(\theta) = E_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right], \tag{1}$$

where:
E_{π_θ} – refers to expected value of the function being optimised under the policy determined by the parameters ;
θ – represents the model parameters;
γ – is the discount factor for future rewards;
r_t – denotes the reward at time step *t*;
t – refers to time step in the process, starting from t = 0 and continuing indefinitely;
π_θ – represents the policy parameterised by θ, which defines the probability distribution over actions given the current state.

This mathematical framework allows the SIC module to optimise its performance iteratively by learning from both historical and real-time data inputs (Dulac-Arnold *et al.*, 2021; Schulman *et al*., 2017; Sutton *et al*., 2018).

The SIC module consists of several interconnected blocks (Figure 1), each responsible for a distinct aspect of the forecasting process. These blocks work together to form a self-improving system capable of refining its predictions over time. The key components include:

- *Data Analysis Block (DAB):* responsible for collecting, cleaning, and processing data from various sources. This block ensures that all input data is pre-processed to maintain consistency, accuracy, and relevance for subsequent analysis and model training;
- *Learning and Adaptation Block (LAB):* utilises machine learning algorithms and reinforcement learning techniques to analyse historical and current data, identify patterns, and adjust the forecasting models accordingly. The LAB's continuous learning capabilities enable the model to adapt to new data and improve its predictions over time;
- *Performance Evaluation Block (PEB):* evaluates the performance of the forecasting

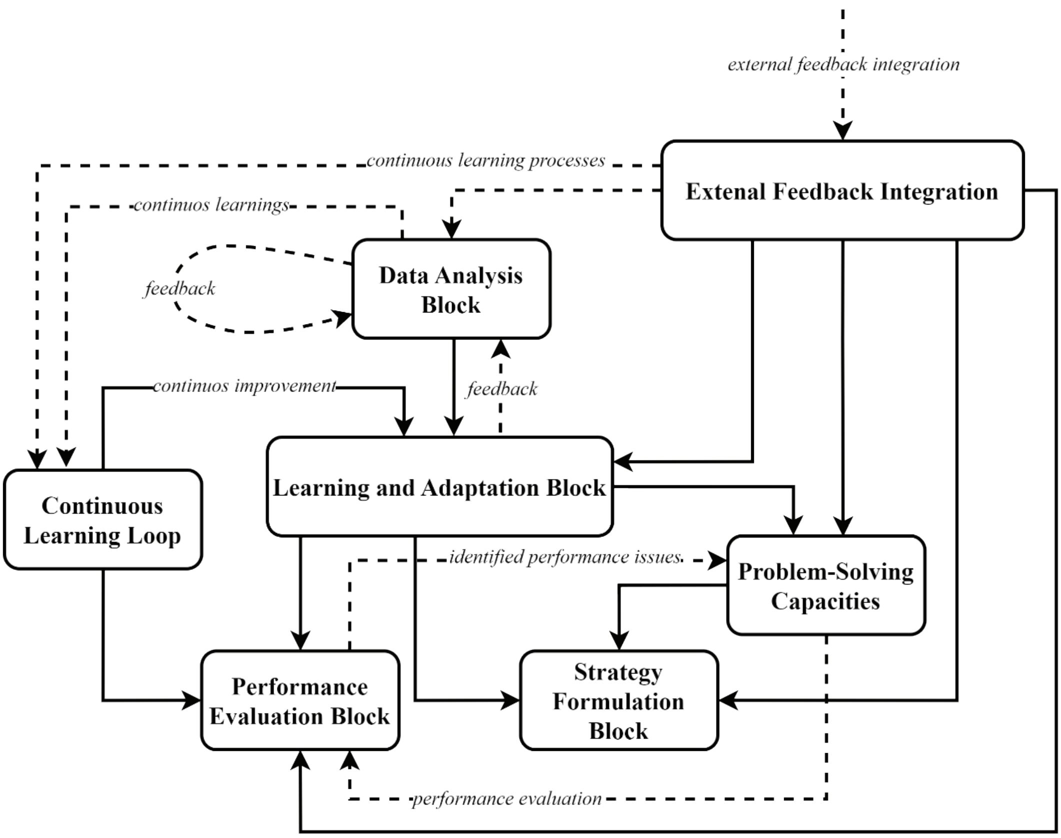

Figure 1. Self-Improvement Cycle Module.

models using key metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared values. This block provides feedback on the model's accuracy and reliability, guiding further improvements;

– *Strategy Formulation Block (SFB):* develops strategic plans to achieve predefined goals, using tools such as SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis and resource allocation algorithms. The SFB ensures that forecasting models are aligned with organisational objectives and can effectively respond to new challenges;
– *Problem-Solving Capacities (PSC):* identifies and addresses issues within the forecasting process using techniques, such as root cause analysis and solution development. This block ensures that problems are resolved promptly and that the model remains robust and reliable;
– *Continuous Learning Loop (CLL):* facilitates ongoing learning and adaptation by integrating feedback from various sources, including user inputs, external data, and performance evaluations. The CLL ensures that the forecasting models continuously improve and remain effective over time;
– *External Feedback Integration (EFI):* incorporates external insights and benchmarks into the forecasting models, ensuring that they remain relevant and accurate in the face of changing conditions. The EFI's feedback loops help update the models with new external data, enhancing their predictive capabilities.

The SIC module utilises a diverse range of data sources to enhance its forecasting accuracy. These include:

– meteorological data: high-resolution weather data from meteorological databases, including real-time and historical data, to provide accurate inputs for renewable energy forecasting (e.g. wind speed, solar radiation, and temperature);
– energy production records: data from renewable energy production facilities, such as wind farms and solar power plants, to validate and refine forecasting models;
– external benchmarks and expert reviews: data from global energy benchmarks and expert reviews to ensure that the SIC module's predictions align with industry standards and best practices;
– real-time sensor data: real-time inputs from sensors deployed at energy generation sites, providing up-to-date information on current energy output and environmental conditions.

Data collection is an ongoing process that supports the SIC module's dynamic adaptation capabilities. The continuous flow of new data ensures that the module can refine its predictions based on the most current information available.

The core algorithmic approach used in the SIC module is reinforcement learning, which allows the system to learn from past experiences and continuously adjust its model parameters. Techniques such as policy gradients and Q-learning are used to optimise the model's decision-making processes (Bennett *et al*., 2021; Sutton *et al*., 2018). Additionally, reflective practice principles are integrated into the algorithmic framework, enabling the system to critically evaluate its past performance and make iterative improvements.

Reflective practice, inspired by Schön's concept of continuous learning and adaptation, plays a crucial role in guiding the SIC module's transitions from one learning cycle to the next. After each forecasting cycle, the model assesses its performance by comparing predicted outcomes against real-world data, which is then fed back into the system for further optimisation. This mirrors the human cognitive process of reflecting on actions, incorporating feedback, and adjusting to improve future performance (Schön, 2017).

The SIC module also incorporates supervised learning techniques for initial model training and uses reinforcement learning for ongoing adaptation and refinement. This hybrid approach ensures that the module can both learn from labelled historical data and adapt to new, unlabelled data in real-time (Moles *et al*., 2024; Zhao *et al*., 2024). Reflective practice principles are used not only to enhance the learning from historical data but also to ensure that the system remains adaptive in the face of evolving conditions.

The iterative nature of reflective practice in the SIC module ensures continuous self-assessment and adaptation, which is critical for maintaining model accuracy and relevance over time. By embedding these reflective practices within the feedback loops, the SIC module can effectively adapt to new data inputs, adjust its forecast models, and refine its strategies in response to changing environmental conditions. This aligns with the principles of adaptive systems, where models are not static, but evolve over time to maintain their relevance and accuracy (Jarrar *et al*., 2020; Lucas & Turner, 2023; Schön, 2017).

The integration of reflective practice ensures that the SIC module remains responsive to new challenges and can improve its forecasting capabilities through ongoing learning and adaptation. These processes are foundational to the SIC module's ability to maintain high levels of forecasting accuracy, particularly in complex and dynamic environments such as renewable energy forecasting.

Results and Discussion

This section presents a detailed analysis of the SIC module's architecture, theoretical foundations, and universal applicability. The discussion is divided into two main parts:

– theoretical analysis of SIC elements: each element of the SIC module is analysed, focusing on its role in the overall architecture, its theoretical underpinnings, and its importance in improving forecasting accuracy. Grounding the module in established machine learning and AI principles demonstrates how each block contributes to the system's continuous learning and adaptability;
– theoretical justification for SIC's universality: this part explores how the SIC module, although initially developed for renewable energy forecasting, can be applied across various domains. Reflective practices and adaptive learning mechanisms are integrated to address the variability and uncertainty present in numerous fields, ranging from financial forecasting to supply chain management.

1. Theoretical analysis of SIC elements.

1.1. The Data Analysis Block (Figure 2) within the SIC module systematically processes and prepares data to ensure that renewable energy forecasts are accurate, consistent, and relevant. The DAB oversees all input data and uses advanced statistical and machine learning methods to guarantee data quality, enabling robust analysis and model training.

The DAB's processes include data collection, initial data processing, real-time data filtering, analysis, and performance evaluation. These stages work in unison, supported by feedback loops that continuously inform the system, allowing the SIC module to self-improve over time.

The Data Collection component gathers data from multiple sources: historical records, real-time sensor data, global benchmarks, and pre-processed models. A combination of IoT (Internet of Things) sensors, web scraping, and Application Programming Interface integration is used to pull in real-time and historical data. Ensuring the integrity and diversity of these data sources is vital for effective forecasting. Key sources include meteorological databases, energy production records, and real-time weather feeds, which provide the necessary inputs for accurate predictions.

The data collected in this phase is often heterogeneous, with varying formats, scales, and levels of quality. To maintain integrity, the DAB employs statistical methods such as Pearson's correlation coefficient to verify relationships between variables and K-fold cross-validation to assess model performance. This ensures that the data is suitable for subsequent machine learning models, reducing biases that may distort predictions.

Once collected, the data undergoes initial processing. This stage involves cleaning, normalising, and pre-processing the data to eliminate inconsistencies. Techniques such as outlier detection and missing data imputation are critical here.

Outlier detection in data analysis is crucial for maintaining the integrity and accuracy of forecasting models. Techniques such as Z-scores (2) and Interquartile Range (IQR) are commonly applied to identify and mitigate the influence of outliers, which can significantly skew results if not properly managed.

$$Z = \frac{X - \mu}{\sigma}, \qquad (2)$$

where:
X – data point;
μ – mean;
σ – standard deviation.

These methods work by flagging data points that deviate substantially from the dataset's central tendency, allowing for their exclusion or adjustment before further analysis. As Dash *et al.* (2023) demonstrate, the effective handling of outliers through IQR not only refines data quality, but also improves the overall accuracy of machine learning models used in renewable energy forecasting.

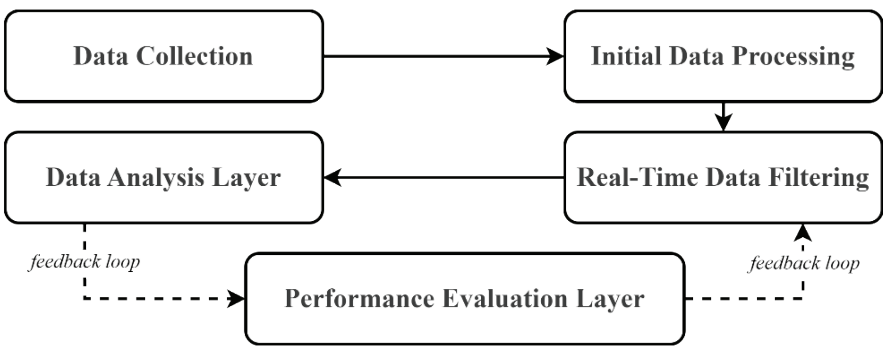

Figure 2. Data Analysis Block.

In dealing with missing data, imputation techniques such as K-nearest neighbours (KNN) are used to fill gaps and maintain the completeness of datasets. KNN imputation operates by estimating missing values based on the characteristics of the nearest neighbouring data points, ensuring that the dataset remains robust for analysis. This approach is particularly effective for handling non-linear data patterns that are prevalent in renewable energy forecasting. By addressing the issue of missing data, KNN imputation helps preserve the continuity and reliability of the data, enabling more accurate model training and predictions in dynamic energy environments.

Real-Time Data Filtering is an essential function within the DAB, which ensures that incoming real-time data is processed efficiently and accurately. In the dynamic environments typical of renewable energy forecasting, such data is often subject to volatility, noise, and anomalies that can significantly distort the model's predictions if not properly managed. As part of the DAB, Real-Time Data Filtering cleanses this data by applying noise-reduction techniques, including Moving Average Filters (3) and Kalman Filters. These filtering methods ensure that only relevant and reliable data proceeds to the subsequent analysis stages, enhancing the overall performance of the forecasting models and enabling more accurate predictions (dos Santos *et al*., 2023; Pirooz *et al*., 2020).

By smoothing out short-term fluctuations, Moving Average Filters reduce random noise, allowing the system to focus on longer-term trends in the data.

$$S_t = \frac{1}{N}\sum_{i=0}^{N-1} X_{t-1}\,, \tag{3}$$

where:
S_t – represents the smoothed value at time t;
N – number of periods;
X_{t-1} – observed values over that period.

Meanwhile, Kalman Filters provide a more sophisticated approach by recursively estimating the state of the dynamic system, adjusting the predictions based on new data inputs. These filtering processes, as integral parts of the DAB, ensure that the forecasting models within the SIC module remain robust and adaptive, continuously refining their predictions in the face of real-time data variability. They enable the SIC module to dynamically adjust its models, ensuring that they remain effective in the face of variable and noisy data sources.

The Data Analysis Layer performs in-depth statistical analysis and identifies trends in the processed data. Machine learning models, such as Radial Basis Function Networks (RBFNs) and other supervised learning algorithms, are used to analyse patterns and forecast future energy outputs. Studies by Warrier (2024), and Wurzberger and Schwenker (2024), highlight how advanced machine learning techniques, including RBFNs, improve model accuracy for forecasting. These techniques excel at capturing non-linear relationships in data, making them particularly suitable for complex energy systems.

After the data has been analysed, the Performance Evaluation Layer assesses the model's effectiveness using metrics, such as accuracy, precision, recall, and MAE. This layer is fundamental in maintaining the model's accuracy and reliability. In addition to MAE, other performance metrics such as F1-score and RMSE are considered. These metrics are especially valuable when dealing with imbalanced datasets, as they provide a more holistic evaluation of a model's performance.

The SIC module employs continuous feedback loops to ensure that each stage of the DAB informs subsequent stages. Evaluation results from the Performance Evaluation Layer create feedback that adjusts data collection, processing, and analysis methods. These feedback loops enable the SIC module to learn and improve continuously over time, reinforcing the principle of reflective practice.

1.2. The Learning and Adaptation Block serves as the heart of the SIC module, responsible for continuously refining the forecasting models by integrating real-time feedback and adjusting model parameters. Through a combination of supervised learning and reinforcement learning techniques, the LAB enables dynamic adaptability, ensuring that the models evolve based on performance data and changing conditions. The LAB functions by processing data through several interconnected layers, including the Data Ingestion Layer, Data Processing Layer, and Data Analysis Layer. These layers work in tandem to transform raw data into actionable insights that drive a model's adjustments and improvements. The core of the LAB's functionality lies in reinforcement learning, particularly policy gradients and Q-learning methods, which allow the SIC module to optimise decision-making processes. These methods are essential for dealing with the inherent variability in renewable energy data such as changes in weather patterns affecting wind and solar energy generation. The LAB's learning process is continuously informed by performance evaluations, which assess how well the model is performing against key metrics, including MAE, RMSE, and precision/recall metrics. LAB's core components are illustrated in Figure 3: Data Ingestion Layer, Data Processing Layer, Reinforcement Learning Layer, Model Adjustment

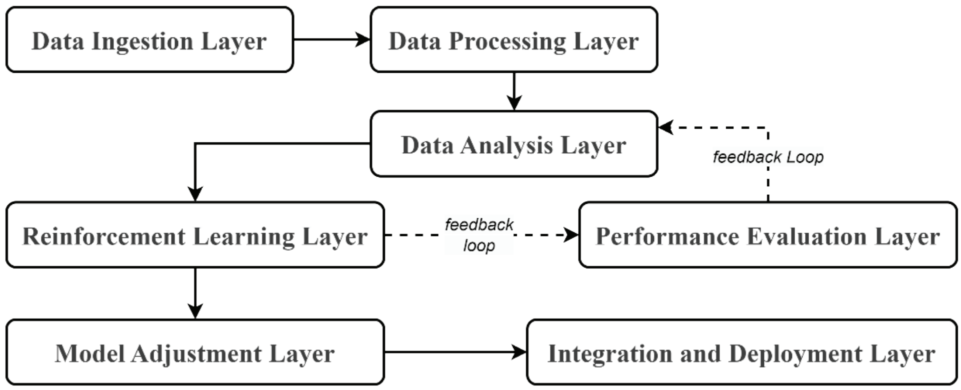

Figure 3. Learning and Adaptation Block.

Layer, Performance Evaluation Layer, and Integration and Deployment Layer. Each component contributes to the system's adaptability and accuracy in renewable energy forecasting.

The Data Ingestion Layer collects raw data from a variety of sources, including real-time sensor data, weather forecasts, and historical datasets. This diverse data is essential for continuously training and updating the forecast models, ensuring that they remain relevant and adaptive to current trends. The theoretical justification for this process is grounded in the need for comprehensive, up-to-date datasets, which provide a robust foundation for accurate renewable energy forecasting. Ensuring the quality of this data is paramount, as it directly impacts model performance. Mathematically, several techniques are employed to maintain data quality. The Z-score (2) method, often used to detect outliers, maintains data quality by discarding data points that exceed statistically acceptable ranges. In addition, normalisation using the min-max method (4) provides scaling of the data in the interval [0,1], which is essential for comparing different data sets and ensuring consistency in data processing. (Kim *et al*., 2024; Yaro *et al*., 2023).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}, \quad (4)$$

where:
X – the original data point;
X_{max} – maximum values of the data set;
X_{min} – minimum values of the data set.

This rescaling is crucial for maintaining consistency across heterogeneous datasets and preventing discrepancies that could arise from varying data scales.

The Data Processing Layer focuses on cleaning, normalising and transforming the received data to ensure that it is suitable for analysis and model training. Techniques include data normalisation and feature extraction using Principal Component Analysis (PCA) and reducing the dimensionality of the data while retaining the largest variance (Jia *et al*., 2022).

The Data Analysis Layer provides LAB with the ability to derive actionable insights from the processed data. This layer uses a combination of statistical techniques and advanced machine learning algorithms to identify meaningful patterns, trends, and anomalies in the data. The statistical methods used include time series analysis, which is crucial for understanding the temporal dynamics of renewable energy production. In addition, clustering techniques such as K-means clustering help to classify data points based on similarities, allowing the identification of distinct patterns that could influence energy output. Machine learning algorithms, including Support Vector Machines (SVM) and Random Forests, are used to discover complex, non-linear relationships in the data, providing a solid foundation for accurate model training and updates (Del Ser *et al*., 2022; Gao *et al*., 2022). Insights from the Data Analysis Layer are used to inform the Reinforcement Learning Layer and subsequent model adjustments, ensuring that the SIC module continues to adapt to new data and changing environmental conditions. By continuously analysing the data in this way, the SIC module can improve its forecasting capabilities, improve model accuracy, and ultimately contribute to more reliable renewable energy forecasting.

LAB's adaptability is based on reinforcement learning, the application of learning techniques that adjust predictive models in the Reinforcement Learning Layer based on new data and performance feedback, allowing the SIC module to learn from past results and adjust its strategy. Reinforcement learning techniques, such as Q – learning (5) and policy gradient algorithms, optimise the decision-making process by allowing the SIC module to explore different actions over time (Bennett *et al*., 2021; Jang *et al*., 2019; Sutton *et al*., 2018). Using reinforcement learning techniques, LAB can identify the most effective strategies to improve prediction accuracy.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max_{\alpha'} Q(s',a') - \\ - Q(s,a)], \tag{5}$$

where:
α – the learning rate;
γ – the discount factor;
r – the reward;
s – the current state;
a – the current action;
s' – the next state;
a' – the next action;
$Q(s,a)$ – the action-value function;
$max_{\alpha'} Q(s',a')$ – represents the maximum expected future reward for the best action in the state .

The Performance Evaluation Layer assesses the model's performance using metrics such as accuracy, precision, recall, and MAE. The evaluation results create a feedback loop, providing insights that guide the Model Adjustment Layer, which adjusts the model parameters based on performance data, ensuring that the forecasting models continuously improve over time. The LAB's decision-making process is grounded in policy gradients (1), where the objective function J(θ) is maximised through reinforcement learning techniques. By optimising this objective function, the LAB ensures that the SIC module can learn effectively from both historical and real-time data inputs.

The Integration and Deployment Layer is responsible for integrating the updated models into real-time operational environments, such as renewable energy grids and energy management systems. This ensures that the models are ready for practical application and capable of processing new data inputs effectively. Real-time deployment allows the models to operate dynamically, adapting to the evolving conditions of renewable energy production. This layer is also equipped with mechanisms for continuous monitoring and updating, ensuring that the deployed models remain robust and responsive to any changes in external conditions or operational requirements.

The Learning and Adaptation Block incorporates feedback loops at multiple stages, ensuring continuous refinement of the data processing and model training processes. These loops allow for iterative improvements in model accuracy and adaptability by integrating real-time feedback into the learning process. This cyclical process of learning and adapting enables the SIC module to continuously enhance its forecasting accuracy.

By structuring the LAB in this way, the SIC module fosters continuous learning and improvement, ultimately resulting in more accurate and reliable renewable energy forecasts.

1.3. The Performance Evaluation Block assesses the forecasting models by applying a variety of performance metrics. These evaluations guide iterative improvements within the SIC module. The primary function of this block is to measure the accuracy, precision, and reliability of the models, ensuring they consistently meet the desired forecasting standards.

PEB operates through several interconnected layers that assess the model's performance using key statistical and machine learning metrics (Figure 4). Feedback generated from these evaluations is crucial for refining the models and enhancing their predictive accuracy.

The PEB calculates key performance indicators, such as MAE, RMSE, and R-squared values, to assess model accuracy and reliability. These metrics provide a quantitative basis for evaluating model performance.

MAE measures the average magnitude of errors in the predictions, providing a straightforward metric for evaluating model accuracy (6).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{6}$$

where:
y_i – the actual value;
$\hat{y}_i$ – the predicted value;
n – is universally the number of data points across all performance metric formulas (6, 7, 8, and 10).

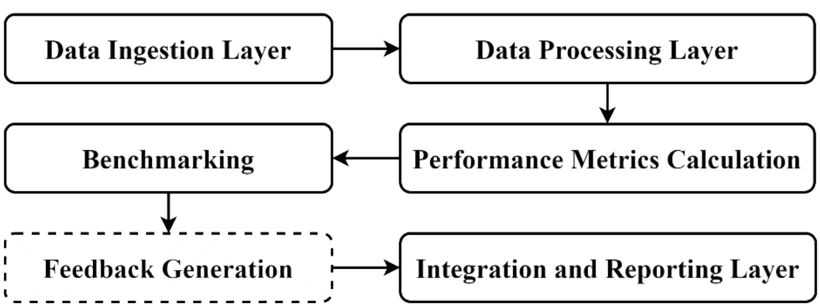

Figure 4. Performance Evaluation Block.

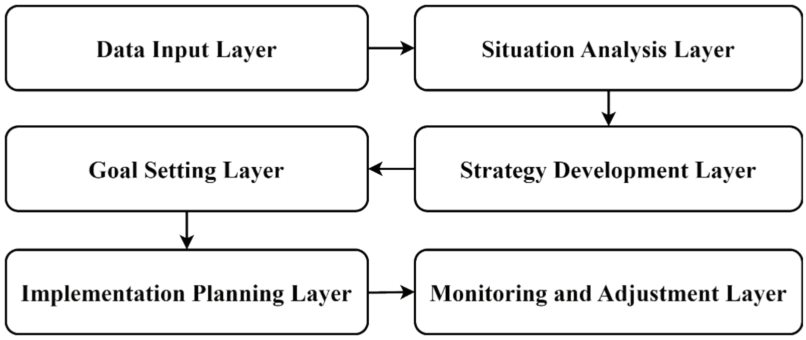

Figure 5. Strategy Formulation Block.

MAE is especially useful for understanding the overall accuracy without being overly sensitive to outliers (Bandara *et al*., 2020).

RMSE provides a measure of the square root of the average of squared differences between predicted and observed values (7). It is more sensitive to large errors due to its squared nature, making it valuable when significant deviations are particularly concerning (Chai & Draxler, 2014).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{7}$$

R-squared (Coefficient of Determination) indicates the proportion of the variance in the dependent variable that is predictable from the independent variables (8). It serves as a measure of model fit and explains how well the forecasting model captures the underlying data patterns.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}, \tag{8}$$

where:
$\bar{y}$ – the mean of the observed data (Nagelkerke, 1991).

Performance metrics are calculated at regular intervals to continuously assess model performance. The PEB implements both simple and advanced metrics, depending on the complexity of the model being evaluated and the sensitivity required for error detection. Each metric provides unique insights into a model's performance, allowing for more informed decision-making during the model adjustment process.

Additionally, benchmarking is employed within the PEB to compare the performance of the current forecasting models with other established models or industry benchmarks. This comparison enables the SIC module to gauge its effectiveness relative to other systems and make necessary improvements (Nearing *et al*., 2018).

After computing the performance metrics, the PEB generates feedback that is fed into the Learning and Adaptation Block (LAB) and other relevant blocks. The feedback is used to adjust model parameters, refine algorithms, and improve prediction accuracy over time by iteratively updating model parameters by minimising the loss function using gradient descent (9).

$$\theta = \theta - \alpha \nabla_{\theta} J(\theta), \tag{9}$$

where:
α – the learning rate;
θ – represents the model parameters;
∇_{θ} – represents the gradient of the loss function with respect to the model parameters θ;
$J(\theta)$ – the loss function.

Continuous integration of this feedback loop ensures that models remain adaptable and responsive to new data inputs (Hougen & Shah, 2019; Nearing *et al*., 2018).

The PEB engages in continuous interaction with the other components of the Self-Improvement Cycle module, particularly with the Data Analysis Block and the Learning and Adaptation Block. This interaction occurs through established feedback loops, which are integral to the processes of performance evaluation, benchmarking, and feedback generation. By sharing detailed performance metrics and analytic insights, the PEB provides critical information to these blocks, enabling them to make data-driven adjustments and iterative improvements. This collaborative framework ensures that the SIC module operates as a cohesive, self-improving system, capable of responding effectively to dynamic and non-stationary environments, thereby maintaining the accuracy and adaptability of its forecasting models.

1.4. The Strategy Formulation Block (SFB) is designed to provide a comprehensive framework for the development of strategic plans (Figure 5). This block synthesises various analytical tools and strategic frameworks to ensure that forecasting models are in harmony with broader organisational objectives while being adaptive to new challenges.

The SFB's mathematical foundation is built upon decision theory and optimisation techniques, which are used to formulate action plans that maximise the model's performance while minimising risks. The SFB integrates mathematical techniques such as resource allocation algorithms and optimisation models. These techniques are essential for distributing limited resources efficiently across various strategic initiatives. The resource allocation process can be framed as an optimisation problem, where the objective function aims to maximise the expected utility or minimise costs (Li, 2020). For example, Linear Programming (LP) is often employed in optimise resource distribution, with the objective function (10) defined as:

$$\max Z = \sum_{i=1}^{n} c_i \, x_i, \tag{10}$$

where:
c_i – represents the utility or cost associated with resource *i;*
x_i – the quantity of resource *i.*

The Situation Analysis Layer within the SFB block involves a detailed assessment of both internal and external factors that could influence the performance of the forecasting model. By leveraging SWOT analysis, the module can systematically identify strengths, weaknesses, opportunities, and threats relevant to the model's application in renewable energy forecasting. Similarly, PEST (Political, Economic, Social, Technological) analysis is used to assess the broader environmental factors, such as political, economic, social, and technological factors that could impact the forecasting model.

This situational assessment allows the SIC module to be adaptive, ensuring that it is responsive to changes in the external environment. The analysis is supported by data-driven insights derived from historical data, real-time updates, and external benchmarks, which provide a comprehensive understanding of the current landscape.

Based on the results of the situation analysis, the Goal Setting Layer is responsible for defining clear, measurable objectives that the forecasting models should aim to achieve. This process is guided by the SMART (Specific, Measurable, Achievable, Relevant, Time-bound) criteria, ensuring that the goals are specific, measurable, achievable, relevant, and time-bound. By establishing precise targets, this layer ensures that the forecasting models are not only aligned with the broader strategic objectives of the system but are also continuously optimised to meet specific performance metrics. The mathematical formulation of goals within this layer often involves optimisation techniques such as multi-objective optimisation, where the model seeks to balance competing objectives, such as minimising forecasting errors while maximising model efficiency and adaptability (Yilmaz & Sen, 2023).

In renewable energy forecasting, resource allocation may involve optimising investments in different energy sources (solar, wind, etc.), considering their variability and forecasted output (Mystakidis *et al*., 2024). Additionally, adaptive strategies ensure that forecasting models remain responsive to real-time data, enabling rapid shifts in focus when external conditions change.

1.5. The Problem-Solving Capacities (PSC) block (Figure 6) is designed to identify and address issues that may arise in the forecasting processes. The block functions by leveraging various analytical methods (e.g. anomaly detection, root cause analysis, pattern recognition, and optimisation algorithms) to detect problems, analyses their root causes, and implements solutions effectively. Its purpose is to ensure that the SIC module operates smoothly by resolving issues promptly and preventing future occurrences.

The PSC block integrates feedback from other blocks, such as the Performance Evaluation Block, and uses it to continuously improve the forecasting models. The block is composed of several key components, each contributing to its ability to identify and solve problems.

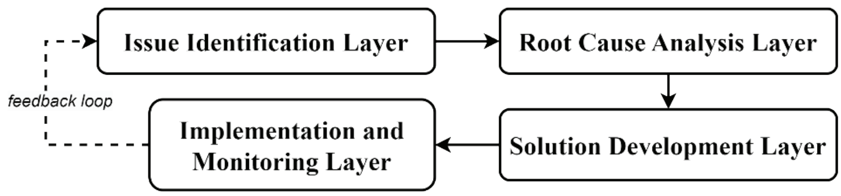

Figure 6. Problem-Solving Capacities block.

The Issue Identification Layer is responsible for detecting anomalies and potential issues within the system, often using anomaly detection algorithms and pattern recognition techniques. These techniques are essential for identifying deviations from expected behaviour that could signal problems in the forecasting process. From a mathematical perspective, anomaly detection can be modelled using statistical methods such as Gaussian distribution to define normal behaviour, while Z-scores (2) help in identifying outliers. Given a set of data points $X = \{x_1, x_2, \dots, x_n\}$, the anomaly detection function (11) can be expressed as:

$$Z(x_i) = \frac{|x_i - \mu|}{\sigma}, \tag{11}$$

where:
x_i – represents the value of data point being evaluated;
μ – the mean;
σ – the standard deviation of the data.

In more complex scenarios, machine learning algorithms such as autoencoders or isolation forests are applied, particularly when dealing with High-Dimensional data. These advanced techniques allow the system to identify subtle anomalies that may not be immediately evident using traditional statistical approaches.

The Root Cause Analysis Layer investigates the underlying causes of identified issues by employing systematic methods such as Fishbone diagrams, the Five Whys technique, or Bayesian networks (Chockalingam *et al*., 2019; Serrat, 2017). These tools help break down complex problems and identify the root causes by examining the relationships between variables and systematically questioning the processes that lead to the issue. From a mathematical standpoint, root cause analysis in complex systems often relies on Bayesian networks, which represent the relationships between variables in the form of a directed acyclic graph. Each node in this graph corresponds to a variable, while the edges depict the conditional dependencies between them. The probability of specific outcomes is then calculated using Bayes' theorem (12) (Annis, 2006).

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}, \tag{12}$$

This theorem supports the effective identification and analysis of cause-effect relationships within complex systems. By helping to update the probability of an event occurring based on new evidence, it becomes particularly valuable in scenarios where multiple factors contribute to a system's failure. This probabilistic approach lays the foundation for targeted interventions and systematic problem resolution.

The Solution Development Layer formulates and evaluates potential solutions to the identified issues within the SIC module. The layer utilises optimisation techniques and simulation models to predict the effectiveness of each solution before implementation. This process ensures that the most effective strategies are chosen for addressing the identified problems, and the system remains efficient and reliable over time (Mancarella, 2014; Mancò *et al*., 2024; Shiwei *et al*., 2023). Solutions can be optimised using a variety of techniques, including linear programming and evolutionary algorithms such as genetic algorithms. Genetic algorithms simulate the process of natural selection by evolving a population of candidate solutions over multiple generations. The goal is to maximise a fitness function , which measures the effectiveness of each solution. In a genetic algorithm, the population of candidate solutions undergoes selection, crossover, and mutation operations to progressively improve the quality of the solutions. Over time, this process converges toward an optimal or near-optimal solution, making genetic algorithms particularly useful for solving complex, multi-dimensional optimisation problems where traditional methods may struggle to find global optima (Albadr *et al*., 2020; Harada *et al*., 2022).

The Implementation and Monitoring Layer is responsible for putting the chosen solutions into practice and closely monitoring their effectiveness within the system. If the solution does not yield the expected results, this layer initiates corrective actions to adjust the system and address any unresolved issues. The monitoring process involves continuously tracking the system's performance to ensure that the implemented solutions contribute positively to the system's overall goals (Gill *et al*., 2024). This layer often relies on real-time data analysis and control theory principles to ensure that the system operates efficiently. Feedback loops play a critical role in monitoring the system's behaviour and adjusting its operations in response to discrepancies between predicted and actual outcomes. Proportional-Integral-Derivative controllers are a common tool used in continuous system monitoring and adjustment (Gbadega & Sun, 2023; Mahender *et al*., 2023). These controllers calculate the error between a desired setpoint and the actual system output and apply corrective measures in real-time to minimise this error.

The Problem-Solving Capacities (PSC) block interacts extensively with other components within the SIC module through integrated feedback mechanisms.

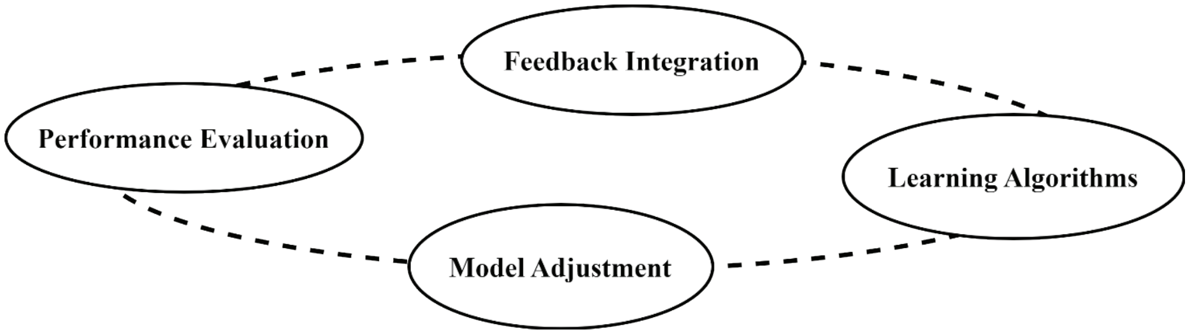

Figure 7. Continuous Learning Loop.

These connections enable continuous refinement of problem-solving strategies by drawing on real-time performance data and the results of implemented solutions. The iterative nature of the process fosters a dynamic learning environment, where forecasting models adapt effectively to emerging challenges.

The feedback mechanisms ensure that the SIC module remains resilient and capable of adjusting dynamically as new data and insights are incorporated. The continuous exchange of feedback between blocks enhances the system's accuracy, robustness, and adaptability in complex, evolving scenarios. By embedding advanced mathematical models and algorithms at every stage, the PSC block plays a crucial role in driving the ongoing enhancement and effectiveness of the SIC module.

An integrated theoretical and mathematical framework underscores the essential function of the PSC block in sustaining the performance and adaptability of the SIC system over time.

1.6. The Continuous Learning Loop (CLL) ensures that forecasting models are not static, but instead continuously evolve by learning from past experiences and integrating real-time data (Figure 7). This process reflects the concept of reflective practice, where the system constantly assesses its performance, learns from its outcomes, and iteratively improves itself. The CLL plays a critical role in maintaining the adaptability and accuracy of forecasting models by enabling them to respond effectively to dynamic and non-stationary environments such as those encountered in renewable energy forecasting.

The CLL is directly related to reflective practice, as it involves continuous learning and adaptation of the system based on the evaluation of past performance and lessons learned. Reflective practice is traditionally associated with a person's ability to analyse their actions and learn from experience (Leitch & Day, 2006; Schön, 2017), but its principles can also be effectively applied in algorithmic systems that are able to regularly evaluate their predictions and adapt to changing data.

The CLL improves with each cycle by integrating new data and adjusting models according to feedback and evaluation results. This is also a key point in the concept of reflective practice, where the system is continuously improved based on previous mistakes and successes, thus ensuring constant development and adaptation. The CLL brings reflective practice to the algorithmic level, allowing predictive systems to use this principle of human intelligence to regularly adjust and improve their models, making them both more accurate and more responsive to the variability and complexity of real-world data (De Burgh-Day & Leeuwenburg, 2023; Rosé *et al*., 2019).

The CLL utilises machine learning and reinforcement learning techniques to analyse incoming data. These algorithms are responsible for identifying patterns, learning from both historical and real-time data, and refining the predictive models accordingly. The insights gained from these learning algorithms drive the adjustment of forecasting models, which includes fine-tuning model parameters, selecting relevant features, and retraining the models to integrate new data and insights.

After adjustments are made to the model, its performance is evaluated using key metrics such as MAE, RMSE, and R-squared values. This evaluation provides quantitative measures of the model's accuracy and reliability, helping to determine how well the model performs in real-world conditions (Plevris *et al*., 2022).

The final stage in this process involves feeding performance evaluation results back into the learning algorithms. This feedback loop is critical for continuous improvement, as it enables the model to learn from its past performance and make iterative refinements to improve predictions. Through this iterative cycle of learning, adjusting, and evaluating, the CLL ensures that the forecasting models remain adaptive and capable of responding to dynamic changes in data.

1.7. The External Feedback Integration (EFI) block (Figure 8) serves as a critical component

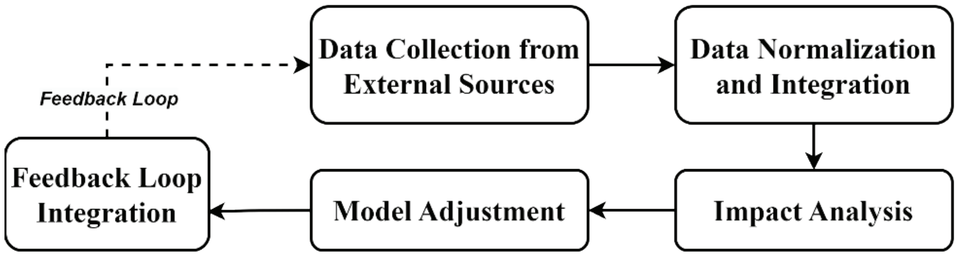

Figure 8. External Feedback Integration.

in maintaining the relevance, adaptability, and precision of the forecasting models. By systematically incorporating data from external sources, such as global benchmarks, real-time environmental data, and industry-specific trends, the EFI block ensures that the model remains up-to-date and responsive to changing external conditions.

The feedback loops in this block allow the SIC module to continuously learn from external environments, integrating these insights into the forecasting models and enabling them to adapt in real time. The EFI block's role is pivotal in handling non-stationary data, especially when dealing with dynamic, unpredictable factors such as renewable energy generation.

The EFI block aligns with the broader theory of adaptive systems and feedback loops that are essential in AI and machine learning models. By continually feeding external data into the model, the EFI block helps prevent model drift - a common issue where static models lose relevance over time as external conditions change. The integration of external feedback supports the development of more resilient and robust models that can predict more accurately in fluctuating conditions.

Reflective practice, previously discussed in the context of the CLL block, is also relevant here. The concept of incorporating feedback to improve performance is foundational to many adaptive learning systems. Schön's reflective practice theory can be applied algorithmically in the EFI block, where external data is critically evaluated and integrated to ensure that the system is continuously learning and evolving.

External data often comes in various formats and scales, making normalisation essential before integration into the forecasting models. Techniques such as Min-Max Normalisation (4) and Z-Score Normalisation (2) are employed to standardise these external data inputs, ensuring compatibility with the internal system data and maintaining consistency across different datasets.

After normalisation, the external data is subjected to impact analysis to assess its influence on the forecasting models. Techniques, such as causal inference and correlation analysis, are utilised to understand how changes in external factors affect model performance. Additionally, Granger Causality Testing may be applied to determine if external variables have predictive power for future model outcomes (Horvath *et al*., 2022; Scharf & Wang, 2023; Wang *et al*., 2022).

Following the impact analysis, the EFI block applies gradient-based optimisation techniques to adjust model parameters based on external feedback. For instance, Stochastic Gradient Descent (9) can be used to iteratively update model weights, thereby minimising forecasting errors.

The feedback loop integration ensures that external insights are not merely a one-time adjustment but are continuously incorporated into the learning process (Kaufmann *et al*., 2023). This ongoing feedback informs the iterative refinement of the models. Reinforcement learning principles can be applied in this context, allowing the system to continuously adapt based on external rewards and penalties, thus improving its ability to respond effectively to new data and evolving conditions.

The SIC module, as theoretically designed, demonstrates a solid foundation for improving forecasting accuracy in renewable energy applications. Based on a comprehensive mathematical framework and supported by reflective practice principles, the module is expected to enhance the performance of forecasting models. The integration of machine learning, reinforcement learning, and real-time data ensures that the system can dynamically adapt to new conditions and continuously refine its predictions.

The theoretical performance of the SIC module, grounded in well-established methodologies such as gradient-based optimisation and causal inference techniques, suggests that significant improvements in key metrics such as MAE and RMSE should be achievable. The module's ability to handle dynamic and non-stationary environments is further reinforced by its external feedback integration and continuous learning loops, which collectively contribute to model adaptability and resilience.

2. Theoretical Justification for the SIC Module's Universality

While initially developed for renewable energy forecasting, the SIC module demonstrates universal applicability across a variety of domains. By integrating reflective practices and adaptive learning mechanisms, the module is well-suited to handle the variability, complexity, and uncertainty.

The SIC module presents a novel framework for enhancing forecasting accuracy across a range of dynamic environments, with a specific focus on renewable energy applications. By integrating machine learning, reinforcement learning, and reflective practice principles, the module is designed to dynamically adapt to evolving conditions and continuously refine its predictions over time. This combination of techniques allows the SIC module to handle non-stationary data more effectively than traditional models, which often struggle to adapt to real-time changes. While primarily focused on renewable energy, the adaptive framework of the SIC module could also extend to applications in financial forecasting and supply chain management, where similar challenges of variability and uncertainty are present.

One of the significant advantages of the SIC module lies in its ability to incorporate external feedback into the forecasting process. Comparative studies with other advanced models such as those proposed by Zohdi *et al*. (2022) and Ali *et al*. (2023) highlight the effectiveness of external feedback in enhancing machine learning models predictive capabilities. The SIC module builds on this concept by implementing multiple feedback loops at different stages of the learning process, ensuring continuous improvement. This capability is crucial when dealing with renewable energy generation, where fluctuations and unpredictability are common challenges.

Reflective practice serves as a key differentiator for the SIC module compared to traditional forecasting models. While conventional models often rely on static datasets and fixed algorithms, the SIC module integrates reflective practice principles to enable ongoing evaluation and iterative improvement of its forecasting models. Reflective practice allows the SIC module to "learn from experience", an idea initially conceptualised by Schön (2017) and applied here at the algorithmic level. This ongoing reflection and adaptation ensure that the SIC module is not just a passive model reacting to data inputs but an active system that continuously evolves based on feedback, performance metrics, and new insights. This reflective approach is especially valuable in dynamic and non-stationary environments such as renewable energy forecasting, where adaptability is critical to maintaining accuracy and relevance.

By embedding reflective practice into the core of its learning mechanisms, the SIC module contrasts with models such as LSTM-MSNet or XGBoost, which focus heavily on predictive accuracy but lack the iterative self-improvement cycle that reflective practice offers. The ability to critically evaluate its past performance and make ongoing adjustments allows the SIC module to maintain resilience in the face of changing conditions, a feature that gives it an edge over models that do not incorporate such adaptive feedback loops (Bandara *et al*., 2020).

From a mathematical perspective, the use of gradient-based optimisation techniques and causal inference in the SIC module aligns with established methodologies in machine learning. Techniques such as Stochastic Gradient Descent and Granger Causality Testing provide a strong foundation for refining model parameters and understanding the impact of external factors on forecasting outcomes. These methods have proven effective in enhancing model accuracy, as demonstrated in studies by Horvath *et al*. (2022) and Scharf & Wang (2023).

Beyond renewable energy, the universality of the SIC module lies in its flexible architecture, which can be applied across various domains. Whether forecasting financial markets, managing supply chains, or analysing healthcare trends, the SIC module's integration of reflective practices and adaptive learning mechanisms enables it to handle the variability and uncertainty inherent in many fields. By iteratively learning from new data and refining its models, the SIC module is designed to remain relevant in changing environments, making it a valuable tool for a wide range of predictive applications.

In summary, the SIC module offers a comprehensive, theoretically grounded approach to forecasting in dynamic environments. The integration of reflective practice, reinforcement learning, and external feedback loops ensures that the module remains adaptive, resilient, and capable of handling the variability inherent in complex systems. While further empirical validation is necessary to confirm its practical effectiveness, the theoretical and mathematical foundations of the SIC module suggest that it has the potential to significantly improve forecasting accuracy across diverse applications.

Conclusions

1. The Self-Improvement Cycle module developed in this study offers a novel and theoretically grounded framework for enhancing forecasting accuracy in dynamic environments, particularly in renewable energy applications. By integrating machine learning, reinforcement learning, and reflective practice principles, the SIC module is designed

to continuously adapt to evolving conditions and learn from real-time feedback.

2. One of the primary strengths of the SIC module lies in its ability to handle non-stationary and volatile data, which is a common challenge in renewable energy forecasting. Unlike static models that tend to lose accuracy over time as external conditions change, the SIC module incorporates multiple feedback loops that facilitate ongoing learning and adaptation. This dynamic capability positions the SIC module as a more resilient and responsive tool for forecasting in environments characterised by unpredictability, such as wind and solar energy generation.
3. Moreover, the SIC module's theoretical foundation in reflective practice is a significant contribution to the field. By borrowing from psychological and pedagogical principles, the SIC module continuously evaluates its own performance, allowing for iterative improvements based on both internal performance metrics and external feedback. This reflective process is crucial for maintaining long-term model accuracy and ensuring that the forecasting system remains robust in the face of new challenges.
4. The universal applicability of the SIC module extends beyond renewable energy forecasting. By integrating adaptive learning mechanisms and feedback loops, the SIC module can be employed in various domains, including financial forecasting, supply chain management, and other areas where accurate predictions are vital in dynamic environments. This versatility underscores the SIC module's potential to contribute significantly to forecasting efforts across multiple sectors.
5. While the theoretical and mathematical foundations of the SIC module suggest its potential to enhance forecasting accuracy, future empirical validation is necessary to confirm its practical effectiveness. Implementing the SIC module in real-world scenarios will provide valuable insights into its performance, helping to refine its design and further improve its predictive capabilities.
6. In conclusion, the SIC module represents a comprehensive and adaptive forecasting system that leverages cutting-edge AI and machine learning techniques. Its integration of reflective practice and continuous learning positions it as a promising tool for improving forecasting accuracy, not only in renewable energy but also across a wide range of dynamic fields.
7. While the primary focus of the SIC module is on renewable energy forecasting, its adaptive framework suggests potential applications in other fields, such as financial forecasting and supply chain management. These areas also face challenges related to variability and uncertainty, making the SIC module's design highly relevant. Future empirical testing in these domains could provide valuable insights and contribute to further refining the module's adaptability and predictive capabilities.

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