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Development of a Reinforcement Learning-Based Solar Decomposition Model for Predictive Control Using Limited Measurement Data

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Abstract

The prediction of Diffuse Horizontal Irradiance (DHI) for the following day is essential for maintaining a stable power supply and minimizing energy losses. In this study, the proposed model predicts the DHI for an entire year using only two weeks of DHI data and readily obtainable meteorological parameters. The model proposed in this research maintains the reliability of the physical equations inherent in existing decomposition models while incorporating reinforcement learning to enhance error reduction. The model proposed has demonstrated the capability to perform long-term solar decomposition calculations without the need for further model updates.

Introduction

The process of using models to forecast the next day's energy demand and supply of a building, thereby providing the optimal operational scenario, is known as Building Predictive Control (MPC). In MPC, solar irradiance serves as critical input data for building and renewable energy systems, including photovoltaic and solar thermal energy systems (Enriquez et al, 2016). Particularly, for the calculation of incident energy by orientation, it is necessary to separate Global Horizontal Irradiance (GHI) into Diffuse Horizontal Irradiance (DHI) and Direct Normal Irradiance (DNI), a process known as solar decomposition. Accurate solar decomposition is a crucial process that directly impacts the overall application of MPC, including the utilization of building and renewable energy systems. However, generally, the collection of DHI data is challenging due to difficult measurements and the need for additional equipment, which leads to significant costs; consequently, most buildings manage only GHI data (Aler et al., 2017). Therefore, it is common practice to infer DHI using solar decomposition models based on the typically measured GHI. Solar decomposition models are developed by inferring equations that best describe the output variable, DHI, based on measured GHI and other meteorological data from the target region. At this point, solar decomposition models originated from the research of Liu & Jordan and are developed to describe the meteorological characteristics of the target region (Liu and Jordan, 1960). Such engineering methods lead to regional deviations when conventional solar decomposition models, due to their empirical nature, are applied outside the specific area they were originally developed for. There have been attempts through various studies to find a universal formula for solar decomposition models (Bertrand et al, 2015; Engerer, 2015; Ineichen, 2008; Tapakis et al, 2016; Yang 2013). Recently, a study conducted by Gueymard and Ruiz-Arias tested 140 solar decomposition models across seven continents (Gueymard and Ruiz, 2016). However, the results of the study showed that none of the analyzed solar decomposition models could be considered universal. On the other hand, research has been conducted to calibrate solar decomposition models to reflect local characteristics by developing new regional coefficients that reflect the climate features of Seoul, instead of the original coefficients of the existing models. The research results demonstrated that it was possible to some extent to improve the errors inherent in existing solar decomposition models. However, even with the modified regional coefficients incorporated, the majority of the error patterns inherent in the existing solar decomposition models were maintained, and the model development also required approximately two years' worth of data measured in the target area. (Seo and Kim, 2019). In addition, once regional coefficients are determined, it becomes difficult to modify them according to climate change and regional differences, which reduces the applicability on-site. Therefore, it is challenging to utilize the conventional decomposition models, which are based on simple physical equations, for the operation planning of renewable energy facilities or predictive control outside the target region. Moreover, attempts have been made to develop location-specific solar decomposition models using data-driven approaches such as deep learning (Alam et al., 2009; Elminir et al., 2007); however, these methods typically require long-term meteorological data, spanning at least the typical solar cycle of one year, making it challenging to apply these models in general buildings where it is difficult to accumulate such extensive DHI data.

The present study aims to overcome the limitations of existing solar decomposition models. The proposed model in this research boasts the following advantages. First, unlike conventional models that require over a year's worth of measured meteorological data to be operational, the proposed model can be implemented with approximately two weeks of measured data. Next, a model that does not require regional coefficients is developed. Finally, the study proposes a solar decomposition model based on reinforcement learning (RL), an approach not previously attempted, and aims to explore its potential.

Research method and Procedure

In this research, we propose and comparatively analyze the performance of two methods for enhancing the solar decomposition model. The first method involves re-estimating the coefficients of the existing solar decomposition model. This approach is known as a model improvement method that has been suggested through various prior studies. The coefficient estimation method has the advantage of being able to reflect the DHI characteristics of local areas while utilizing the equation structure of existing solar decomposition models.

The second method improves upon the solar decomposition model by directly learning from its computational errors. This method employs machine learning techniques to identify and correct the inaccuracies within the model, making it more precise and reliable for predicting solar radiation. Assuming that the extant solar decomposition models generate a predictable error pattern, it is anticipated that employing a learning-based approach to rectify these errors would yield enhanced performance compared to merely amending the algorithmic structure. The technique employed for error learning in this study is reinforcement learning, and detailed information regarding the construction of both models is described in the following section.

The data employed for training and evaluation is the Seoul region TMY2 dataset, and each model assumes a scenario where continuous DHI data acquisition is challenging, using only about two weeks of local data to forecast the DHI for the upcoming year (Table 1).

Table 1 Features of learning data

Data	Seoul.TMY 2	**Time interval**	1hour
Train period	Jan.1st – Jan.14th	**Validation period**	Jan. 15th – Dec. 31st

Reference model. Watanabe model

In this study, the proposed model advances by estimating the coefficients of the existing solar decomposition models. Numerous solar decomposition models have been developed to date, and a performance comparison study of solar decomposition models published in 2016 introduced approximately 140 models (Gueymard and Ruiz, 2016). Solar decomposition models utilize various input parameters, and their performance varies according to the type and characteristics of the input data used in the model and the specific features of the target region. In this study, the Watanabe model (Watanabe, 1983), which has been discussed in various papers, is selected as the reference model.

The Watanabe model is a model developed based on GHI and DHI measurements taken over a year in Japan. The Watanabe model calculates the diffuse solar ratio (K_{DS}) by classifying the sky condition into clear and cloudy days based on the clearness coefficient (K_t) of the direct solar separation model and the hypothetical clear sky clearness coefficient ($K_{t,clear}$). This is expressed in equations (1) to (4).

$$K_t = I_{GHI} / I_o \bullet sinh \tag{1}$$

$$K_{t,clear} = 0.4268 + 0.1934 \bullet sinh \tag{2}$$

$$\text{If } K_t \geq I_{GHI},\ K_{DS} = K_t - (1.107+0.03569sinh+1.681sin^2h) \bullet (1-K_t)^3 \tag{3}$$

$$\text{If } K_t < I_g,\ K_{DS} = (3.996 - 3.862sinh + 1.54sin^2h)(K_t)^3 \tag{4}$$

Proposed model 1. Optimized Watanabe model

In this study, similar to previous research, we apply a method to improve the model's performance by estimating the coefficients of the Watanabe model, which has been selected as the reference model. Previous research typically uses data measured over a period of more than one year to account for seasonal variations. However, this study assumes a scenario where measurement data is scarce for specific buildings or regions, therefore, it utilizes a minimal input dataset of 14 days to estimate the model's coefficients. In the context of the study, the estimated coefficients are the entire set of six parameters that constitute the Watanabe model, which can be referenced in equations (1) through (4). The optimization algorithm applied for learning is

Particle Swarm Optimization (PSO), as discussed in the works of Marini and Walczak, 2015, and Gaing, 2004.

PSO is an algorithm that mimics the flocking behavior of birds or schools of fish to find the optimal solution. The fundamental principle of PSO is that the particles share information with each other, allowing them to quickly converge on the best solution. The learning conditions for PSO are as shown in Table 2. The lower and upper bounds for PSO were set from -1000 to 1000. This represents a very wide range when considering that the coefficients of the original Watanabe model are distributed between 0.03 and less than 4. Additionally, among the PSO options, the time spent searching for the optimal value was set to infinity, and the optimization goal was to perfectly match the actual DHI, thus the Objective limit was set to 0. In other words, this study aimed to explore a wide range of conditions to re-estimate the coefficients of the Watanabe model under the given circumstances.

Table 2 Bounds of the Watanabe model parameters to be optimized

Watanabe parameters	**Under bound**	**Upper bound**
Para1 : 1.107		
Para2 : 0.03569		
Para3 : 1.681	-1000	1000
Para4 : 3.996		
Para5 : 3.862		
Para6 : 1.54		
PSO options		
Swarm size – 2000, Max time – Inf, Objective limit - 0		

Proposed model 2. RL with Watanabe model

Reinforcement learning (RL) is a method of learning where an agent, situated within an environment, independently performs actions in a given state and learns through trial and error to maximize rewards, thereby updating its policy. In the reinforcement learning process, an algorithm must be chosen for the agent's learning. A prominent learning algorithm commonly employed is Q-learning, which proceeds without a model. However, Q-learning stores the outcomes for all states and actions in a table format, which consumes a significant amount of computational resources and may not converge when tackling complex problems. Consequently, it has been primarily applied to problems that can be solved with a limited number of states and actions. Meanwhile, the Deep Q-learning (DQN) algorithm has addressed the shortcomings of traditional Q-learning by utilizing deep neural networks. It has demonstrated the capability to achieve decision-making beyond human-level performance in domains such as classical games and the game of Go, where a vast number of possible scenarios exist (Mnih et al., 2015). Therefore, in this study, we also utilize the DQN algorithm to train the agent for solar decomposition, and the learning process mirrors that shown in Figure 1.

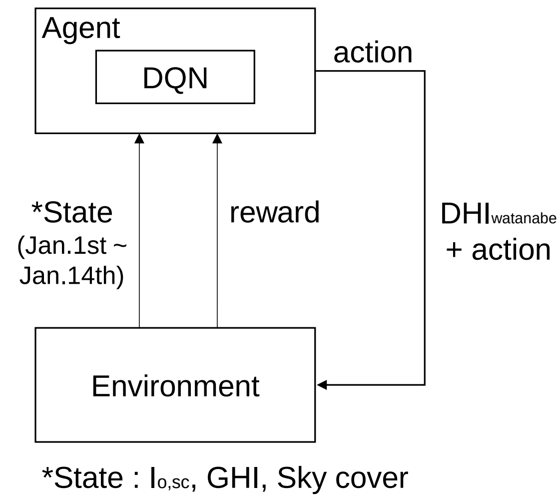

Figure 1 Development Process of a Reinforcement Learning Model Combined with a Solar Decomposition Model

First, the agent receives state information for a randomly selected time (1~24h) from the training dataset. Here, the state includes Global Horizontal Irradiance (GHI), Extraterrestrial Irradiance (Io), and Sky Cover information. In the context of performance assessment, the study employs existing measured data for GHI. For applications such as predictive control, data on solar irradiance for the following day can be acquired from an advanced solar forecasting model, capable of deducing future solar irradiance levels. Furthermore, for the training process, the annual Io on an hourly basis has been calculated in accordance with the methodology outlined in Duffie and Beckman (2013). The variables GHI and Io, chosen as States in the study, can indirectly describe seasonal variations. Therefore, it is possible to develop a reinforcement learning model that reflects the annual solar characteristics of a specific region, even with a relatively small amount of measured data collected over a period of two weeks.

In the model's architecture, the agent is programmed to operate within a meticulously defined energy range, choosing actions from –500 W/m^2 to 500 W/m^2, with the granularity of these actions being a precise 10 W/m^2. Upon selecting an action, it is systematically integrated into the diffuse solar radiation calculations derived from the established physical separation model. This integration is crucial as it provides a comparative baseline against the empirically measured solar radiation data, enabling the computation of the reward (R_t) in accordance with the stipulated formula in Equation (5).

The reward formula is designed to recognize positive errors, meaning that if the agent selects an action that overestimates the scattered solar radiation compared to the actual measured value, this is also considered an error. Therefore, the maximum reward the agent can receive at any given timestep is 0, which occurs when the agent perfectly represents the actual measured diffuse solar radiation. The agent repeats this process, continually updating its policy to maximize the reward throughout the training period. In this context, $DHI_{measured}$ refers to the baseline Diffuse Horizontal Irradiance obtained from the TMY2 dataset, and $DHI_{watanabe}$ signifies the DHI calculated from the direct separation model. The parameter settings used for the reinforcement learning are as presented in Table 3.

$$R_t = DHI_{measured} - (DHI_{watanabe} + action) \quad (5)$$

If $DHI_{watanabe} + action > DHI_{measured}$ then, reward

$$R_t = R_t \cdot -1$$

Table 3 Reinforcement Learning Training Parameter Settings

Parameter	Option and values
Action (W/m^2)	-500 – 500 (interval 10)
Max episode	2000
Agent	DQN
Execution environment	GPU (RTX – 3060ti)

Simulation result

Performance of the Watanabe model

In this study, learning or optimization proceeds with the objective of enhancing the solar decomposition model. Therefore, if the solar decomposition model employed is of superior quality, it is anticipated that the accuracy of the refined model will be higher in the prediction stage. The assessment of the model is conducted using the Root Mean Square Error (RMSE), which is derived from Equation 6.

$$RMSE = \sqrt{\frac{\sum_1^n (DHI_{\text{measured,t}} - DHI_{\text{test,t}})^2}{n}} \quad (6)$$

Figure 2 represents the seasonal performance of the Watanabe model. The Watanabe model exhibited enhanced performance during the summer with an RMSE of 107W/m^2, which is an improvement over the other seasons where the error was around 150W/m^2. In the graph, points closer to the diagonal line indicate higher model accuracy. Across all seasons, most points were distributed above the diagonal line, indicating that the model tended to overestimate the scattered solar radiation compared to actual measurements.

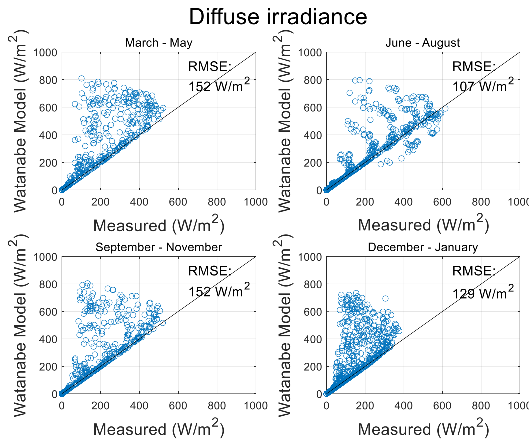

Figure 2 Performance of the Watanabe Model by Season

In Figure 3, regardless of the season, the performance of the Watanabe model is analyzed based on the clarity of the sky. The model demonstrated relatively superior performance on overcast days. This can be attributed to the phenomenon where, on cloudy days, the Global Horizontal Irradiance and Diffuse Horizontal Irradiance become very similar, and the Watanabe model accurately depicts this occurrence.

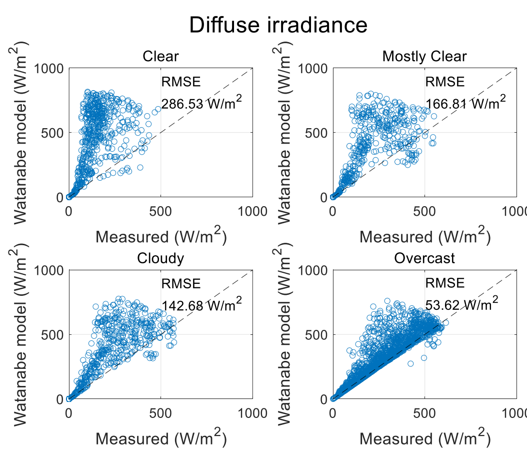

Figure 3 Weather-Dependent Watanabe Model Performance

Proposed Model Performance

Optimized Watanabe model

In this section, the performance of a model with modified coefficients of the Watanabe model is assessed. The proposed model learns from only two weeks of data and adjusts the coefficients to capture the regional characteristics of Seoul in the Watanabe model. Figure 4 represents the learning performance of the model. In the figure, it is observed that the Watanabe model exhibits significant errors in periods of cloudy weather. This indicates that the learning period featured a distribution of both clear and cloudy days. Here, it is anticipated that if coefficients that closely depict the DHI occurrence patterns over the past 14 days are estimated, the DHI prediction error for subsequent periods, which were not used in the learning, will decrease.

The optimization results indicate that, unlike the original Watanabe model, which overestimated DHI, the learning period displayed superior performance. The learning performance of the Optimized Watanabe model exhibited a behavior very similar to the actual data, with an RMSE of 15W/m².

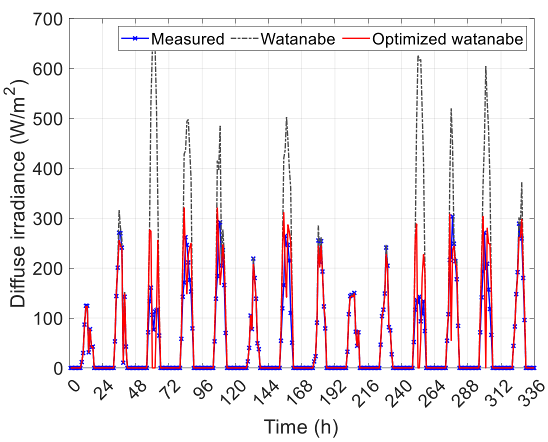

Figure 4 Learning Performance of the Optimized Watanabe Model

Figure 5 presents the results of comparing the prediction performance for the period following the initial learning phase, which spanned from January 1st to the 14th. During the subsequent week, from January 15th to the 21st—a period similar to the training phase—the Optimized Watanabe model achieved an RMSE of 65 W/m², which represents an improvement of more than 71 W/m² in prediction error compared to the same duration. However, a month after the learning period, the Optimized Watanabe model showed an increased error, with an RMSE of 109 W/m², indicating performance comparable to the original Watanabe model. As the time gap between the learning and prediction points widened, the model's error gradually increased, diminishing the advantages of the optimized model. During the period from July 15th to 21st, both models demonstrated excellent DHI prediction performance, which can be attributed to the fact that for most of the prediction period, the sky cover was very cloudy, approaching a value of 100. This confirms that the general characteristic of the Watanabe model, which has shown good performance on cloudy days, was a contributing factor. The Optimized Watanabe model displayed excellent performance during the training period and in the time closely following the training phase. This indicates that with continuous data collection and model updating, it could be utilized as a predictive control model for building applications. However, in environments where continuous data measurement is challenging, the Optimized approach may be difficult to utilize because the model coefficients estimated from the training data have a dominant influence. Table 4 presents the results of the changes to the Watanabe model's parameters through the optimization process. In this study, the search range for parameters was wide to find the optimal combination among the most diverse possibilities, resulting in significant differences in the parameter outcomes of the two models.

Table 4 Results of Watanabe Model Parameter Optimization

	Origin Watanabe	Optimized Watanabe
Parameter 1	1.107	-569.171
Parameter 2	0.03569	-975.066
Parameter 3	1.681	-907.466
Parameter 4	3.996	520.9592
Parameter 5	3.862	1000.0
Parameter 6	1.54	151.5977

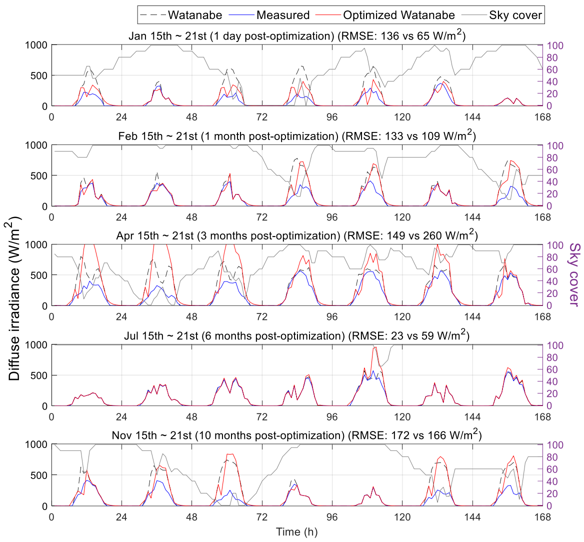

Figure 5 Prediction Performance of the Optimized Watanabe Model

RL with Watanabe model

In this section, the performance of the RL (Reinforcement Learning) with Watanabe model is evaluated. Like the previous models, the RL with Watanabe model allows the agent, which is the main learning entity, to learn the relationship between the error of the Watanabe model from January 1st to 14th and the weather conditions of the same period. Once the learning is complete, the trained agent performs solar decomposition for a year without additional training. Figure 6 represents the performance of the model during the training period, from January 1st to 14th. As mentioned, the Agent autonomously learns the method of action to rectify the errors of the Watanabe model. As can be discerned from the figure, the Agent seldom takes action on overcast days when the Watanabe model exhibits superior performance, thereby preserving the intrinsic efficacy of the model. However, on days when significant errors occur in the Watanabe model, the Agent undertakes actions to offset these errors. For instance, during the 48-72 hour forecast period where the error peaks, the Watanabe model exhibited an error of 588W/m^2, predicting a DHI of 76W/m^2 as opposed to the actual measured value. At this juncture, the agent took an action of -500W/m^2, thus yielding a DHI calculation closely aligned with the measured data. Such actions were consistent throughout the entire learning period. Despite the capability of taking positive actions, the agent consistently opted for negative or zero actions, which appears to reflect its learning of the Watanabe model's tendency to overestimate DHI. Such behavioral patterns of the agent suggest that, as the Watanabe model consistently overestimates DHI across all sections, it can be anticipated that the reinforcement learning model will provide improved long-term forecast performance. Moreover, while the current maximum negative action the agent can take is -500W/m^2, it is posited that if a broader range of actions is made available in the future, the error of the reinforcement learning model is expected to diminish further.

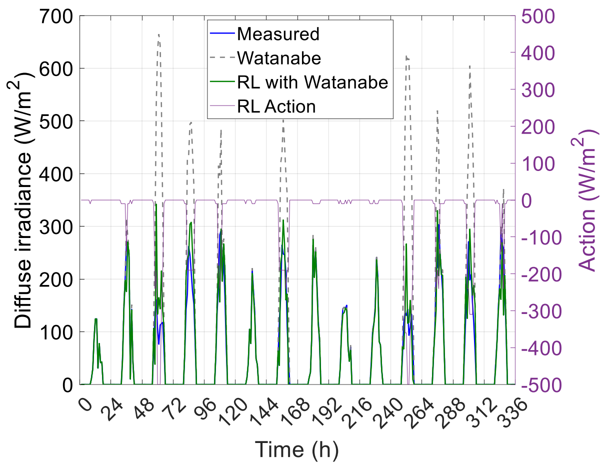

Figure 6 Learning Performance of the RL with Watanabe Model

Figure 7 illustrates the period-specific forecast performance of the RL with Watanabe model. Initially, in the week following the learning period, starting on January 15th, the reinforcement learning model exhibited a calculation performance similar to Measured, with an error of 72W/m^2. This is comparable to the Optimized model's RMSE of 65W/m^2 during the same period. The RL with Watanabe model demonstrated a sustained prediction accuracy with an RMSE of 84 W/m^2 and 104 W/m^2 at one and three months post-training, respectively. When compared to the Optimized model, which exhibited an RMSE of 109 W/m^2 and 260 W/m^2 for the same periods, it is evident that the RL model maintained its predictive performance over the long term without the necessity for further updates post-training.

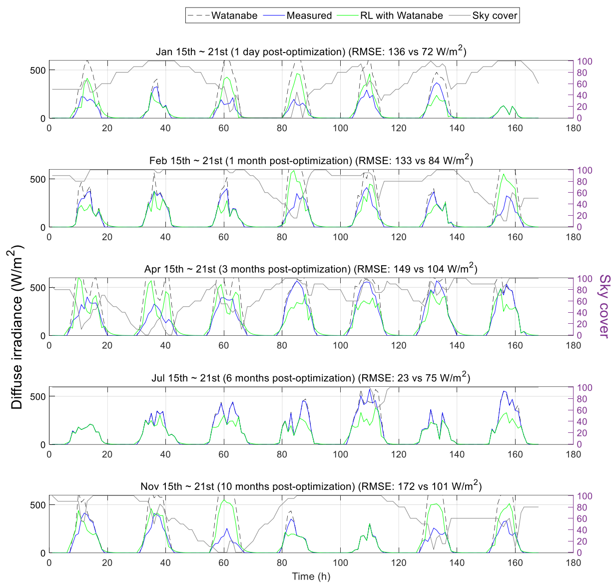

Figure 7 Prediction Performance of the RL with Watanabe Model

Errors in the RL model tend to occur on days with high sky cover, where the performance of the Watanabe model is superior. On such days, minimal additional correction through action is required; however, the behavior error of the agent, trained to mitigate the tendency of the Watanabe model to overestimate DHI, manifests instead. It is anticipated that the performance of the model will improve with further training or with the addition of more data.

Figure 8 illustrates the monthly performance of the scatter solar radiation prediction by the models proposed in this study. The Optimized model demonstrated lower errors in January, November, and December, which exhibited similar meteorological conditions to the period during which the model was trained. However, for the other months, the Optimized model exhibited higher computational errors compared to the existing Watanabe model. While the Optimized model showed superior performance during periods with meteorological conditions similar to its training phase, its error margin significantly increased with seasonal changes.

The Reinforcement Learning (RL) model exhibited superior performance over the Watanabe model in most months, particularly showing improved effects in months where the Watanabe model's errors were significant (January, February, March, September). Unlike the Optimized model, which modifies the coefficients of the Watanabe equation, the RL model was trained to directly correct errors. This approach allowed for error improvement across seasonal changes, even with limited training data of 14 days, due to the consistent error patterns of the Watanabe model. The annual average RMSE for the Watanabe, Optimized, and RL models were 125, 156, and 91 W/m², respectively, and the performance of these models is summarized in Table 5.

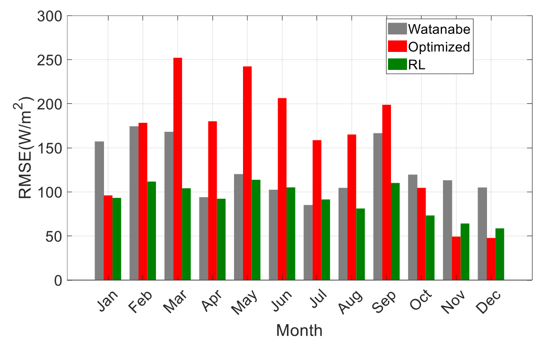

Figure 8 Monthly Comparison of Solar Decomposition Model Performance

Table 5 Monthly Comparison of Solar Decomposition Model Performance

	Watanabe	**Optimized**	**RL**
Month	RMSE (W/m^2)		
Jan.	156	96	93
Feb.	174	178	111
Mar.	167	252	104
Apr.	93	180	92
May.	120	242	113
Jun.	102	206	105
Jul.	84	158	91
Aug.	104	165	81
Sep.	166	198	110
Oct.	119	104	73
Nov.	112	49	64
Dec.	104	47	58
Average	125	156	91

Limitations and Future Research Directions

In this chapter, the limitations of the proposed reinforcement learning-based solar irradiance decomposition model are discussed, along with future research directions to overcome these limitations. Firstly, the study operated under the assumption of limited data availability, resulting in the agent being trained on a very minimal dataset spanning only two weeks. To objectify the model's performance, it is essential to undertake training and evaluation under a more diverse range of meteorological conditions. Currently, the model utilizes data from only the first two weeks of January, regardless of seasonal and weather conditions. In future research, the model will be tested under various conditions, including clear and cloudy days, summer and winter seasons, and using training data spanning more than two weeks. Additionally, while the current evaluation of the model is confined to a single location, future studies will necessitate the evaluation of the model across regions with diverse climatic conditions.

Conclusion

This study proposes a reinforcement learning method that learns from the errors of existing solar decomposition models to predict future scattered solar radiation, a critical input for predictive control of buildings. The proposed model assumes a building environment where it is typically challenging to obtain scattered solar radiation and learns from approximately 14 days of data to predict the diffuse horizontal irradiance for the upcoming year without further updates. To compare its effectiveness, an Optimized model, which directly modifies the coefficients of the model using traditional optimization techniques, was also developed and evaluated alongside the proposed model.

The Optimized model exhibited improved performance compared to the traditional Watanabe model under weather conditions similar to the training period. However, it demonstrated significant errors in different weather conditions, leading to reduced effectiveness in annual predictions. In contrast, the Reinforcement Learning (RL) model employed an agent trained to learn the specific error patterns of the Watanabe model under certain meteorological conditions. This approach resulted in consistently enhanced performance compared to the Watanabe model, regardless of the prediction timing. This indicates that the Watanabe model consistently overestimates the diffuse solar radiation throughout the period, and the agent learned this characteristic to take actions that offset the errors of the Watanabe model. The proposed model, despite only using limited data from 14 days and parameters easily obtainable from weather forecasts and solar geometry calculations, suggests a reinforcement learning method that comprehends the characteristics of traditional direct solar decomposition models, enabling it to depict the annual pattern of Diffuse Horizontal Irradiance. This study serves as an initial exploration into simplified models for calculating diffuse solar radiation for the application of Model Predictive Control. It is anticipated that the model's accuracy will improve as more detailed predictive information becomes available from weather forecasts and as more abundant solar radiation data is collected for model training.

Nomenclature

DHI	Diffuse horizontal irradiance
DNI	Direct normal irradiance
GHI	Global horizontal irradiance
DQN	Deep Q-learning
MPC	Model predictive control
PSO	Particle swarm optimization
RL	Reinforcement learning
K_t	Daily clearness index
I	Solar irradiance [W/m^2]
KDS	Diffuse irradiance rate
R_t	Reward
$DHI_{mesured,t}$	Measured DHI over time t [W/m^2]
$DHI_{test,t}$	Predicted DHI over time t [W/m^2]

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