Spatio-Temporal Distributed Solar Irradiance and Temperature Forecasting

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***Abstract*— Integration of large-scale renewable energy plants to the power system is a challenge as the power generation is variable, and energy management systems require accurate prediction of weather parameters applicable to the sustainable generation of the renewable resources. Frequency control, economic dispatch and unit commitment problems in power system operations depend on forecasted renewable energy generation and power consumption as the renewable energy penetration increases. The weather measurements for this study were taken from four weather stations located on Clemson University buildings. Due to the lack of sustaining winds, wind power is not an option in the area. Therefore, solar irradiance and temperature are considered as the parameters that affect the power system operation. In this paper, computational approaches implemented in Cellular Computational Networks (CCNs) are discussed. CCN is effective in weather parameter estimation due to its capability to simultaneously capture spatial-temporal characteristics of the respective weather parameter. CCN predictions are compared against their temporal counterparts. In this paper, particle swarm optimization (PSO) based computational unit input selection is discussed.**

***Index Terms*— Cellular computational networks, spatial-temporal characteristics, solar irradiance prediction, temperature prediction**

I. Introduction

Weather predictions are required for operations that are affected by weather variations such as agriculture and power system control. For agriculture, long term predictions are more suitable and short term variations does not create a huge impact unless it is an emergency weather condition. However, the power system control function is both affected by long term and short term weather variations. Weather parameters such as rainfall, wind speed and solar irradiation affect the power system functions such as annual generator maintenance schedule and power generation planning in long-term. With the increased weather dependent renewable energy generation in the power system, the impact of short term weather variations to the power system reliability has become high.

A study done by National Renewable Energy Laboratory (NREL) [1] on the impacts of variability and uncertainty of solar photovoltaic generation has shown that the improved day-ahead PV forecast reduces production costs with only a little effect on the load-generation balance. The NREL report further concludes that a faster dispatch (5-minute) frequency can provide more economic gain in solar PV integration than conventional 1-hour intervals. Therefore, short term predictions have a stronger impact to the power system with the uncertainty in weather parameters. Temperature is also an important weather parameter for energy management function of the power system. This is due to its impact on the load. The heating and cooling loads of the power system depends on the ambient temperature. Solar irradiance and temperature are increasingly becoming important weather parameters in load centers. The 'duck-curve' [2] is one of the challenging consequence of increasing solar power penetration. Therefore, predictability of solar power generation and ambient temperature related electric load consumption could be advantageous for the energy management of load centers with a high solar power penetration.

Physical model based weather parameter predictions such as Numerical Weather Prediction (NWP) and statistical methodologies such as neural networks are used in literature to develop weather prediction tools. In [3], 1 minute rain distribution is predicted with numerical weather prediction data. Challenges in NWP in complex terrains are discussed in [4]. In [5], weather forecasting analysis of different connectionist and statistical models is done. The authors have implemented multi-layer perceptron (MLP), elman recurrent neural network (ERNN) and radial basis function network (RBNN) to analyze the efficiencies of wind speed and temperature forecast.

NWP based forecasts evaluates physical properties of the terrain in a fine resolution in order to infer predicted weather parameters. However, a typical statistical weather prediction does not use sufficient spatial information to improve predictions. This drawback can be compensated by the use of a cellular computational networks (CCN) [6,7] which can

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integrate a number of weather prediction stations effectively. It can communicate spatial data among the stations in the network in order to increase the spatial awareness.

In [8], prediction of solar irradiance of utility scale solar PV plants are discussed. An echo state network (ESN) based CCN of the solar irradiance sensors is used to predict the solar irradiance for very short term predictions. In [9, 10], the authors describe a number of computational approaches entailing the use of neural networks including CCNs for wind speed prediction using spatio-temporal wind speed and wind direction. The authors analyzed wind speed predictions of 15 minute, 30 minute and one hour ahead for possible applications in economic dispatch of power systems with wind plants. Wind speed predictions are done using multilayer perceptron and recurrent neural networks as computational units of the CCN.

Human brain consists of billions of neurons without permanent connections. Our learning involves making and breaking of synaptic links among neurons in our brain. Researchers have made effort in demonstrating this phenomenon in learning systems. In [11], author discusses a number of learning systems which possess evolving connections as oppose to permanent synaptic weights. An evolving self-organizing map is discussed in [12]. In [13], evolving fuzzy neural networks are introduced and they are capable of adapting the network structure and the functionality.

CCN based short term solar irradiance and temperature predictions are presented in this paper. Multilayer perceptron neural network architecture is used in developing CCN. The rest of this paper is structured as follows. CCN architecture is discussed in Section II. The hardware setup of the weather stations located around Clemson University is discussed in Section III. Computational units of the CCN is presented in Section IV. In Section V, particle swarm optimization based CCN input optimization approach is discussed. Results and discussions are provided in Section VI and concluding remarks are made in Section VII.

The main contributions of this paper are as follows:

1. Multi-time horizon solar irradiance and temperature predictions using CCN
2. Input selection of the CCN using PSO.

II. CELLULAR COMPUTATIONAL NETWORK (CCN)

Cellular computational network is a distributed and scalable architecture for studying complex interconnected systems [6]-[7]. Spatially distributed large solar power plants and weather dependent power system load can be modeled using CCN in predicting weather, energy generation and power consumption. The CCN utilizes spatial-temporal information of the power stations in predicting solar irradiance and temperature.

A CCN consists of connected cells, where each cell represents a distinct component in the system. A cell consist of a computational unit, a learning unit and a communication unit. The computational unit is chosen based on the purpose of the CCN designed. Computational intelligence (CI) paradigms such as, neural networks, fuzzy logic, swarm intelligence and evolutionary algorithm approaches are more suitable in implementing the computational unit.

The purpose of the computational unit is to produce an output by utilizing available information. The learning unit improve the performance with time by learning from historic data. The communication unit facilitates the communication among interconnected cells. The unit includes input/output interface for sending and receiving information from the other cells. The connectivity among the cells is defined based on the structure of the system.

In this study, two CCNs are implemented to predict the solar irradiance and temperature in spatially distributed weather stations. Neural networks have been used as the computational unit of each cell. Section IV describes the neural network architectures implemented in CCNs.

III. HARDWARE SETUP

Weather stations are located in four locations around Clemson University and broadcast weather information to real-time power and intelligent systems (RTPIS) laboratory through internet. In RTPIS lab the weather prediction is done using CCN framework. Each weather station sends the following weather data:

$$L_i(t) = [Ir(t)_i, T_i(t), W_i(t), D_i(t)] \tag{1}$$

where $L_i(t)$, $Ir_i(t)$, $T_i(t)$, $W_i(t)$ and $D_i(t)$ are weather parameters, solar irradiance, temperature, wind speed and wind direction of location i at time t respectively.

Fig. 1 shows the hardware setup of weather stations using TCP/IP protocol and the stacked predictions of solar irradiance and temperature. Spatial distribution of the weather stations is also depicted. Wind speed prediction is infeasible due to the erratic nature in measurements.

IV. COMPUTATIONAL UNITS IN CCN

The computational units are homogeneous [6] in construction for the purpose of multi-location weather predictions. The inputs of all the computational units of a weather parameter are common and comprises of spatial and temporal information of the respective weather parameter. The proposed framework can easily be scaled up to a higher number of weather stations as each cell is capable of learning spatial dynamics without the knowledge of the internal units of the neighboring cells. Only respective weather parameters of the neighboring cells are used to extract spatial dynamics.

In this study, the performance of two neural architectures are compared, namely, multilayer perceptron (MLP) and Elman recurrent neural network. The MLP neural network is designed to have two time delayed inputs addition to the current time inputs to constitute the temporal information in the network. In Fig. 1, the neural network computational unit of a weather parameter prediction of site 1, when all the cells are connected with all the neighbors, is depicted. The computational unit is implemented as a multilayer perceptron with ten hidden layer neurons. The inputs are indicated at each input neuron. $\hat{y}_i(k)$ is the predicted parameter for location i at discrete time k, $y_i(k)$ is the measured parameter for location i at discrete time k and Δ is the prediction horizon.

It could be inefficient to use all the cells as neighbors due to potential uncorrelated cells and added computational burden. Therefore, measures are taken to optimize the cell inputs as discussed in the next section.

V. CCN Configuration Optimization

The communication unit of cells configure the input/ output connectivity of the CCN framework. In [9,10], a homogeneous cell connectivity is considered. It could be effective for small amount of cells. However, as the cell population grows, it could be ineffective in prediction accuracy as well as inefficient in computations. Therefore, a heterogeneous cell network is studied in this paper.

In a cellular network with n cells and m possible input parameters, there are $2^{m\times n\times(n-1)}$ possible input combinations for all the cells. It is challenging to determine the optimal cell configuration when n *and* m increase. In this study, a binary particle swarm optimization (BPSO) algorithm [14] is implemented to choose the optimum network connections.

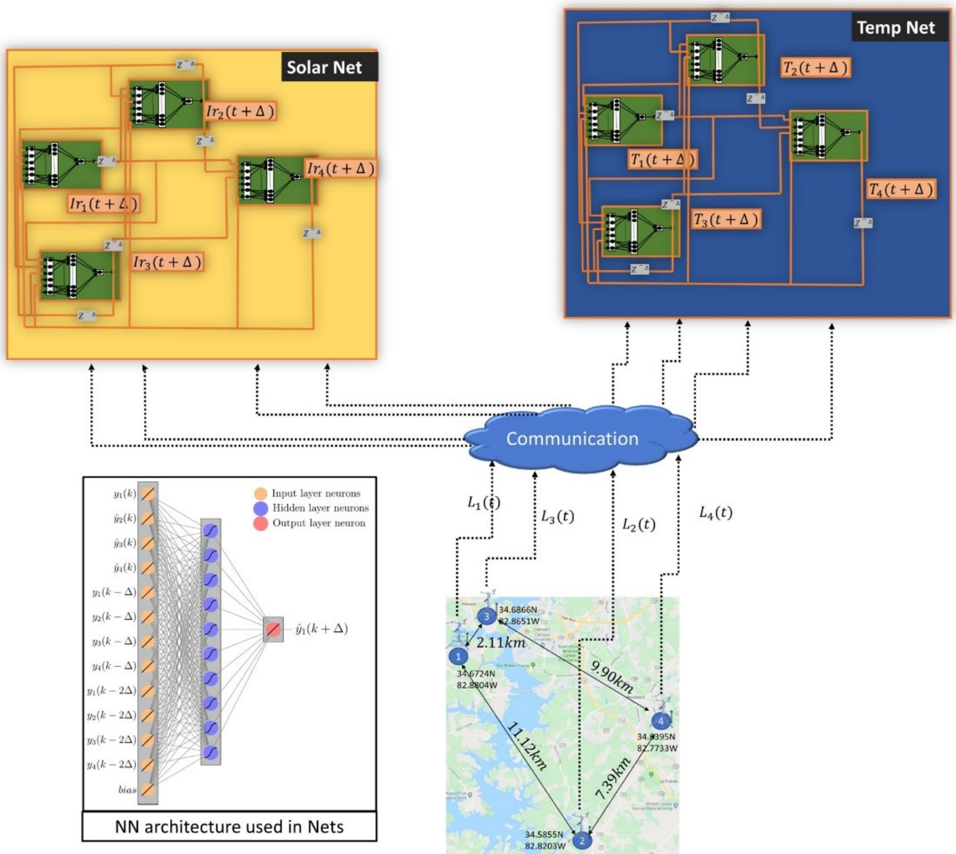


Figure 1. Spatial distribution of the weather stations.

BPSO[15] algorithm is an adaptation of the Particle Swarm Optimization algorithm for the discrete scenario. PSO is a nature-inspired algorithm that mimics a flock of birds to carry out its optimization. BPSO employs a set of *particles* spread through the search space each of which computes the objective value at its current location. These particles would move through the search space at each iteration according to two main equations of PSO.

A particle would initiate itself at a random location of the search space initially and would retain two major pieces of information as it moves. First, it would memorize the *'personal best'*, the best objective value the particle has calculated during all iterations so far and its location. Second, it would maintain a *'velocity'* using which, the next location of the particle in its next iteration to be decided. The velocity of each particle is calculated using the following formula:

$$V_{d,t+1}^{k} = w_t^k \times V_{d,t}^{k} + c_1 \times rand_{1,d,t}^{k}\left(X_{p,d,t}^{k} - X_{d,t}^{k}\right)$$
$$+c_2 \times rand_{2,d,t}^{k} \times (X_{g,d,t}^{k} - X_{d,t}^{k}) \qquad (2)$$

Here, $V_{d,t}^{k}$ is the velocity of the dth dimension of the kth particle at iteration t. w_t^k is the *'inertia'* of the kth particle at iteration t. In the current study, the inertia value is chosen to start at 0.9 and then linearly reduce to 0.4 at the end of the set number of iterations. c_1 is the *'cognitive constant'* and c_2 is the *'social constant'* for the PSO system. These values are generally set to values between 1 and 2. $rand_{1,d,t}^{k}$ and $rand_{2,d,t}^{k}$ are random values between 0 and 1 generated at each iteration. $X_{d,t}^{k}$ is the current location of the particle. $X_{p,d,t}^{k}$ is the current personal best and $X_{g,d,t}^{k}$ is the current *'global best'*. That is, the location of the best objective value found so far by any particle in the system. At the beginning the velocity of every particle is initiated to zero.

The next position each particle moves to in the next iteration is decided in BPSO by calculating a value between 0 and 1 using the velocity and comparing it with a generated random value. The function used to convert the velocity to a value between 0 and 1 in this study is the log-sigmoid function. Since the next position of each dimension can only be either 0 or 1 for binary PSO, the next location is decided as follows:

$$X_{d,t+1}^{k} = \begin{cases} 1, & rand_{3,d,t}^{k} - \frac{1}{1+e^{V_{d,t}^{k}}} \leq 0 \\ 0, & rand_{3,d,t}^{k} - \frac{1}{1+e^{V_{d,t}^{k}}} > 0 \end{cases} \quad (3)$$

Fig. 2 illustrates the flowchart of the BPSO algorithm. A particle of the BPSO algorithm corresponds to a possible input selection for the cells. Therefore, each dimension would correspond to the selection/ omission of an parameter that is available for the cells. The fitness function of the BPSO is as follows:

$$fitness = -\sum SF_i \quad (4)$$

$$SF_i = \left(1 - \frac{MAPE_{i,prediction}}{MAPE_{i,temporal}}\right) \quad (5)$$

where SF_i is the skill factor (SF) of the i^{th} weather station's measurements and MAPE is the mean absolute percentage error. SF compares the predictions with the temporal predictions, which uses only temporal parameter values. The temporal reference is used to measure the capability of CCN in inferring spatial trending which is absent in the temporal network.

As it could be seen from Fig. 1, weather stations are located irregularly which is similar to the practical situation due to the constraints in siting.

The challenge is to infer weather predictions from the available weather measurements and previous predictions. The irregularly distributed weather stations suggest different spatio-temporal correlation among the weather stations. Three different time horizon predictions are studied in this paper to investigate the spatial correlation's dependence on the prediction time horizon. The prediction time horizons considered are 5-minute, 10-miinute and 15-minute.

VI. Results and Discussion

The data used for this study is extracted from four sites shown in Fig. 1. The input data is measured in five second intervals. However, the data is averaged over a one-minute time period to filter the noise. The data samples received in the server computer needs to be synchronously generated. Therefore, an hourly time reset done in each data logger according to network time protocol [16].

The optimum inputs selected by the BPSO algorithm for 5, 10 and 15 minute ahead predictions of solar irradiance and temperature are shown in Fig. 3. Value one in squares indicate a contribution from a site to the prediction of a cell. Eg:- for the 5 minute ahead solar irradiance predictions of cell 1, site 2 and 4 data are used. Site 3 is less frequently used. In Fig. 1, it could be seen that sites 1 and 3 are closely located. Therefore, this result could be due to non-availability of new information to infer from site 3. On the other hand, for cell 2 predictions, none of the other sites are dominantly contributing. It is clear from the figure that site 2 is quite isolated from other sites.

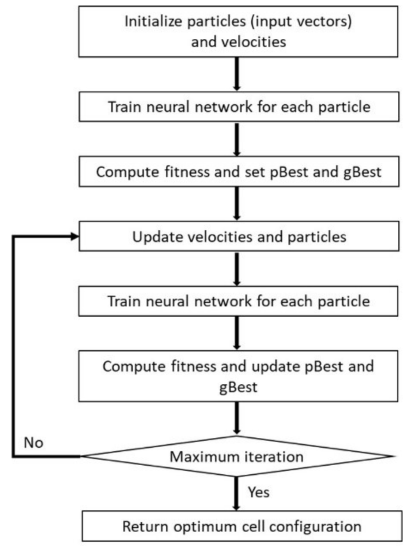


Figure 2. Flowchart of the PSO based optimum cell configuration estimation.

Predictions			Inputs			
Cell	Parameter	Time Ahead	Site 1	Site 2	Site 3	Site 4
Cell 1	Solar	5 min	1	1	0	1
		10 min	1	1	0	1
		15 min	1	1	0	1
	Temperature	5 min	1	0	1	1
		10 min	1	1	0	1
		15 min	1	1	1	0
Cell 2	Solar	5 min	0	1	0	0
		10 min	1	1	0	1
		15 min	0	1	0	1
	Temperature	5 min	0	1	0	1
		10 min	0	1	0	0
		15 min	0	1	1	1
Cell 3	Solar	5 min	0	0	1	1
		10 min	0	1	1	1
		15 min	1	1	1	1
	Temperature	5 min	1	0	1	0
		10 min	0	1	1	1
		15 min	0	1	1	1
Cell 4	Solar	5 min	0	1	0	1
		10 min	0	0	0	1
		15 min	0	1	0	1
	Temperature	5 min	0	0	0	1
		10 min	0	0	1	1
		15 min	0	1	1	1

Figure 3. The optimum input combinations for predictions

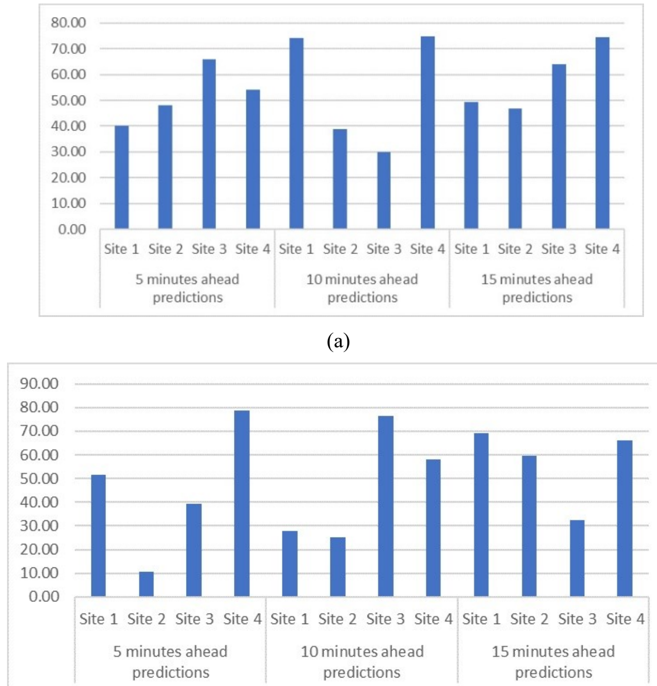
Cell 3 predictions have the least contribution from site 1 and most of the contribution from sites 2 and 4. It is consistent with the observation in cell 1 predictions. Cell 4 predictions does not have much contribution from other sites with some predictions having inputs from sites 2 and 3 measurements. The evolution of the PSO global best is shown in Fig. 9 for solar irradiance and temperature prediction networks.

To compare the performance of the predictions, Skill Factor and MAPE values are used. The MAPE of CCN and temporal predictions are shown in TABLE I. Relevant SFs of CCN predictions are shown in Table II which are calculated using (5). Graphical representations of 15- minute ahead predictions of solar irradiance and ambient temperature depicted in Fig. 5 and 6 respectively.

The weather stations used for this study are located approximately 1.5m above a building. Therefore, the turbulence created due to the closeness to a surface makes the wind speed measurements changing too fast. Such fast changes cannot even be filtered by taking the average over one minute period. On the other hand, cut in speed of a typical wind turbine is 3-4 ms^{-1}. As it could be seen in the wind speed curves, none of them surpass 3 ms^{-1}. Therefore, wind speed is not a significant weather parameter for the chosen area as far as distributed energy resources are considered.

Solar irradiance is more dependent on time of the day, day of the year and clearness of the atmosphere. The clearness of the atmosphere is measured in terms of clearness index. Data used for this study were recorded in November, 2019. The clearness index for the month of November in Clemson and surrounding area is 0.51 [17]. Temperature is also a result of solar irradiance, the cloud cover and wind. However, the temperature variation is lower compared to the solar irradiance due to the 'thermal inertia' of the air mass and low wind speeds in Clemson and suburbs.

A comparison of the skill factors is depicted in Fig. 4. A positive skill factor indicates better prediction capability of spatio-temporal (CCN) compared to temporal networks. For solar irradiance prediction, sites 1 and 4 have the best SF in 10 minutes ahead prediction while sites 2 and 3 have the best SF in 5 minutes ahead predictions. For temperature prediction, sites 1 and 2 have the best SF in 15 minutes ahead prediction, site 3 has the best SF in 10 minutes ahead prediction and site 4 has the best SF in 5 minutes ahead predictions.



(a)

(b)

Figure 4. Comparison of prediction SFs of (a) solar irradiance and (b) temperature.

TABLE I
MAPE OF THE WEATHER PREDICTIONS USING SPATIO-TEMPORAL AND TEMPORAL NETWORKS

Weather Parameter	Predictor	5 minutes ahead predictions				10 minutes ahead predictions				15 minutes ahead predictions			
		Site 1	Site 2	Site 3	Site 4	Site 1	Site 2	Site 3	Site 4	Site 1	Site 2	Site 3	Site 4
Solar Irradiance	Spatio-temporal	0.0237	0.0643	0.0259	0.0104	0.0218	0.0876	0.0413	0.0096	0.0193	0.0832	0.032	0.02
	Temporal	0.0397	0.1241	0.0761	0.0227	0.0841	0.1432	0.0591	0.0383	0.0382	0.1568	0.0889	0.0783
Temperature	Spatio-temporal	0.0239	0.0254	0.0185	0.0367	0.0499	0.0432	0.0357	0.0497	0.0551	0.0588	0.0448	0.059
	Temporal	0.0494	0.0284	0.0305	0.174	0.0692	0.0576	0.1506	0.1188	0.1786	0.146	0.0663	0.1733

TABLE II
SF OF THE WEATHER PREDICTIONS USING SPATIO-TEMPORAL NETWORKS

Weather Parameter	5 minutes ahead predictions				10 minutes ahead predictions				15 minutes ahead predictions			
	Site 1	Site 2	Site 3	Site 4	Site 1	Site 2	Site 3	Site 4	Site 1	Site 2	Site 3	Site 4
Solar Irradiance	40.30	48.19	65.97	54.19	74.08	38.83	30.12	74.93	49.48	46.94	64.00	74.46
Temperature	51.62	10.56	39.34	78.91	27.89	25.00	76.29	58.16	69.15	59.73	32.43	65.95

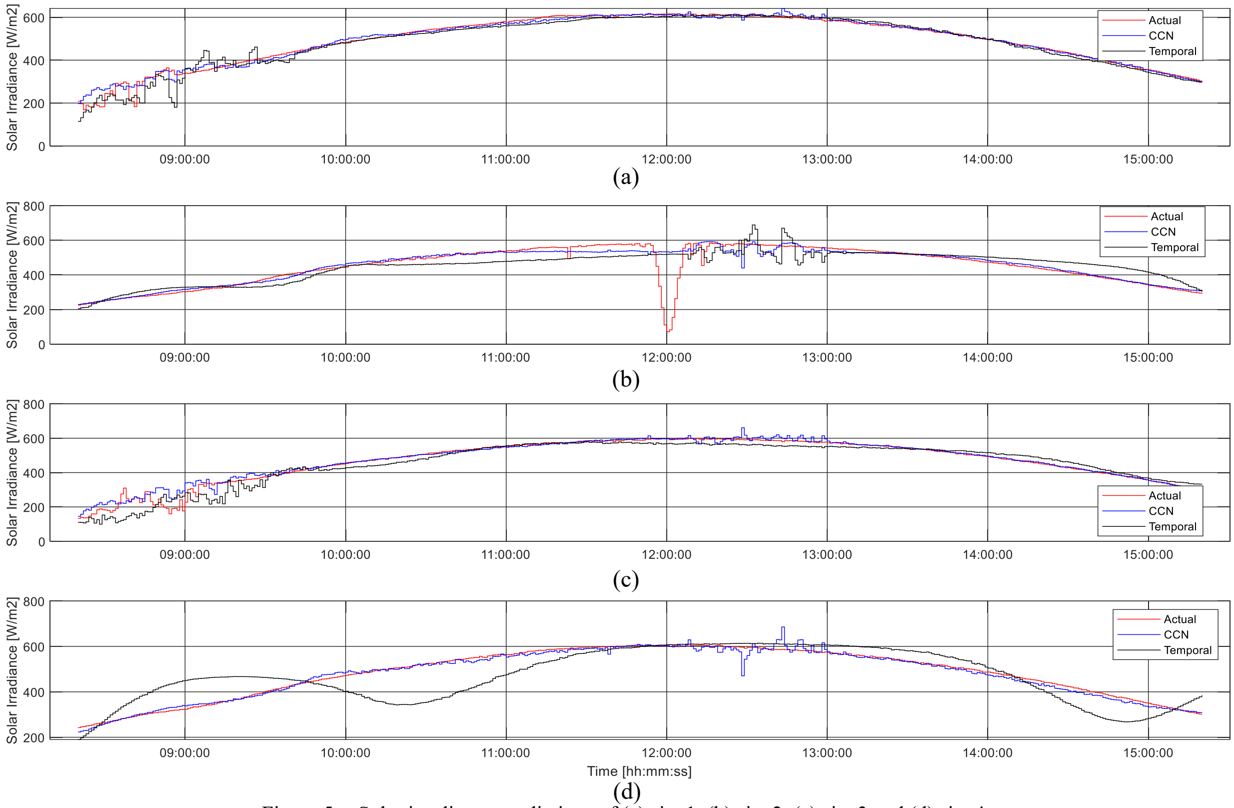


Figure 5. Solar irradiance predictions of (a) site 1, (b) site 2, (c) site 3 and (d) site 4.

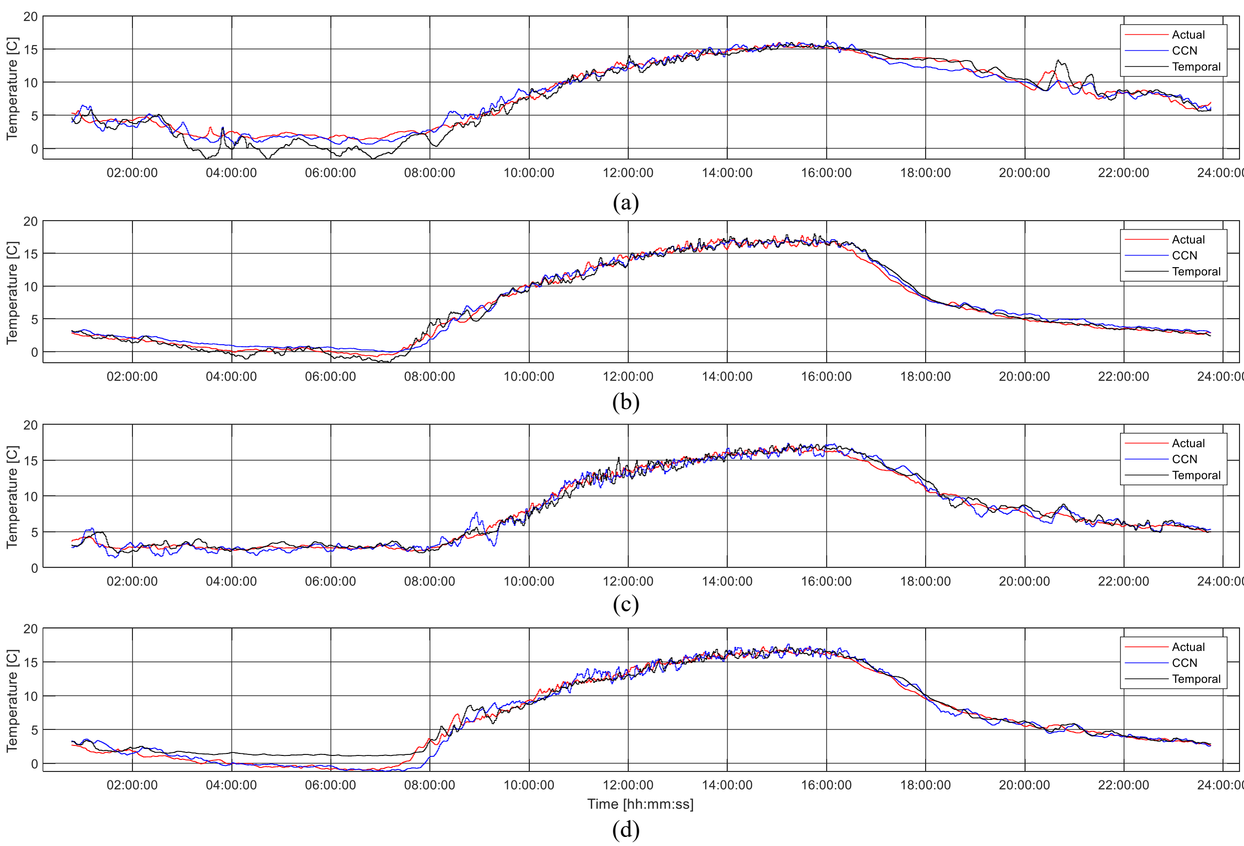


Figure 6. Temperature predictions of (a) site 1, (b) site 2, (c) site 3 and (d) site 4.

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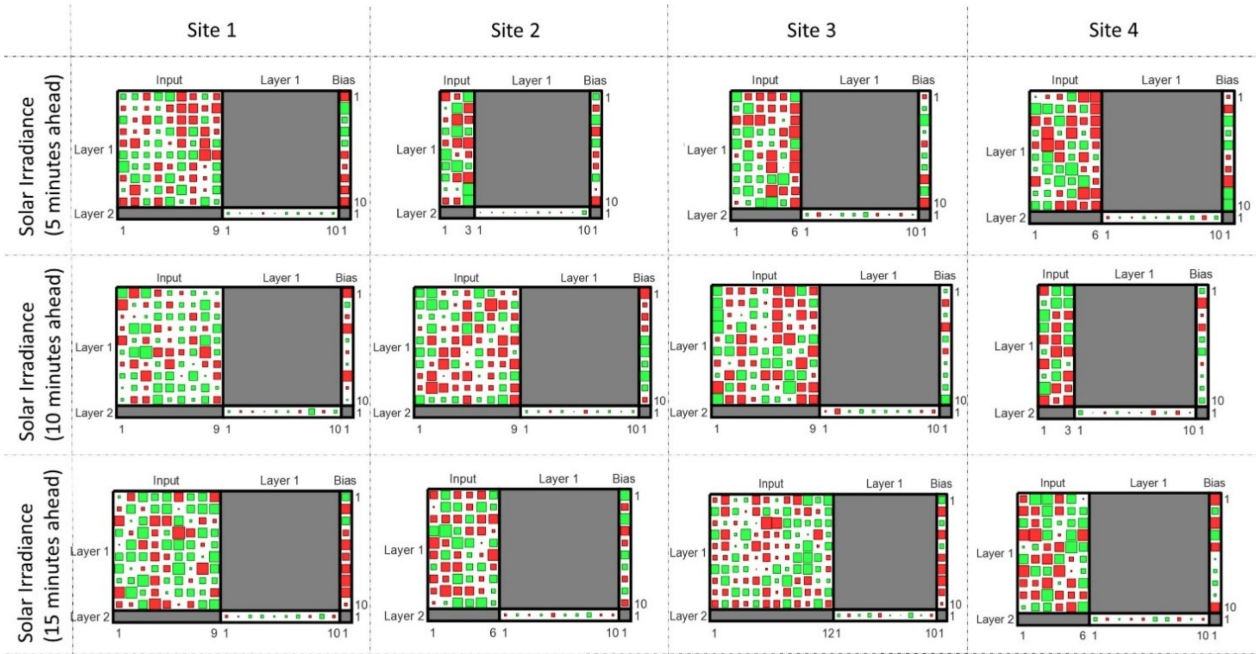

Figure 7. Hinton maps of solar irradiance predictions.

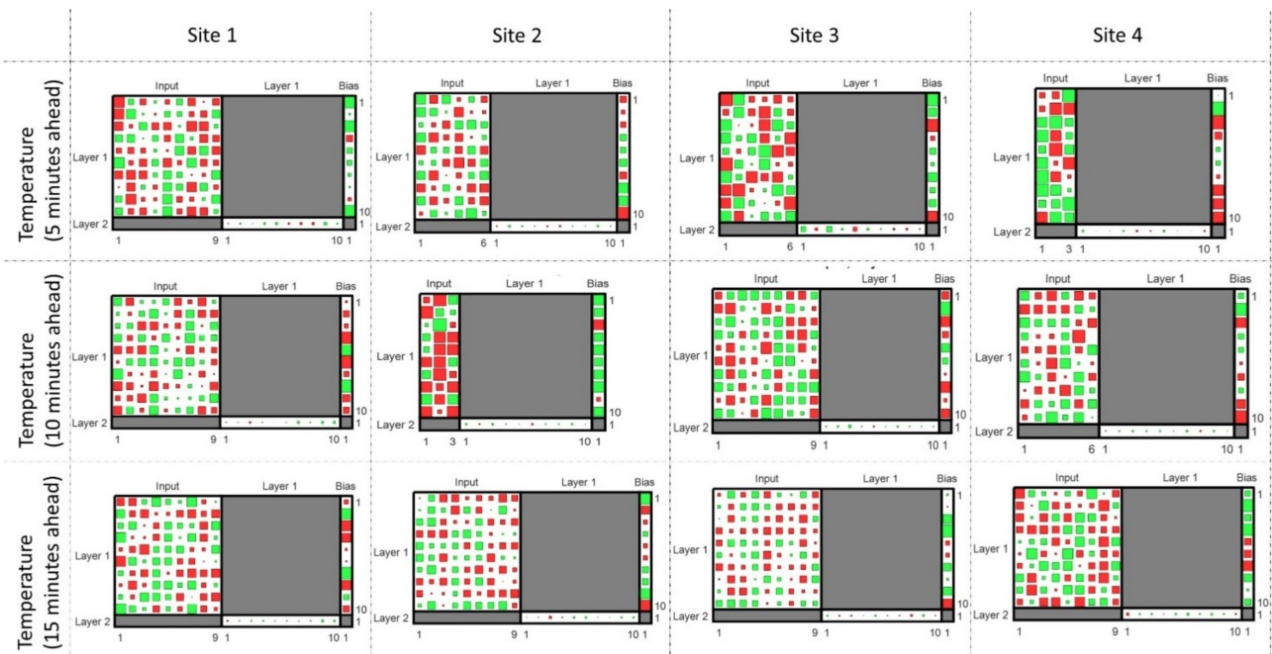

Figure 8. Hinton maps of temperature predictions.

Hinton maps of the neural networks are shown in Fig. 7 and 8. Positive weights are shown in green and negative weights are shown in red. Inputs are organized as shown in the computational unit depicted in Fig. 1 and the inputs contributing to the predictions can be viewed in Fig. 3.

VII. Conclusion

In this study, effectiveness of CCN in weather parameters, namely, solar irradiance and temperature are examined. Weather station sites are located around Clemson University and weather measurements are brought to the RTPIS lab located in the Riggs building.

A binary particle swarm optimization algorithm is implemented to find the optimum input combinations of the cells. Predictions for 5, 10 and 15 minutes ahead predictions studied to check if there is a pattern in parameter correlation and prediction accuracy. A PSO algorithm is used to select the optimum inputs of the CCN computational units.

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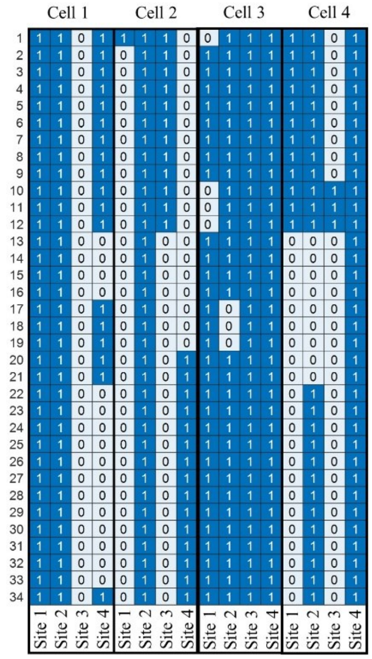
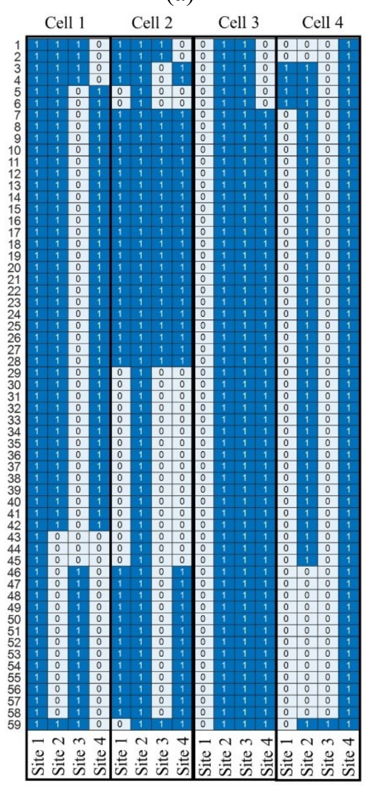


(a)



(b)

Figure 9. Evolution of best input combination for (a) solar irradiance and (b) temperature CCNs..

Temperature measurements have low variations and solar irradiance measurements have the highest variation.. However, CCN predictions of solar irradiance and temperature measurements could outperform temporal predictions.

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