Online Sensorless Solar Power Forecasting for Microgrid Control and Automation

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Abstract— **Meteorological conditions such as air density, temperature, solar radiation etc. strongly affect the power generation from solar, and thus, the prediction and estimation process should consider weather conditions as critical inputs. The nature of weather forecast is highly unpredictable, so many applications use meteorological data from in-place on-site sensors to add to the forecast and some use complex networks with complicated mapping. The in-situ sensor approach and dense mapping methods, however, present several drawbacks. First, the use of sensors give rise to extra operational, installation and maintenance cost. Second, it requires significant amount of time to capture and accumulate data for various occasions and scenarios, and in addition, sensor itself can be the cause of error measurements. The complex methods are computational inefficient and may present suboptimal convergence. This paper presents a sensorless solar output power forecasting based on historical weather (publicly available from met office) and PV data. The algorithm uses simple to implement neural networks with few neurons and hidden layers for its training and allows for day a head forecast. The proposed methodology presents a guideline on how to select the relevant data from weather and how it affects the accuracy and training time of neural network. The benefit of developed method is an improvement on the energy management, utilization and reliability of the microgrid.**

Keywords—Solar forecasting, microgrid control, energy management, neural network

I. INTRODUCTION

The increasing installation and integration of renewable energy sources (RESs) and their intermittent and largely unpredicted nature along with their dependence on weather conditions affect the power flow and overall operation and control of electricity grid, especially at microgrid level. Thus, it is important to have appropriate monitoring and control system for the effective operation, control, management and distribution of energy sources, maintaining in this way power balance and stability of the network. In microgrids, this may also help in attaining significant energy autonomy and savings [1, 2]. Appropriate algorithms are therefore required to provide knowledge of future power generation from renewables so as to decide in advance on the switching of back-up systems, e.g. demand side management, and also defer costly system upgrades by effective and intelligent utilization of available energy sources.

Forecasting thus plays a very important role for the optimal scheduling of energy management and power flow and consequently, the control and automation of energy sources in a microgrid. It helps in improving the efficiency and reliability of the microgrid. Several forecasting methods are published in the literature and these are mainly divided into statistical, physical, machine learning and hybrid techniques [3, 4]. In physical methods (PMs), the physical state (such as features of topographical site) and environmental variables (such as atmospheric and climate parameters) are used along with historical data to predict and estimate the forecasted solar radiation [5, 6]. The accuracy and stability of these methods are directly affected by the weather conditions [7] and are computationally inefficient [8]. The statistical methods, such as exponential smoothing [9], multiple-regression [10], auto-regressive integrated moving average (ARIMA) [11] and auto-regressive moving average (ARMA) [12] provide good performance accuracy in the range of few mins to hours of forecasting horizon. However, due to fixed parameters they are not robust to sudden changes in weather conditions and are not equally accurate for long term forecasting. There have been several attempts to increase the estimation accuracy and reduce the demand on computational power by considering current weather input data and errors from past predictions by using feedback. The Statistical Methods (SM) are still improving to achieve better accuracy and lower computational memory. Machine learning (ML) algorithms (such as neural networks and space vector machine [13]) are becoming widespread methods in several applications.

In this paper, the focus is employing artificial neural network (ANN)-based solar power forecasting. The neural network estimation techniques can be divided into sensor and sensorless approaches. The authors in [14] uses the onsite data for temperature and solar radiation (recorded for 30 days) to predict the solar power forecasting for one-hour ahead. The model used consists of a prediction network based on ANN and wavelet transform. Likewise, Elman network-based day-ahead solar forecasting is used in [15] and utilizes the temperature and total solar irradiance measured on-site. A feedforward neural network in [16] predicts the solar irradiance for a horizon of one month using a 10-neuron based single neuron layer. The dataset used for training is based on on-site historical irradiation accumulated for the past 15 days. The authors in [17] uses lidar and in-situ camera to record and accumulate the information for wind and cloud cover for training a feedforward ANN. This method predicts the solar for a forecast horizon of up to 15 mins. The cleansing and pre-processing of on-site metrological data for high-frequency disturbances based on wavelet decomposition and later using it to train a single layer neural network is presented in [18]. A backpropagation 3-layered neural network trained and updated using in-situ 25-days scrolling window data for temperature, solar irradiance, and humidity is discussed in [19]. The hidden layers use 50, 30 and 1 neurons respectively and is suitable for forecasting over a year.

Work relying on in-situ sensors is also published in the literature. The authors in [20] uses a combination of Fuzzy and recursive NN for enabling the prediction of solar based on month of weather training data such as humidity and cloud. A PV forecasting for 24-h horizon using online weather forecast service has been discussed in [21] where each weather type uses a self-organized map and 3-layer radial basis function along with a single hidden layer. Prediction of PV power for day-ahead using historical weather data and clear sky model has been discussed in [22]. A comparison among single and double layered ANN showed that the single layer having 120 neurons presented better performance than double layer. Furthermore, authors in [23] combined social network optimization (SNO) with ANN using the clear sky model enhancing in this way the prediction accuracy. The Deep Neural Network (DNN) suggested in [24] uses neural network with many number of hidden layers and neurons to predict the PV forecasting, which makes the system complex. In addition, five weather inputs are used (month of year, hour of the day, cloud cover, temperature and relative humidity) and also the input representing the solar irradiation is ignored. However, in this paper, the number of inputs have been reduced with an increased accuracy measured in terms of MAE (compared to one in [24]).

The work presented in this paper does not rely on in-situ sensors and uses only the historical data for network training and prediction of solar power. Furthermore, a feedforward network with less inputs (2) and lower number of neurons (20, 30, 10) in three hidden layers are employed. The intermittent nature of weather is captured by training the network using historical data with a time resolution of 1-h and 1-year of data length.

The rest of the paper is organized as follows: Section II discusses the conventional approach for solar forecasting. The proposed algorithm is presented and discussed in Section III. Section IV presents and analyse the results obtained. Section IV gives a brief discussion on the impact of forecasting on the automation and control of microgrids. Finally, the paper concludes in Section VI.

II. Conventional Approach for Prediction

The conventional systems typically uses a two-level methodology [21]. In the first stage, the measured on-site data for irradiance (G_t^h) is used to develop its mapping and relationship with the historic weather forecasted data (W_t^h) for a particular region and specific forecasting horizon, h. This results in a trained irradiance forecast model G'_{mdl} at time t given in (1).

$$Trained\ model \Longrightarrow G'_{mdl} = G'_{mdl}(G_t^h, W_t^h) \qquad (1)$$

In the second level, at time $t'' > t$, the developed relationship is used conversely to estimate the forecasted irradiance $G_{t''}^{h\prime}$ based on the weather forecast at the new time t'' and results in the irradiance from the best match to the historical data.

$$G_{t''}^{h\prime} = G'_{mdl}\left(W_{t''}^h\right) \qquad (2)$$

Finally, once the forecasted irradiance $G_{t''}^{h\prime}$ is estimated, the PV output power is calculated using the PV physical model [25].

$$P_{t''}^{h\prime} = f^{sas} A^{sf} G_{t''}^{h\prime} \eta^C \eta^{cell} \qquad (3)$$

where, f^{sas} represents the surface area fraction for active solar cells, A^{sf} is the solar panel total surface area (m^2), η^C is the conversion efficiency of DC to AC converter and η^{cell} is the efficiency for cell.

The conventional method uses sensory data in order to enable training of G'_{mdl}, thus it requires installing various on-site sensors at each facility resulting in installation, operation and maintenance costs [26, 27]. Furthermore, another issue with conventional method is that it requires efforts and long time for the accumulation sufficient data and its pre-processing for the accurate and desired training of forecasted model. In this paper, using neural network, fast and accurate of estimation of solar output power is enabled with fewer number of inputs from the weather and without employing on-site sensors.

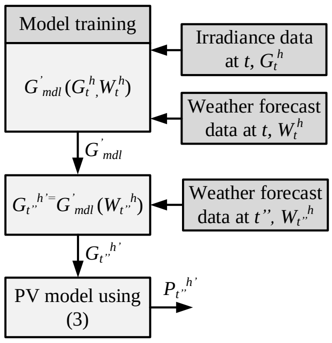

Fig. 1: Conventional approach towards forecasting.

III. Proposed Forecasting Algorithm

The proposed neural network based sensorless concept for solar power forecasting also considers PV historic data and weather parameters, but is much less-complex than conventional methods, hence it is called Less-Complex Neural Network (LCNN). The algorithm employs a smaller number of inputs as well as exhibits less implementation complexity than the intelligent methods, and does not involve sensor and hence lower cost as compared to conventional forecasting. The reduction of inputs to the neural network is desirable to overcome the various issues for the developed algorithm that arises from using excess input parameters. These issues include the training of neural network that requires excessive time, especially for fully interconnected neurons in the network. Also, it increases the risk of suboptimal convergence for error function due to the presence of large number of local optimum values [28]. Further, to enable the precise interconnection and mapping of involved parameters, densely populated data sets are required [29]. The proposed algorithm uses less inputs and small data sets, which makes the computational requirement less complex and implementation more viable whilst improving the forecasting accuracy. Therefore, the analysis presented focuses on choosing the most dominant weather input parameters that affect the performance of algorithm and present better accuracy with less complexity. The proposed algorithm provides increased accuracy with smaller size and minimal data.

Solar power generation is heavily influenced by weather conditions, which have coarse granularity and unpredictable nature, and this is critical to the prediction performance. Thus, to make the algorithm robust to variations in weather, a design methodology is suggested to determine the best combination of weather inputs for desirable estimation performance and accuracy based on historical data. In other words, an intelligent training, using the most dominant weather parameters, is incorporated in the training phase to increase accuracy and present good estimation to future variations.

A neural network is developed and trained for several inputs, year information, and different data sizes. The model of neural network presents a non-linear behaviour with a set of input, output and hidden layers, as shown in Fig. 3. The input layer is used to capture the incoming data (such as weather and PV historic data) and the hidden layers involve the process of learning from the captured data with several interconnected neurons. The output layer uses the information from input parameters, via hidden layers, and generates the corresponding output for a specific set of input values. A linear 'pure line' neural unit is used as an activation function for the output layer to calculate the output from the net input, whereas, all the hidden layers employ hyperbolic tangent sigmoid for transfer characteristics, shown in Fig. 2.

$$tansig(a) = \frac{2}{(1+e^{-2a})-1} \tag{4}$$

The expression in (4) is equivalent to using hypertangent $tanh(a)$. The implementation of $tanh\ (a)$ is slightly slower in processing as compared to (4) and thus, using (4) is a good trade-off when the exact shape of hypertangent is not very important and hence this is ignored, for faster processing speed.

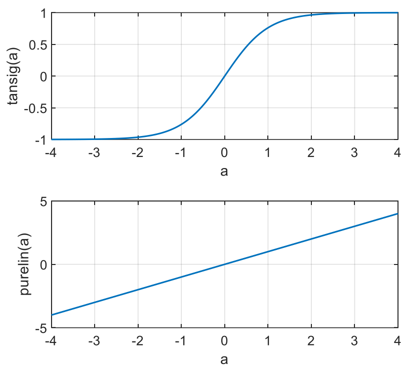

Fig. 2: The activation functions for hidden and output layers of the proposed network.

The training of neural network is enabled using the Levenberg-Marquardt (LM) backpropagation algorithm where the bias values and weights are updated according to LM optimization. The LM method is often the fastest algorithm in the backpropagation domain and is considered as the primary selection for supervised learning. The learning process is accompanied by performance threshold limits to stop the training process (such as the MAE and MSE). The LM method aims to achieving the training speed of network without involving the calculation of Hessian matrix. Instead, an approximate Hessian matrix, given in (5), is used by LM and is replaced in the original quasi-Newton approach.

$$H = J^T J \tag{5}$$

Likewise, the gradient is given as

$$t\nabla = J^T e \tag{6}$$

where, J represents the Jacobian matrix having the first order derivative of error vector in the network with respect to bias values and weights; e signifies the errors vector. The solution of Jacboian matrix can be enabled using standard backpropagation technique. This presents less complexity as compared to finding H. The quasi-newton update for the LM algorithm using Hessian approximate is given as:

$$y^{k+1} = y^k - [J^T J + \mu I]^{-1} \nabla \tag{7}$$

where, μ is a scalar factor adaptively increased or decreased after each successful iteration and results in the reduction of performance function throughout the iterative process of the algorithm. The value of μ is decreased after each iteration to shift the training towards the quasi-newton which is more accurate and faster. The only instant when μ is increased is the scenarios where performance function starts increasing after a certain iteration.

The flow diagram of proposed method for PV output power forecasting is presented in Fig. 4 and the proposed LCNN algorithm is shown in Fig. 5

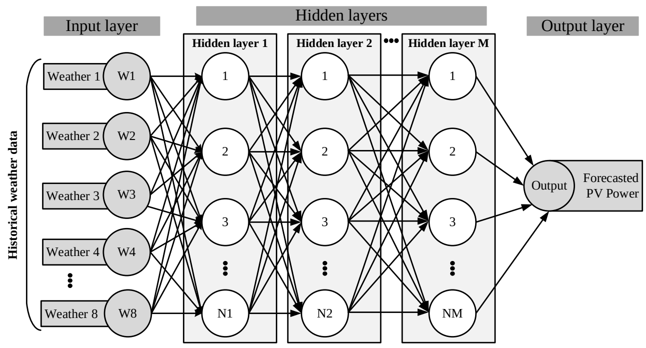

Fig. 3: The multilayer neural network for solar power estimation using historic PV and weather data.
N represents the number of inputs and
M represents the number of hidden layers.

Historic PV and weather data from previous years is obtained available publicly [30] and is used for offline training of neural network. The aim would be minimizing estimation error but at the same time lowering the computational complexity involved in the execution of the developed algorithm. The impact of various weather inputs affecting the estimation response is analysed, presenting thus a design guideline. Alongside, training data sets are arranged as combinations of different year and its impact on the performance of neural network is examined. The performance accuracy is measured using several indices such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). These indices are always positive, and close to zero values are considered to provide better estimation [31, 32]. The MAE calculates the average significance of the entire dataset, giving equal weights to all errors of model, giving and giving information about long-term accuracy. RMSE gives high weight to large errors, more useful when large errors are particularly undesirable, and thus robust in dealing with large deviations. The mathematical expression representing the errors indices are presented in Table 1.The proposed method targets increased accuracy and lower implementation complexity in terms of forecasting measured as MSE and MAE. The algorithm starts with an initial setting of neural network and trains it for a specific length of data with different inputs, whilst the MSE and MAE are recorded and saved. When the number of inputs is reduced to one, the initial training phase ends and inputs with lower MSE and MAE are chosen as providing the best estimation. Thereafter, the parameters of neural network are varied to get the optimal accuracy. The detailed analysis along with the measurements and prediction results are discussed in the section IV.

The learning process is affected by the number of hidden layers (M) and neurons therein (N), training data, batch size (B), number of epochs (E), and the input parameter combination. Therefore, these parameters are carefully determined for better prediction performance. The initial parameters for the selection of suitable weather inputs for the estimation process are chosen as: the number of neurons in the hidden layers 1, 2 and 3 are selected as 20, 30 and 20 respectively; number of epochs is 1000; the training algorithm as discussed previously is LM; the performance function is mean square error (MSE); and the data division is random. After the selection of best inputs, the appropriate final architecture for microgrid and control may be defined.

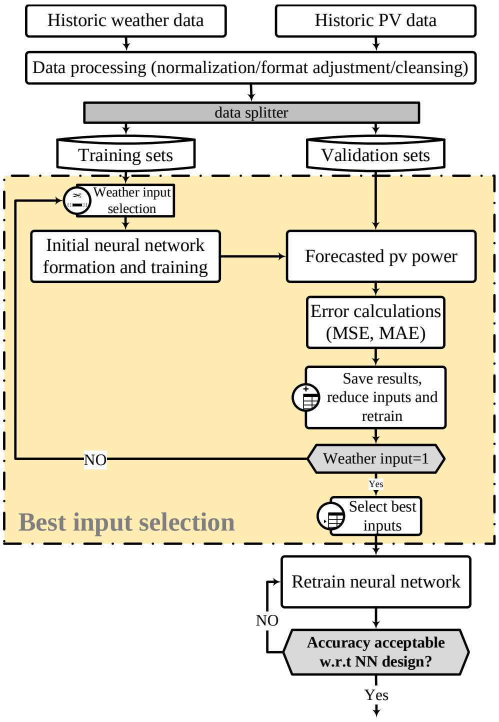

Fig. 4: The proposed LCNN algorithm for PV output power forecasting.

IV. Results and Discussion

The validation of proposed algorithm is carried out using several cases where the best input and data size are chosen based on the accuracy indices and training time. The PV and weather data (1 hour resolution) for Newcastle upon Tyne, UK have been acquired from [30] for 2016, 2017 and 2018. Results are presented in this section for various inputs and data sizes.

The estimation accuracy is analysed using the indices listed in Table 1. Analysis of the impact of inputs on the performance of NN shows that the weather inputs, such as, air density and solar surface irradiance highly influence the prediction accuracy among the various combination of inputs used. Results obtained are presented in Tables 2 and 3. As can be noticed, the temperature and solar surface irradiance give best results, as compared to other combinations. It is worth mentioning that using 8 inputs provides better accuracy, but this is at the expense of increased implementation complexity of forecasting algorithm as more data and inputs would be needed for making an estimate of solar power. On the other hand, the two combination inputs (which is least for achieving convergence) results in almost similar accuracy. As can be

Table 1: The performance evaluation indices for estimation accuracy.

Evaluation indices	Equations
Mean absolute error (MAE)	$\sum_{t_l=0}^{t_u=24} (\lvert e_t \rvert) \Big/ t_u$
Mean absolute percentage error (MAPE)	$\left(\sum_{t_l=0}^{t_u=24} \left(\lvert e_t / P_{pv,t}^{a} \rvert \right) \Big/ t_u \right) \times 100$
Mean square error (MSE)	$\sum_{t_l=0}^{t_u=24} (e_t{}^2) \Big/ t_u$
Root mean square error (RMSE)	$\sqrt{\sum_{t_l=0}^{t_u=24} (e_t{}^2) \Big/ t_u}$
Note: e_t is forecasting error and $P_{pv,t}^{a}$ is actual PV power	

seen from Table 2, one input is not sufficient for training the neural network so as to imitate the solar model.

Thus, the air density and surface irradiance are selected as weather inputs and the neural network is retrained by varying the number of neurons and hidden layers. Finally, the parameters resulting in even better accuracy are chosen and utilized further for estimation and prediction of solar output power (to be used for microgrid operation and control).

Second analysis presents the performance of neural network when it is trained using one-year data and used to predict and estimate the PV power for 6-months. Likewise in this case, the network performance is analysed for several weather inputs and its impact is studied on the estimation accuracy and training time. Similar to previous case, the air density and solar surface radiation are the most dominant inputs affecting the performance of algorithm and presents better accuracy with least number of inputs. Thus, these two inputs are selected and the neural network is then fine-tuned, based on the selection of best input.

A further analysis using the two selected inputs is carried out where the number of neurons in hidden layers are varied and the type of training algorithms is changed to get even better accuracy and faster training time. The analysis showed that the number of neurons in the hidden layer 1, layer 2 and layer 3 are respectively equal to 20, 30 and 10. This arrangement of neural network reduces the MSE, MAE and RMSE to 0.0012, 0.0171 and 0.0343 respectively, as compared to results presented in Table 3, with a reduction of 80 s in training time. Thus, the proposed methodology presents a guideline on how to select the relevant data from weather and how this selection affects the accuracy and training time of neural network. The benefits of the proposed method are improved accuracy and reduced computational complexity, which are important for efficient and reliable control and automation of the microgrids.

V. Impact of Forecasting on the Control and Automation of Microgrid

While clean technologies address the need for a sustainable energy, their inherent variability and dependence on weather conditions introduces challenges to their integration into electricity grid and complications to microgrids dynamic control. Forecasting plays a very important role for the optimal scheduling of power and consequently, the control and automation of microgrids,

Table 2: The impact of various weather input on the prediction/estimation accuracy and training time of neural network. The network is trained using three-year data (2016, 2017 and 2018) and tested for estimating one-year data (2016 data is used as base for comparison)

Number of inputs	Input type	Mean Square Error (MSE)	Mean Absolute Error (MAE)	Mean	Root Mean Square Error (RMSE)	Training time (secs)
8	1 2 3 4 5 6 7 8	9.2883e-04	0.0132	5.5411e-04	0.0305	245.4828
5	1 5 6 7 8	9.4807e-04	0.0135	0.0010	0.0308	257.62
	1 2 5 6 8	0.0012	0.0161	4.0310e-04	0.0349	412.2884
4	1 2 5 6	0.0015	0.0197	3.3750e-04	0.0388	184.1187
4	1 2 5 7	0.0064	0.0417	0.0014	0.0797	174.8379
4	1 5 6 8	0.0013	0.0172	1.6601e-04	0.0364	488.1201
4	1 5 7 8	0.0044	0.0339	-6.7623e-04	0.0664	313.0426
3	1 2 6	0.0015	0.0195	4.8424e-04	0.0390	264.7673
3	1 2 8	0.0267	0.1157	0.0024	0.1635	296.8515
3	1 6 8	0.0014	0.0187	5.0592e-04	0.0379	143.0419
2	1 6	0.0015	0.0199	1.3137e-04	0.0392	352.0361
2	6 8	0.0017	0.0203	7.9572e-04	0.0418	254.7605
2	5 6	0.0015	0.0188	4.4020e-04	0.0384	271.3456
2	1 2	0.0287	0.1202	0.0061	0.1695	169.2251
2	6 2	0.0018	0.0208	0.0012	0.0428	556.3987
1*	6	0.0076	0.0498	7.4935e-06	0.0870	1.6753e+03

Note: 1=Temperature, 2=Precipitation, 3=snowfall, 4=snow mass, 5=air density, 6=solar surface radiation, 7= top of atmosphere radiation, 8=cloud cover, *non-converging.

whether these are grid connected or operating in islanded mode. Forecasting of renewable energy generation (and in some cases load demand) helps in energy management, power flow control and supply-demand balance by providing knowledge of future power potential and deals with the inherent intermittent nature of renewables (PV in this case). This is demonstrated in the simple schematic diagram in Fig. 5.

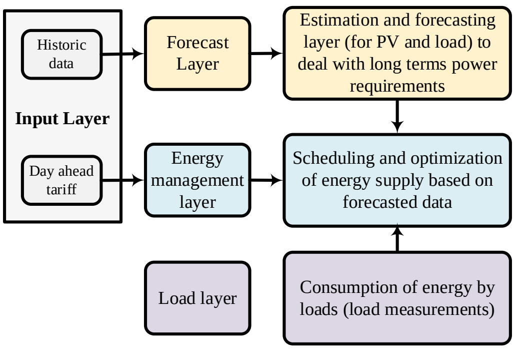

Fig. 5: Schematic illustration of forecast-based microgrid operation and control.

With the use of smart meters, microgrids are able to communicate with the central control (back-office) and receive weather forecast data from the meteorological agencies and then use this data with the proposed tool to predict future local PV power generation. Based on this prediction, the microgrid controller can determine how best to optimize the energy available to meet the expected local demand. Hence, the proposed prediction method can aid micorgrid control and automation by providing improved energy management and dynamic power flow control during normal continuous variations in weather conditions. Therefore, allowing better use of local renewable energy generation to meet local energy demand (energy self-sufficiency), minimize grid losses and avoid the need for additional grid capacity.

VI. Conclusion and Future Work

Forecasting plays a very important role for the optimal scheduling of power and consequently, the control and automation of microgrid. This paper proposes a neural network-based forecasting of solar power aimed at utilizing historic weather and PV data for the prediction. The algorithm uses a smaller number of inputs from weather data in order to reduce the computational complexity of having several input variables to the neural network. In addition, the proposed method uses a simple neural network with few neurons and hidden layers for its training and allows, with reasonable accuracy, for day a head forecast. The proposed methodology presents guidelines on how to select the most relevant data from weather data available and how this selection affects the accuracy and training time of the neural network. The benefits of developed method is an improvement in the dynamic energy management and control of microgrids, thus better use of local renewable energy generation to meet local energy demand.

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Table 3: The impact of various weather input on the prediction/estimation accuracy and training time of neural network. The network is trained using one year data (2018) and tested for 6 months data (2016 data is used as base for comparison)

Number of inputs	Input type	MSE	MAE	Mean	RMSE	Training time (secs)
8	1 2 3 4 5 6 7 8	0.0012	0.0185	-0.0081	0.0349	45.2474
5	1 5 6 7 8	0.0011	0.0163	-0.0072	0.0327	128.3599
	1 2 5 6 8	0.0013	0.0192	-0.0105	0.0364	61.2623
4	1 2 5 6	0.0013	0.0195	-0.0088	0.0361	66.7609
4	1 2 5 7	0.0053	0.0389	-0.0077	0.0729	95.4979
4	1 5 6 8	0.0013	0.0184	-0.0085	0.0354	125.8869
4	1 5 7 8	0.0053	0.0389	-0.0046	0.0729	111.3945
3	1 2 6	0.0015	0.0189	-0.0087	0.0392	85.9601
3	1 2 8	0.0290	0.1134	0.0330	0.1702	56.7494
3	1 6 8	0.0014	0.0195	-0.0088	0.0368	60.6337
2	1 6	0.0013	0.0198	-0.0101	0.0357	134.8992
2	6 8	0.0017	0.0194	-0.0022	0.0413	119.3282
2	5 6	0.0013	0.0189	-0.0077	0.0367	183.8711
2	1 2	0.0347	0.1239	0.0365	0.1864	47.3152
2	6 2	0.0021	0.0213	-0.0030	0.0457	106.9602
1*	6	0.0311	0.1092	0.0054	0.1764	34.0761
Note: 1=Temperature, 2=Precipitation, 3=snowfall, 4=snow mass, 5=air density, 6=solar surface radiation, 7= top of atmosphere radiation, 8=cloud cover, *non-converging.						

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