Neural Network Self-Organizing Maps Model for Partitioning PV Solar Power

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Summary
The growth in global population and industrialization has led to an increasing demand for electricity. Accordingly, the electricity providers need to increase the electricity generation. Due to the economical and environmental concerns associated with the generation of electricity from fossil fuels. Alternative power recourses that can potentially mitigate the economical and environmental are of interest. Renewable energy resources are promising recourses that can participate in producing power. Among renewable power resources, solar energy is an abundant resource and is currently a field of research interest. Photovoltaic solar power is a promising renewable energy resource. The power output of PV systems is mainly affected by the solar irradiation and ambient temperature. this paper investigates the utilization of machine learning unsupervised neural network techniques that potentially improves the reliability of PV solar power systems during integration into the electrical grid.

Keywords:
Ant colony clustering, electric grid, photovoltaic, solar panel

1. Introduction

The demand for electrical power is increasing globally. This is due to the significant growth in global population and industrialization. Accordingly, electric power providers must increase power generation. Presently, conventional power resources, such as fossil fuels are mostly relied on for power generation. However, there are numerous economical and environmental concerns associated with the generation of power from such recourses. Alternative power recourses that can potentially mitigate the economical and environmental are of interest. Renewable energy resources are promising recourses that can participate in producing power. Among renewable power resources, solar energy is an abundant resource and is currently a field of research interest. Photovoltaic (PV) solar panels are systems that convert solar energy into electrical energy. The advances in PV solar panels technology, such as the reliability and low production costs make them a substantial system for generating power and further integrate such systems into the electrical grid. PV solar power is significantly spreading and is predicted to account for 60% of all renewable capacity additions through 2025 [1].

The power generated from PV solar power systems is disturbed by solar irradiation and ambient temperature [2]. This leads to instability issues when integrating such systems into the electrical grid. Accordingly, integrating PV solar power systems requires extensive examining to ensure the reliability of the electrical grid.

Artificial intelligence and neural network techniques are being utilized to solve problems in many fields. Inspired by the effectiveness of neural network techniques, the utilization of such techniques to enhance the generation and operation of integrating PV solar power systems into the electrical grid. For that, this paper investigates the utilization of machine learning unsupervised neural network techniques that potentially improves the reliability of PV solar power systems during integration into the electrical grid.

The remainder of the paper is structured as follows. Section 2, presents the background of the neural network based self-organizing maps algorithm. Section 3, presents the methodology to partition the PV solar power while reducing the efforts of the extensive simulations for integrating PV solar power systems into the electrical grid. The experimental results of the application of self-organizing maps are shown in Section 4. The conclusions are drawn is Section 5.

2. Neural Network Self-Organizing Maps

Kohonen self-organizing maps (SOM) were developed by Tuevo Kohonen in 1982 [3]. A self-organizing map (SOM) or self-organizing feature map (SOFM) is a topological unsupervised neural network that projects high-dimensional input patterns into a reduced dimensional space that can usually be visualized in a one-dimensional or two-dimensional lattice structure. Each unit in the network (lattice) is known as a neuron, and adjacent neurons are connected to each other. The input patterns are fully connected to network neurons through adaptable weights. These weights are updated as input patterns are projected into the network, and then assigned to the best matching unit (winning neuron) based on a competition function. As more inputs (data points) are presented into the network, each neuron closest to the input vector adjusts its weight vector

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toward the input vectors. Fig. 1 illustrates the main structure of the SOM. The neurons in the layer of the SOM are arranged originally in physical positions according to a certain topology function. MATLAB offers functions that can arrange the neurons in a grid, hexagonal, or random topology structure. Distances between neurons are calculated from their positions with a distance function. There are four distance functions in MATLAB: dist, boxdist, linkdist, and mandist. For the research presented in this thesis, the gridtop topology and dist distance functions have been used after a few trials and errors. A detailed discussion about SOM is given in Hagan et al. [4] and Kohonen [5]. The basic SOM procedure can be summarized in the following steps [6]:

1- Random initialization of prototype (weight) vectors $m_j^{(0)}$, $j = 1,\ldots, K$.
2- Project an input pattern (data point) x into the network and choose the winning neuron, J_w, based on the minimum distance to x:
3- Update the prototype (weight) vectors,

$$m_j(t+1) = m_j(t) + h_{cj}(t)\left[x - m_j(t)\right] , \quad (1)$$

where $h_{cj}(t)$ is the neighborhood kernel function centered on the winning neuron,

$$h_{cj}(t) = \eta(t) exp\left(\frac{-\| r_c - r_j \|^2}{2\sigma^2(t)}\right) , \quad (2)$$

where r_c and r_j are the positions of the corresponding neuron on the network, $\sigma(t)$ is the monotonically decreasing kernel width, and $\eta(t)$ is the monotonically decreasing learning rate defined by:

$$\eta(t) = \eta_{\circ}\, exp\left(\frac{-t}{T_{\eta_{\circ}}}\right) > \eta_{min} , \quad (3)$$

where $\eta_{\circ}$, $\eta_{\min}$ and $T_{\eta_{\circ}}$ are the initial learning rate, the minimum learning rate, and the time parameter, respectively.

4- Repeat steps 2 and 3 until the maximum number of epochs is reached or no change of neuron position more than a positive number is observed.

It should be noted that in step 3 the prototype vectors are updated and moved closer to the input vector. The winning neuron's weights are altered proportionally to the learning rate, whereas the weights for the neighbouring neurons are updated in inverse proportion to their distance [5]. The SOM performance is significantly sensitive to the initialization of the prototype vector weights. Accordingly, the mapping could generate suboptimal partitions if the weights are not chosen properly. The topology and distance functions can be determined based on trial and error.

The flowchart of SOM in its basic form is shown in Fig. 2.

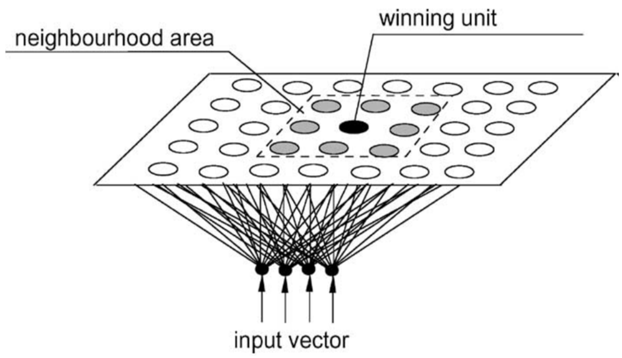

Figure 1: Structure of the SOM with hexagonal distance function. Retrieved from [7].

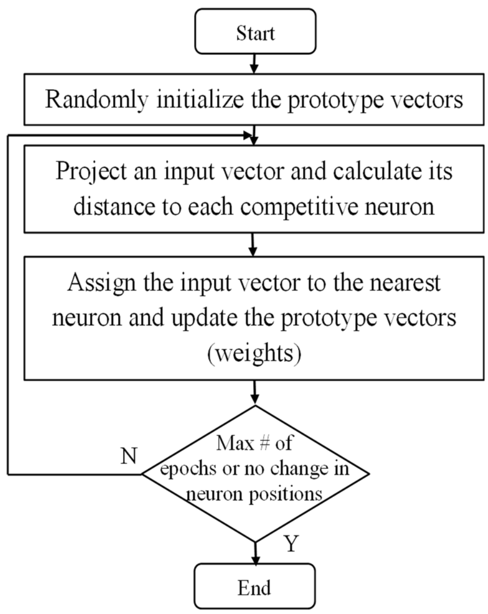

Figure 2: Basic flowchart of SOM.

3. Methodology

Inspired by the effectiveness of neural network self-organization maps, the partitioning of PV solar power systems is obtained by applying such technique on historical data of solar irradiance and ambient temperature time-series observations at a site of interest for previous years. The time-step observations must be able to preserve the short-term instabilities in solar irradiance and ambient temperature. The data is then transformed to daily PV solar power observations. The self-organization maps partition the daily time-series daily PV solar power observations that have comparable observations. A representative from each partition group is achieved. The representative PV solar power is then used in simulation studies from the integration of PV solar power systems into the grid.

3. 1. Preprocessing

Input: Past solar irradiance and ambient temperature for a location of interest.

Output: Cleaned daily time-series observations of irradiance and ambient temperature.

3. 2. Transformation

Input: Cleaned daily time-series observations of solar irradiance and ambient temperature.

Output: Time-series of the equivalent Alternating Current (AC) power generated from the PV system.

3. 3. Partitioning

Input: Time-series of PV solar power observations.

Output: Groupings of PV solar power observations as a result of applying the SOM algorithm.

Description: The results are various partitions of PV solar power observations, grouped according to the perspective of SOM.

3. 4. Validation

Input: Grouping results of SOM.

Output: Validity index value.

Description: The results of the clustering methods are evaluated by Ratio of within-cluster sum-of-squares to between-cluster variation (WCBCR). The WCBCR [8] depends on the sum of squared distances between each data point and its centroid as well as the distances between centroids:

$$WCBCR = ? \frac{\sum_{k=1}^{K} \sum_{x_i \in C_k} d\left(x_i, C_k\right)}{\sum_{1 \le q < p}^{K} d\left(C_p, C_q\right)} . \quad (4)$$

properly defined metrics and indicators (validity indices). An evaluation value with respect to the utilized validity index is an indicator of how well the clustering method grouped the data.

4. Application of SOM on Partitioning PV Solar Power Observations

The presented methodology is applied on historical data for three past years (2010-2012) with ten-minute time-steps of solar irradiation and ambient temperature from the Solar Radiation Research Laboratory [9]. The location of the obtained data has a latitude of 39.74ºN and a longitude of 105.18ºW. The irradiance data with this high time resolution (ten minutes). Accordingly, the 10-minute time resolution results in 144-observations per day.

The SOM has many parameters that can affect clustering results. The initial value, η_0, the minimum value, $\eta_{\min}$, the learning time rate, $T_{\eta 0,}$ and the number of epochs is calibrated in order to improve the neural network's behaviour. The SOM process was repeated for different values of learning rates, $T_{\eta 0,}$ and number of epochs with $\eta_0 = 0.9$ and $\eta_{\min} = 0.02$. The sensitivity of the ratio of WCBCR to the $T_{\eta 0}$ and epochs parameters is presented in Fig. 3.

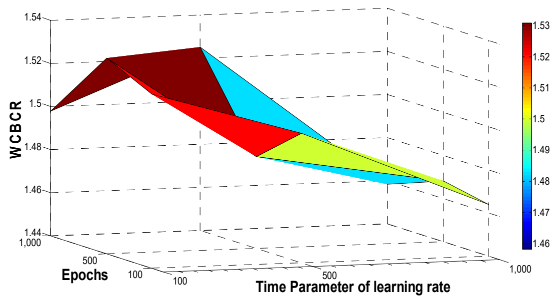

Figure 3: WCBCR values with respect to $T_{\eta 0}$ = {100,500,1000} and epochs = {100,500,1000} for mono-dimensional SOM.

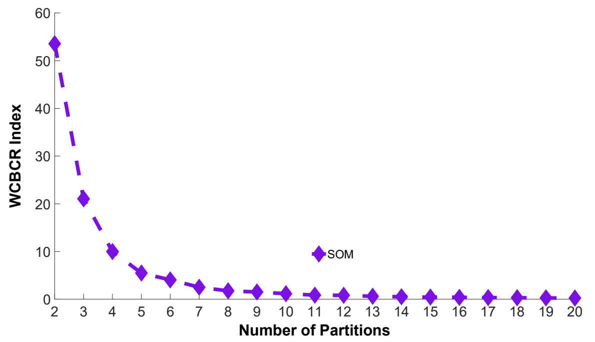

Figure 4: The best results for each grouping for the Fall data set of PV solar power observations for 2 to 20 partitions on the WCBCR validy index.

Table 1: Validity indices of clustering algorithms for eight partitions of Fall.

Validity index	WCBCR
SOM	1.754

Table 2: Compactness, separation, and CPU for eight partitions on Fall data.

	Compactness	Separation	CPU time(second)		
			Best	Worst	Average
SOM	428.323	899.042	21.0917	22.8013	21.3620

Fig. 4 shows the WCBCR validity index plot for 2 to 20 partitions of PV solar power observations. It can be observed from Fig. 4 that eight clusters can be considered as the optimum number of clusters to represent the Fall PV solar power observations data. The compactness and separation of the SOM algorithm results showed that the best results for compactness and separation were obtained from SOM at eight partitions for Fall season (Table 1). It should be noted that in Table 2 the best partition results were chosen based on the WCBCR value. From the compactness and separation results, it can be observed that the SOM algorithm with the WCBCR validity index presented well partitions of PV solar power and the centroid of each partition can be used as a representative PV solar power observation that can be used in studies for integrating PV systems into the electric grid.

5. Conclusions

This paper investigates the utilization of machine learning unsupervised neural network techniques that potentially improves the reliability of PV solar power systems during integration into the electrical grid. a methodology to cluster PV solar power observations was presented. The neural network based self-organizing maps algorithm was used in partitioning PV solar power observations. Presenting well-partitioning of PV solar power observations, improves the results of representatives that can represent the whole group. From the simulation, the SOM algorithm with the WCBCR validation index, produced significantly highly separated and well-compacted partitions. The resulted partition representatives from SOM can be utilized in PV solar power system integration studies while improving the reliability of PV solar power systems during integration into the electrical grid.

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