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**Research Article**

# Modeling of Daily Solar Energy System Prediction using Soft Computing Methods for Oman

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**Abstract:** The aim of this study is to design and implement soft computing techniques called Support Vector Machine (SVM) and Multilayer Perceptron (MLP) for great management of energy generation based on experimental work. Solar energy could be utilized through thermal systems or Photovoltaics (PV) and it is renewable energy source, environmental friendly and proven globally for a long time. The SVM and MLP models are consist of two inputs layers and one layer output. The inputs of SVM network are solar radiation and time, while the output is the PV current. The inputs of MLP network are solar radiation and ambient temperature, while the output is the PV current. The practical implementation of the proposed SVM model is achieved a final MSE of (0.026378744) in training phase and (0.035615759) in cross validation phase. Besides, MLP is achieved a final MSE of (0.005804253) in the training phase and it is achieved (0.010523501) in cross validation phase. The final MSE of cross validation with standard deviation is (0.000527668). The experiments achieved in the predicting model a value of determination factor ($R^2$ = 0.9844388787) for SVM and ($R^2$ = 0.9701310549) for MLP which indicates the predicting model is very close to the regression line and a well data fitting to the statistical model. Besides, the proposed model achieved less MSE in comparison with other related work.

**Keywords:** Machine learning, Oman, solar energy prediction, support vector machine

## INTRODUCTION

The growing in population and industry increased the energy needs. The energy increment leads to increase energy prices, which reflected on many economies and energy shortages in some countries. From the other hand increase fossil fuel prices, climate treaties and policies enhanced the need to look for alternative energy sources. Renewable energy could be the solution for many reasons examples are: it is free, environmental friendly, availability, unlimited, *etc*. Solar energy could be the most important renewable energy type, which utilized using thermal systems or Photovoltaics (PV). Operating cost of PV is very low, since no fuel to be consumed, but their peak power production can be only recognized on a clear sky, with the PV facing the sun. Standby power generators or storage systems are needed in some cases because of the sun light intermittence, which increase the energy system cost. The exceptions are in case of grid connected system or PV used for peak load at peak solar insolation.

The growth in Oman population and industry reflected on energy needs and it could be clear on

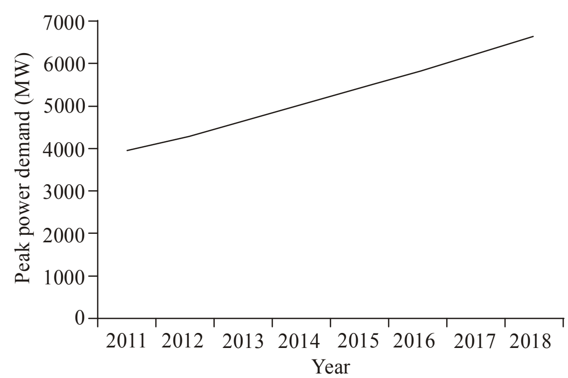


Fig. 1: Oman peak power demand for 2011-2015 and projection till 2018

electricity needs and it will keep increasing in the near future (Fig. 1). The maximum power demand expected to increase from 5,691 MW in 2015 to reach 6,000 in the middle of 2016. In 2018 the forecasted power demand is 6.8 GW, which mean more energy sources and power plants need to be installed (Kazem, 2011; Authority for Electricity Regulation, Oman, 2008). In Oman the power plants mainly used natural gas and a little diesel, especially in rural areas, as fuel. To meet

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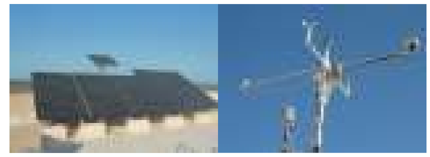
the electricity needs invest in renewable energy is most in Oman. The feasibility of renewable energy in Oman has been investigated in many studies. It is found that solar energy is promising sources in the country. The demand is high in north part of Oman due to the industrial areas and population, which is approximately 55% of population, where it is found that the potential of solar energy in Oman particularly in this region. The day in Oman is long with 10 to 12 h, 342 shining days and free land to install PV systems (Altunkaynak and Özger, 2004; Fakham *et al*., 2011).

Machine learning is a subdivision of artificial intelligence that is developed as a result of studies in pattern classification and recognition for finding mathematical models for various real life problems. Machine learning investigates the construction of algorithms that can learn from the previous data and help in finding a forecast on the data in the current and future time. The machine learning applied iterative and interactive statistical methods in the construction of computational models to obtain the desired results (Chen *et al*., 2011). The factors like efficiency of learning algorithms, the complexity of the problem, methods of representation of data are the most important factors affect the accuracy of the results and future forecasting for data.

This study aims to discuss and implement machine learning methods for great management of energy generation of PV system. Several machine learning methods are used for designing and implementing different phases of a renewable energy power systems based on the problem requirements and its characteristics (Schölkopf and Smola, 2011; Yousif, 2013). Hence, the adaptation of optimal location and structures of renewable power plants is one of the important implementation of learning machine methods. Recently, the Support Vector Machines (SVMs) have been widely implemented into several problems of renewable energy power systems (Banda *et al*., 2014; Sharma *et al*., 2011; Hossain *et al*., 2012). In this study SVM model will be proposed for solar system in Sohar, the second largest city in Oman based on experimental data. This research has been based on data for solar irradiations and installed PV system in Oman. These data were provided by the Solar Cells and Photovoltaic Research Lab in Sohar University.

In a solar cell or PV, the energy of sunlight in the form of photons is imbibed by the semiconductor and then voltage is produced. The uni-directional flow of these electrons across the cell creates a direct current, DC. PV technology is actually old. Solar energy technology and especially photovoltaic has been experimented for more than 70 years and it shows good success.

The AER "Authority of Electricity Regulation" published their first study related to renewable energy in 2008, which has explored there newable energy sources in Oman. They claimed that solar than wind could be the priorities of Oman renewable energy sources (Authority for Electricity Regulation, Oman, 2008). A country wide site selection study was conducted with an assessment of a number of potential sites based on a set of selection criteria suited to potential solar sites has been conducted by PAEW "Public Authority for Electricity and Water" in 2010. In 2011 the Research Council of Oman granted SU "Sohar University" project to investigate, design and assess PV systems in term of technical and economic criteria for Oman. The feasibility study of PV systems in Oman standalone and grid connected are conducted in references (Kazem *et al*., 2011, 2014), respectively.



(a) (b)

Fig. 2: (a): Grid connected PV system; (b): Meteorological station

Kazem *et al*. (2013) proposed optimization of the PV system tilt angle, array size and storage battery capacity using MATLAB numerical method. Load demand and hourly meteorological data has been used. It is found that the PV system sizing ratio for PV array and battery are 1.33 and 1.6, respectively. Also, they claimed that the cost of energy for standalone PV system in Oman is 0.196 USD/kWh.

Kazem *et al*. (2014) investigated and assessed the grid connected PV system in Oman. It is found that the Crist Factor and Yield Factor, two technical criteria, of the grid connected PV system are 21%, 1875 kWh/kWp/year respectively. Meanwhile, the cost of the energy and the payback period, economical criteria, are 0.045 USD/kWh and 11 years, respectively. As a conclusion they claimed that the energy generated by PV systems is cheaper than energy generated by fossil fuel in Oman.

In the current study 24 PV module have been installed in Sohar University in Oman. The rating of PV module is 140W, 17.7 V maximum voltages, 7.91 A maximum current, 22.1 V open circuit voltage, 8.68 A short circuit current and 13.9% efficiency. Three PV systems configurations; standalone, grid connected and tracking systems have been designed and evaluated (Fig. 2a). The meteorological data has been measured and recorded using weather station (Fig. 2b). The grid connected system data (voltage, current, power and energy) has been recorded and monitored. Also, the measured environmental parameters are linked to the productivity of the PV system.

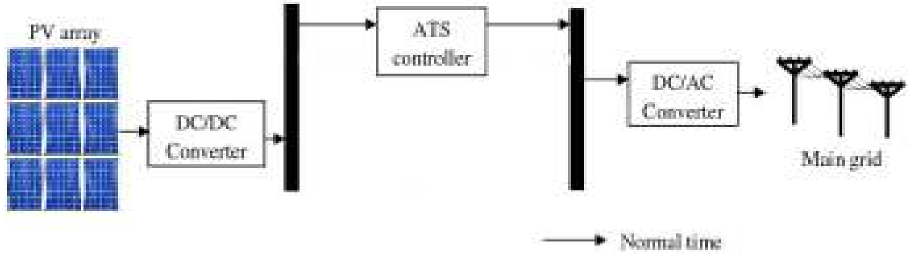



Fig. 3: Solar photovoltaic grid connected system

This research is a part of a research on grid connected PV system (Fig. 3) and consequently the production of the PV system here is needed. This study proposed model predicts the output of grid connected PV system in Oman. The proposed model is based on implementation of artificial intelligent techniques. The SVM is used to classify and predict the future amount of production of the PV system. The system experimental data has been measured in Sohar, Oman.

## LITERATURE REVIEW

Photovoltaic systems quite reliable and has been well tested in space and terrestrial applications. The doubt of PV systems output power is the main drawback of these systems. Therefore this subject has stimulated the researchers to give more focus on finding the solution for this problem either by proposing optimization methods or incorporating hybrid energy sources. Because of PV systems output power uncertainty, many attempts proposed to predict power productivity. In general these attempts are classified into; statistical models based on time series of data, regression based models, empirical mathematical models and finally artificial intelligent neural network based models.

There is number of studies in literature related to the use of machine learning techniques to predict PV performance (Banda *et al*., 2014; Sharma *et al*., 2011; Hossain *et al*., 2012; Caudill and Butler, 1993), including MultiLayer Perceptron (MLP) network, Hetero Associative Neural Network, Probabilistic Neural Networks (PNN), The Self-Organizing Map (SOM), General Regression Neural Networks (GRNN), Recurrent Neural Networks, Hebbian Neural Networks, Adaptive Neural Network Support Vector Machine based Radial Basis Function networks (RBF), Generalized Learning Vector Quantization (GLVQ) and Hybrid Networks (Banda *et al*., 2014). Caudill and Butler (1993) proposed prediction model for solar power generation based on experimental work. Different machine learning techniques has been used. The authors included SVM in the multiple regression techniques. In SVM model they tried polynomial, linear, RBF kernels. They claimed that SVM model accuracy increased up to 27%. Furthermore, principal component analysis has been used to improve the model. Sharma *et al*. (2011) proposed hybrid intelligent predictor. The proposed system used regression models namely, RBF, MLP, Linear Regression (LR), SVM, Simple Linear Regression (SLR), Pace Regression (PR), Additive Regression (AR), Median Square (LMS), IBk (an implementation of kNN) and Locally Weighted Learning (LWL). They claimed that LMS, MLP and SVM are the most accurate models in term of MAE and MAPE. Hossain *et al*. (2012), which used SVM model to predict solar energy, found that SVM accuracy is less than Gaussian Process Regression method. Chen *et al*. (2011) implements a SVM model to estimate the daily solar radiation using air temperatures. The developed SVM model used a polynomial kernel function which performed better than other SVM models. He obtained a highest NSE of 0.999 and the R-square of 0.969, while the lowest RMSE is 0.833 and RRMSE of 9.00.

The multiple linear regressions are adopted after checking with linear models. All the variables are investigated for the functional analysis of the variables. Some predicators like day number with sunshine ratio are investigated using simple multiple regression approach. In multiple linear models various inputs are given with processing logic with activation function to get the desired output. Asl *et al*. (2011) implements a predicting daily global solar radiation model based on meteorological variables, using MLP neural networks. The author claimed that MAPE, R-square and MSE are 6.08, 99.03 and 0.0042%, respectively. Hontoria *et al*. (2005) proposed solar radiation maps for Spain using MLP. A MLP has been trained with hourly solar radiation data of sites in Spain. It is observed that using exogenous variables improves significantly the results for MLP. Table 1 shows a comparison of some MLP proposed models in literature in term of error. It is clear seen that errors associated with predictions (monthly, daily, hourly and minute) are between 4 and 10%. In sum, the use MLP represents a large majority of research works.

## MATERIALS AND METHODS

**Soft computing paradigms:** Soft Computing (SC) is a new computing technique for utilizing real world

Table 1: Comparison of MLP proposed models in literature

| Authors | Location | Error |
|---|---|---|
| Chaabene and Benammar (2008) | Tunisia (Energy and Thermal Research Centre) | *nMBE*= -9.11 %, *nRMSE*<10 % |
| Jiang (2008) | China (8 cities) | Accuracy = 95 % |
| Reddy and Ranjan (2003) | India (2 stations) | MAPE = 4 % |
| Elminir *et al*. (2007) | Egypt (3 stations) | Standard error = 4.2% |
| | | Standard error = 9% |
| Sözen *et al*. (2004) | Turkey (17 stations) | *MAPE*< 7% |

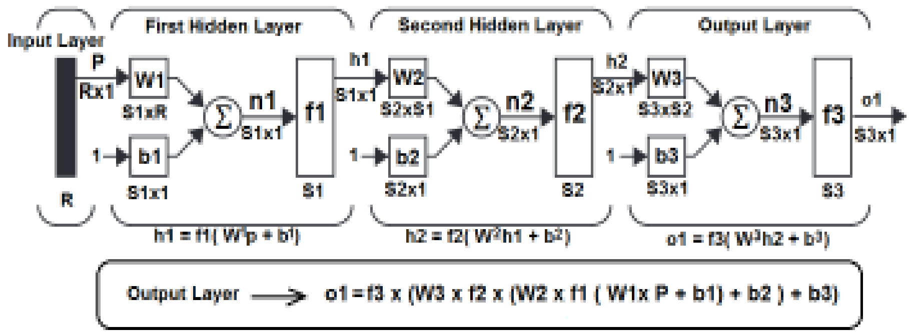



Fig. 4: MLP architecture

problems and provides lower cost solutions. It is mainly consisting of the following techniques: neural networks, fuzzy systems and evolutionary computation. The three techniques of soft computing are differ from one another in their function and time scales of operation which they embed a priori knowledge. The Neural networks implements in a numeric framework, which used to identify their learning and generalization conditions. Fuzzy systems are implemented in a linguistic framework which use to handle linguistic information and then performs approximate reasoning. Nevertheless, the evolutionary computation techniques are powerful methods for searching and optimizing the results. Many researchers all over the world contributed essentially in soft computing to discover solutions for various problems in the modern scientific society applications (Beyer and Schwefel, 2002; Dai *et al*., 2011; Pratihar, 2007, 2013; Mellit *et al*., 2005). The significant directions of soft computing applications are implemented and performed into knowledge representation, learning methods, path planning, control, coordination and decision making. Moreover, the SC can be significantly implemented in the following areas: The biometrics systems, the bioinformatics systems, the biomedical systems, the Robotics applications, Vulnerability analysis. Furthermore, SC is performed successfully in Character recognition, Data mining, Natural Language Processing (NLP) (Yousif, 2013), Multi-objective optimizations, Wireless networks, Financial and time series prediction, Image processing, Toxicology, Machine control, Software engineering, Information management, Picture compression, Noise removal and Social network analysis (Pratihar, 2007), etc.

**Neural networks:** A neural network is considered as a data processing technique that maps an input of a stream of information to an output stream of data. Artificial Neural Network is a powerful data-modeling tool, which can perform complex input/output relationships either linear or non-linear. The most popular ANN techniques are Multilayer Perceptron (MLP) as depicted in Fig. 4. ANN has a number of features that can encourage scientist to implement Neural Network design themes in different applications. The most significant characteristics of ANN are ability of parallelism, uniformity; it can learn from training sets, it can be generalized to adopt new data and adaptive ability (Yousif, 2011). ANN is consisting of three processing layers, input, hidden and output. They connected together using weighted links. The architecture of neural network is the association of neurons into layers and the connection pattern within and between layers. It is illustrated as 'R-S1-S2-S3', which means that the input layer comprises of R inputs and connected to "hidden" layers. This network consists of two hidden layers S1 and S2. This architecture has only one output layer S3. The weights of input and hidden layers determine when each hidden layer is activated. The hidden layers are in turn connected to "output layers". The transfer function and weights of each neuron it should be defined. The training process is used to adjust the weights of the ANN to 'match' set of samples (training set).

**SVM&MLP configuration:** The SVM and MLP network are designed and implemented using a Neuro solution package. Each of them has only one hidden layer and one output layer. Besides, two inputs layers are implemented. The SVM architecture has input data sets (the time stamp and corresponding UPV-Solar) and it has one output data set (Photovoltaic temperature). The data undertaken are generated from 24-PV modules which have been installed at Sohar University in Oman.

The inputs of MLP network layers consist of solar radiation and ambient temperature, while the output is the value of current photovoltaic. The experiment involved of 1000 epochs. In order to regulate the range of each neuron between [-1 and 1], a TANH transfer function is applied. The back propagation learning algorithm (BP) is used to adapt the errors through the layers of the network for adjusting of weights in the hidden layer. BP learning function is computed as follows:

$$\mathrm{E(w)} = \sum_{p=1}^{pt} \sum_{i=1}^{epoch} (\mathrm{di(p)} - \mathrm{yi(p)})^2 \tag{1}$$

where,

E (w) : Error function to be minimized
w : Weight vector
pt : Number of training patterns
epoch : Number of output neurons
di(p) : Desired output of neuron i
yi(p) :A output of the neuron i

The computing of new weight vector w is repeated in training phase until the error function is become a small value and then stopped the recursive computing. This means that the network output is closer to the desired output. The present value of the weight is computed as follows:

$$Wij(n+1) = Wij(n) + \eta\delta i(n) + x\mathrm{j}(n) \tag{2}$$

where, the local error $\delta i(n)$s computed from $Wij(n)$ at the output layer or can be computed as a weighted sum of errors at the internal layers. The constant step size is$\eta$. The Momentum learning is used to speed up and stabilize convergence of network. The update of the weights in momentum learning is computed as follows:

$$Wij(n+1) = Wij(n) + \eta\delta i(n) + xj(n) + \alpha(Wij(n) - Wij(n-1)) \tag{3}$$

The best value of α in the momentum is between 0.1 and 0.9. In the current study, the experiments give evidence that the best value for α is 0.7.

The Mean Square Error (MSE) is used to measure the variation of the predicted values from the measured data, which is computed as follows:

$$MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{pi} - I_i)} \tag{4}$$

Where Ii is the measured value, Ipi is the predicted value and n is the number of observations.

Moreover, in order to determine the relation between two variables (a network output (x) and a desired output (d)), the correlation coefficient (r) is used. Normally, the value of r is in the range of [-1, 1]. If $r$ = 1, this indicates a strong positive relationship (correlation). When $r$ = 0, this give indicate that there is no correlation between these variables. However, if $r$ = -1, then a negative correlation between these variables is registered. The correlation is computed as in Eq. (5):

$$r = \frac{\dfrac{\sum_i (x_i - \bar{x})(d_i - \bar{d})}{N}}{\sqrt{\dfrac{\sum_i (d - \bar{d})^2}{N}}\sqrt{\dfrac{\sum_i (x_i - \bar{x})^2}{N}}} \tag{5}$$

Besides, the coefficient of determination $R^2$ is used to assess the performance of the proposed predicting system and how it is well fitting to the actual results. The coefficient of determination $R^2$ is defined in Eq. (6):

$$R^2 = 1 - \frac{(\sum_i (y_i - f_i)^2}{(\sum_i (y_i - f\bar{y}_i)^2} \tag{6}$$

where,

$y_i$ : The observed value of the actual output
$f_i$ : The predicted value
$\bar{y}_i$ : The arithmetic mean value of the observed targets.

The better a model is will likely predict future outcomes more precisely, which is achieved by value of $R^2$ closer to 1.

## RESULTS AND DISCUSSION

Figure 5 demonstrations the training and cross validation MSE of the MLP network, which is clearly indicating the graph line of training data set in line with

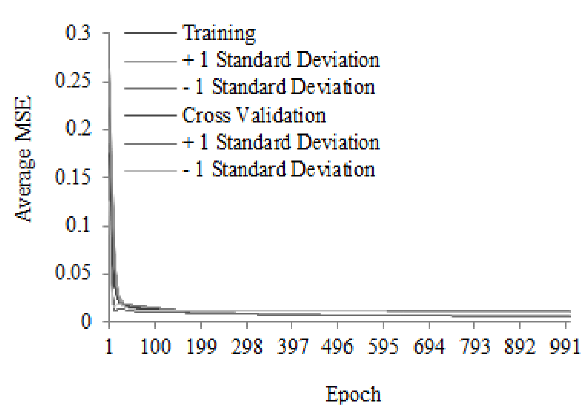



Fig. 5: Average MSE of MLP with standard deviation boundaries for 3 runs

Table 2: Best results of MLP Networks

| All runs | Training minimum | Training SD | Cross validation minimum | Cross validation SD |
|---|---|---|---|---|
| Average of Min. MSEs | 0.00580425 | 0.00031022 | 0.01052350 | 0.00052766 |
| Average of Final MSEs | 0.00580425 | 0.00031022 | 0.01052350 | 0.00052766 |

SD: Standard Deviation

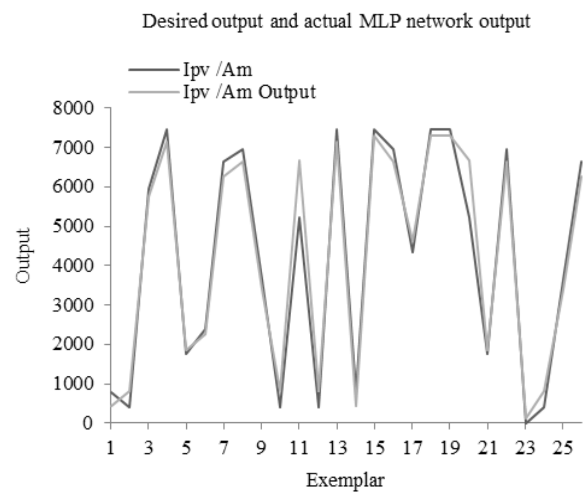



Fig. 6: Desired output and actual MLP network output

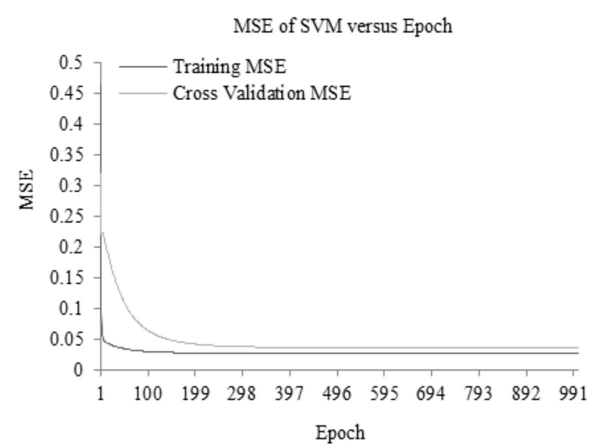



Fig. 7: MSE of SVM versus epoch

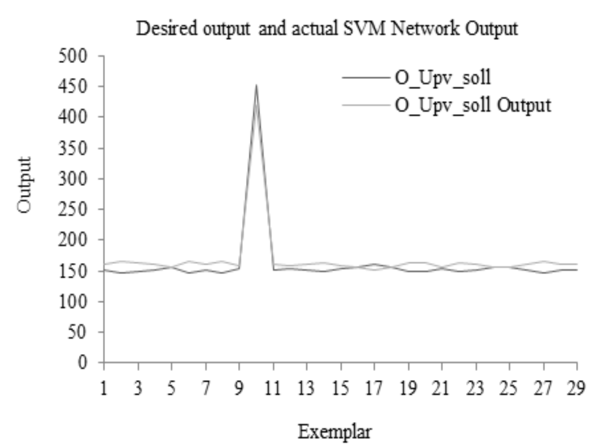



Fig. 8: Desired output and actual SVM network output

Table 3: The minimum MSE and final MSE of SVM network

| Best networks | Training | Cross validation |
|---|---|---|
| Epoch # | 1000 | 1000 |
| Minimum MSE | 0.026378744 | 0.035615759 |
| Final MSE | 0.026378744 | 0.035615759 |

cross validation data sets. The practical implementation of MLP is achieved a final MSE of (0.005804253) in the training phase and it is achieved (0.010523501) in cross validation phase. The final MSE of cross validation with standard deviation is (0.000527668). Table 2 illustrates Average of Final MSEs of training phase, cross validation phase and cross validation with standard deviation results. The experiment is giving evidence that there is a strong relation between the input and the output variables. The correlation factor (r) of MLP network is (0.984952311).

Figure 5 depicts the line graph the average MSE of final MLP with standard deviation boundaries for three runs. While Fig. 6 depicts the graph of the average MSE of the desired current PV output and the MLP network output, which is predicate exactly the tested data. And then can be generalized to utilize any unseen data for the current and future time.

Figure 7 shows the training and cross validation MSE of the SVM network, which is clearly demonstrating the graph line of training data set in line with cross validation data sets.

The practical implementation of SVM is achieved a final MSE of (0.026378744) in training phase and (0.035615759) in cross validation phase as illustrated in Table 3. The experiment is giving evidence that there is a strong relation between the input and the output variables. The correlation factor (r) of SVM network is (0.992188933).

Figure 8 depicts the graph of comparison of desired PV output current and the network output, which is predicate exactly the tested data. And then can be generalized to utilize any unseen data for the current and future time.

## SUMMARY AND CONCLUSION

MLP and SVM networks and models for calculating photovoltaic energy generation based on experimental work in Oman. The proposed models have been evaluated on the basis of Mean Square Error. Table 4 illustrates the comparison of final MSE between the MLP and SVM networks, which is clearly indicate that the MLP network achieved very good result in comparison to SVM results. However, the MSE of MLP is (0.005804253), while Final MSE of SVM is (0.026378744). As a conclusion the results showed that MLP model is more accurate than SVM model in calculating the photovoltaic generated energy in Oman.

Table 4: The comparison of final MSE between the proposed MLP and SVM networks

| Best networks | Training | Cross validation |
|---|---|---|
| Epoch # | 1000 | 1000 |
| Final MSE of MLP | 0.005804253 | 0.010523501 |
| Final MSE of SVM | 0.026378744 | 0.035615759 |

The practical experiments are achieved in the predicting model a value of ($R^2$ = 0.9844388787) for SVM and ($R^2$ = 0.9701310549) for MLP which indicates the predicting models are very close to the regression line and a well data fitting to the statistical models. Besides, the proposed models achieved less MSE in comparison with other related work. The predicting model for SVM network output is generated by a polynomial of forth orders as defined in Eq. (7):

$$y = -0.0001x^4+0.0307x^3-1.269x^2 +15.557x+130.38 \tag{7}$$

While, the predicting model for MLP network output is generated by a logarithmic as defined in Eq. (8):

$$y = 758.1 \ln(x)+2421 \tag{8}$$

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