Volume 9 • Issue 6 • November / December 2015

Editor-in-Chief
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INTERNATIONAL JOURNAL OF
COMPUTER SCIENCE AND SECURITY (IJCSS)

ISSN : 1985-1553
Publication Frequency: 6 Issues / Year

CSC PUBLISHERS
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INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND SECURITY (IJCSS)

VOLUME 9, ISSUE 6, 2015

EDITED BY
DR. NABEEL TAHIR

ISSN (Online): 1985-1553

International Journal of Computer Science and Security is published both in traditional paper form and in Internet. This journal is published at the website http://www.cscjournals.org, maintained by Computer Science Journals (CSC Journals), Malaysia.

IJCSS Journal is a part of CSC Publishers
Computer Science Journals
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INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND SECURITY (IJCSS)

Book: Volume 9, Issue 6, November / December 2015
Publishing Date: 31-12-2015
ISSN (Online): 1985 -1553

IJCSS Journal is a part of CSC Publishers
http://www.cscjournals.org

Published in Malaysia

Typesetting: Camera-ready by author, data conversation by CSC Publishing Services – CSC Journals, Malaysia

CSC Publishers, 2015

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Prediction of the Power Output of Solar Cells Using Neural Networks: Solar Cells Energy Sector in Palestine

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Abstract

The prediction of the output power of solar cells in a given place has always been an important factor in planning the installation of solar cell panels, and guiding electrical companies to control, manage and distribute the energy into their electricity networks properly. The production of the electricity sector in Palestine using solar cells is a promising sector; this paper proposes a model which is used to predict future output power values of solar cells, which provides individuals and companies with future information, so they can organize their activities. We aim to create a model that able to connect time, place, and the relations between randomly distributed solar energy units. The system analyzes collected data from units through solar cells distributed in different places in Palestine. Multilayer Feed-Forward with Backpropagation Neural Networks (MFFNNBP) is used to predict the power output of the solar cells in different places in Palestine. The model depends on predicting the future produce of the power output of solar cell depending on the real power output of the previous values. The data used in this paper depends on data collection of one day, month, and year. Finally, this proposed model conduct a systematic process with the aim of determining the most suitable places for an installation solar cell panel in different places in Palestine.

Keywords: Neural Networks, Solar Cell Energy, Prediction.

1. INTRODUCTION

Society starts searching for other energy resources with more awareness of their responsibility to the environment. Renewable energy experiences a huge expansion, which raises many challenges to the scientific and technical community [1]. Renewable energy is a clean and inexhaustible energy, and it's technology is developing rapidly [1]. In recent years, solar cells increasingly used to produce the energy in Palestine, one of the problems faced are the unpredictability in their production, since they depend on climatic variables of each moment [2]. Currently, distribution companies are responsible for managing and selling the energy into their networks. Palestine has seen an increase in the number of solar parks. The current Palestinian society aims to reduce electrical energy dependence, a better use of resources and greater awareness of the environment. There have been many initiatives in Palestine by the directives of support measures, renewable energy, establishing growth targets for renewable technologies in order to get more energy production comes from these resources [3]. Solar energy is the energy produced by thermonuclear reactions continuously on the surface of the sun, this energy spread in the universe with different energy forms such as light, heat, x-ray, and ultraviolet, these forms of energy forms the solar spectrum. The solar energy is a vital factor of life on the earth, solar spectrum hits the earth with half of its energy level because of the atmospheric shield and the reflection of the energy of the earth's surface, and this energy can be used in different fields like agriculture, heating, cooking, and electricity production [4, 5]. One of the major solar energy usages is to produce electricity, the process that can perform mainly in two methods, thermal solar energy which depends on heating fluids in pipe network running turbines to produce electricity, and photovoltaic solar energy, which uses photovoltaic phenomenon to produce electricity directly from the sunlight [6, 7].

In recent years, solar cells have a deployment unprecedented. The total energy supply from solar cells in Palestine in the year 2007 accounted of 1402 ktoe. The indigenous production contributed 19% of total primary energy supply while the remaining quantity imported from Israel [3]. Solar cell power in Palestine is a natural wealth, which must be explored; the electric distribution companies receive the electricity in its electrical network from two resources; the direct electrical lines from Israel and the solar cell panels installed in some areas in Palestine. There are no plans or estimation process, which used by these companies to determine the demand and the production of solar cells in such place, so the prediction of solar cell output power in such place, will help the company to plan and manipulate the electricity in this area, which will produce stability in electrical connection. For many years, they have tried to learn how to predict future events, so that, they can take preventive action. weather conditions are one of the future events, which directly or indirectly affect us every day, especially in electricity consumption. Therefore, they have developed methods of climate prediction, supported by different models to predict solar cell output power using mathematical prediction systems [8].

In general, a lot of researches have been developed for this purpose, but the most of them, use statistical methods to get results and historical analysis for the collected energy, without using prediction and classification models in order to create a solar energy map, that shows the best regions and provide an advice for people who are concerned in the energy field. In [9] the author used artificial neural network (ANN) control algorithms applied to the solar energy prediction, they proposed an algorithm detects the optimal operation point for photovoltaic and thermal panels by studying the (PV/T) model behavior considering irradiation and ambient temperature. Another related study was made to determine the highest time horizon for generating solar energy prediction by Ercan Izgi et al [10], they used small solar power system application to study and predict the time horizon by dividing the study period of time into short term [5min] in medium term in April, and [3 min] for short term, [40 min] for medium term in August, during April and August RMSE between the measured value and testing value changed between 33-55 in April and 37-63 in August , ANN algorithm used to predict the electricity generated in period 30-300 minutes. The external weather conditions that affect the solar energy generation are studied by Esteban Velilla and others in [11], they used two modules of solar cells [mono-crystalline (55w) and organic solar module (12.4w), the factors monitored by this study are the temperature, relative humidity, and irradiance, that are used as inputs for an ANN algorithm, which developed by the team to train ,validate and test the electric power generated, the result obtained of solar energy produced using organic solar module was better than mono-crystalline module in the extreme conditions of (high temperature, high humidity, and lower irradiance). Electricity sector in Palestine was studied by Ayman Abu AlKher in [12] and others, the study has been divided in two parts, one part to study the current situation of electricity production, consumption, and transmission, the second part is a comparison between Palestine and other neighbors, to highlight the electricity consumption gap, and he used a mathematical and economical model to predict the relation between electricity consumption and economic growth. Solar radiation forecasting study made by Bader M. Alluhaidah and others [13] explained the most effective variables that are used in the solar forecasting process as inputs for ANN, the case study was made in Saudi Arabia. The simple structure offers better results in terms of error between actual and predicted solar radiation values. A method for modelling and prediction of PV-generated power [14] has been developed by Amin Mohammed Sabrian et al, this method uses two kinds of ANN, general regression neural network (GRNN) and feed forward back propagation (FFBP), in the modelling process, he used four inputs for both ANN (max temperature, min temperature, mean temperature, and irradiance) with the power as an output. The data were collected through 5 years from 2006 to 2010 period, it was split into two parts, first 3 years data used for training and 2 years data used for testing, the result in both methods give good results, where FFBP has better performance than GRNN.

One common method for data collection is the using of special data acquisition system based on the wireless sensor network, this method of data collection uses the wireless sensor network connected by Wi-Fi or Wi-Max technologies, to achieve a reliable connection between far sensor nodes [15]. The other useful method is using the local electricity providers, where they have a very useful projects for solar cells energy. They provided us with a very good amount of data that we can use as a start point in our prediction and classification model, we get solar cells values from Al Ojah village in the East, Al-Zababdeh village in the north, and Ramallah city in the middle of Palestine. Another way of collecting previous data is the used of the data in the website "Solar GIS", which is a website that integrated with satellites, google maps and other measurement tools, to measure and estimates the atmospheric variables like temperature, humidity, and solar irradiation, that are the main factors which affect the solar energy production all over the world. The general objective of the proposed model is to develop a system based on Neural Networks (NN), which can predict the short-term values of an output power of solar cells over days, months and one year. Which aims to help companies in planning, managing and forecasting the suitable time and place for the energy production from solar cells. The data used for the process of learning in this model was taken for one year (one value in each 5 minutes) from different locations in Palestine, which allow a possible approximating value of the total power acquired by solar cells. In another hand, it analyzes the behavior of the time series that determine the value of solar cells in one year for different cities of Palestine.

2. ARTIFICIAL NEURAL NETWORK

Supervised NNs depend on the provided input data, this data will be processed using special activation functions, with the final goal of producing output. The current output of the NN will be compared with the desired output for the purpose of training the NNs by updating the weights in each epoch, which produce decreasing in approximation error. Artificial neurons are elements with an internal state that changes depending on the signals it receives, such neurons also have a transition function, which allows them to change the level of activation signals received from neurons, whether connected or from the outside [16]. NNs have a basic structure consisting of a series of entries that reach the neuron, and one or more output are connected to the input of another neuron network, this structure is known as a multi-layered NN [17] as shown in Figure 1.

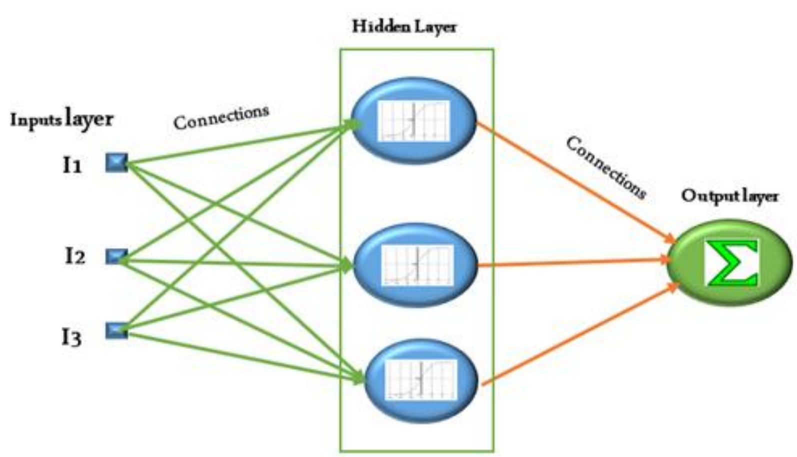

FIGURE 1: Basic Topology of Neural Network.

This type of structure has; an input layer which consists of input patterns. The connections in the hidden layer which are weighted connections between the input layer and the hidden layer, a processing units called neurons receives the input data from the input layer and processing it depends on the activation function, finally the output layer that is used to calculate the output of the NN. NNs are able to learn from input/output data to predict future value. Knowledge of this value can be performed in a time step, which is obtained from samples available at time t, and it can generate a value for time t + 1. It is also possible to predict multiple time steps, which involves taking other values known as the predicted values to generate new future value, NNs play good rule in time series prediction.

The general main steps for the basis NN start by a collection of the data to be used in training, validation, and testing. Preprocessing of the data which is an important stage that increases the performance of the NN, and reduces the number of processors (neurons) required, this will lead to reduce the number of neurons, and give the best curve fitting. Initialization of the NN starts by assigning values for the input weights, this process that most likely done randomly, or using certain algorithms according to the problem. In the NN training process, the activation function is applied to find the relation between the inputs and the outputs, and then updating the weights using the specified algorithms with a number of training data in order to get the best results. To check the validation of the NN, this model uses another set of data called validation data. Finally, the generalization process tests the NN for random and different dataset [17]. The Solar cells output power prediction using silicon cells is affected by several factors like solar irradiation, climate, temperature, relative humidity, dusty weather, cell direction, and the efficiency loss by the time [6]. In our proposed model we will use historical values of the solar cell output power recorded for a period of time (one year), the output values are recorded in (5 min) time horizon, this output power generated and recorded from the target output of the ANN [18].

In order to design the proposed NN, we must identify the problem domain and the factors that affect or determine the problem, it's known that the time series prediction is one of the most complex of the real world application, and it's also well known that the ANN has a good property of solving such complex problems. The training process is the mapping process between the input/output data of the NN when the input patterns provided to the NN with initial weights, the output of the NN are given by the following expression:

$$y_i = f(\sum_{j=1}^{m} w_{ij} x_j + b_i) \tag{1}$$

Where W_{ij} is the weights connection, and X_j are the value of the ith inputs for a simple of the NN, b_i is the NN bias, m is the number of neurons and f is the activation function. The general approximation criterion which uses to determines the improvement of the prediction process, is the error result, which comparing the actual output of the NN with the desired output in the learning process, this error is basically calculated using the following expression:

$$Er = y_{id} - y_{ia} \tag{2}$$

Where y_{id} is the desired value of the output for each i^{th} element and y_{ia} is the actual value of the i^{th} element, normally this criterion is used as a termination condition to stop the prediction process. In this paper, we use the root mean square error which presented by the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{id} - y_{ia})^2}{n}} \leq \theta \tag{3}$$

Where n is the number of the input data, and Θ is the threshold value of the prediction process. The training process continue to adjust the weights until the error criteria are satisfied, the weights updated is performed by the equation 4:

$$\Delta w_{i+1} = \alpha.\ RMSE.\ x_i \tag{4}$$

Where α is the learning rate.
One advantage of the multilayer perceptron neural networks (MLPNN), is that it can predict any time series function if a configuration and an adequate number of neurons in the hidden layers are

available. The MLPNN is an excellent time series prediction, although it is impossible to find a single configuration for each application. The learning process of the MLPNN with backpropagation algorithm is not fixed to any application; a successful method is to try different settings until you get the desired response. The choice of training patterns is performed depending on the explicit needs of the prediction, which will show on the output and the quality of information available. Any changes in the patterns of training require different training parameters of the NN, but the training process remains the same.

3. METHODOLOGY

Developing a methodology to establish prediction is a relationship as accurately and precisely as possible. The values of future solar cell energy output require the knowing of the previous solar cell energy output, these values are used as input to the model, $x_t = F(x_t, \ldots, x_{t-tw}) + \varepsilon_t$, where x_t is the forecasting forward steps with respect to time t, F is the modeling function between the previous and future values, ε_t is the modeling error. Predicting of solar energy output can be performed using different techniques as; prediction by numerical models, prediction by statistical methods, time series prediction based on the application of statistical techniques linear and nonlinear, and prediction coefficient cloud cover from satellite images. Obtaining a final prediction model of solar energy output based on the time series prediction using NNs. Predicting the energy output of solar cell using only numerical models has a high bias and a high mean square error, which depends on the distribution function of the radiance data for the station (at positions predominantly clear sky conditions with errors are smaller). For this reason, we used Multilayer feed- forward with backpropagation neural networks (MFFNNBP) and data of different months, each month presents one season of the year.

Multilayer feed-forward with backpropagation neural networks (MFFNNBP) is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed forward process and then it performs the weights update to be back-propagated to the previous layers in order to recalculate the weights. Our proposed ANN architecture has three parts, one for producing solar energy prediction depending on previous real output measured along one year "2014" from three main solar panels located in Ain-Mousbah – Ramallah, Al-Oja – Jerico, and Al-Zababdeh- Jenin. These three energy collection points provide the power output within 5,10,30,60 minute’s horizon of one month or one-year time horizon, then the data was processed according to the following process shown in figure 2.

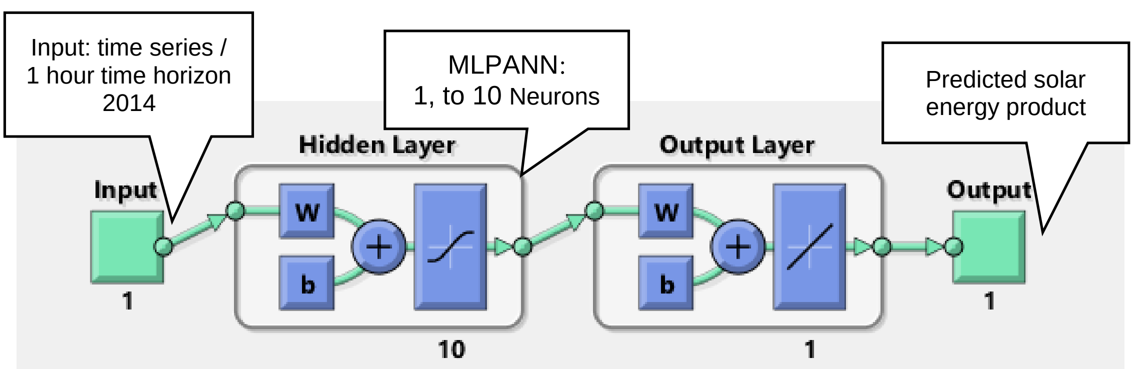

FIGURE 2: Proposed Solar Energy Prediction ANN.

The sigmoid activation function, f^1 is used [14]. In MLPNN, the output of a layer will be an input for the next layer passing from the input layer to the output layer; the equations used for this procedure are illustrated as follows:

$$output = f^{2}(\sum_{j=1}^{n} out_{1}.w_{jk}) \qquad 5$$

Where the output of the first hidden layer out_1, which calculated using the following expression:

$$out_{1} = f^{1}(\sum_{j=1}^{n} in_{i}.w_{ij}) \qquad 6$$

Where f^1 and f^2 are the activation functions for output layer and hidden layer, which calculated as in the following expressions:

$$f^{1} = \frac{1}{1 + e^{-x}} \qquad 7$$

$$f^{2} = x \qquad 8$$

Where, x = input vector. Depending on equations above, the weights are updated use as the following expression:

$$\Delta w_{jk}^{n} = -\mu \frac{dE(w_{jk}^{n})}{d\, w_{jk}} \qquad 9$$

Where μ is the learning rate (normally between 0 and 1). The final output depends on all earlier layer's output, weights, and the algorithm of learning used [14]. Using data collected from previously mentioned solar panels, this data was preprocessed to reduce the noise from the input signal, this process increases the performance of the ANN and reduces the prediction error, using Matlab function called smooth function, then takes the signal and filters the noise by using average filter smooths data, then replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low-pass filtering with the response of the smoothing given by the next difference equation:

$$ys(i) = 12N+1\big(y(i+N)+y(i+N-1)+...+y(i-N)\big) \qquad 10$$

Where $y_s(i)$ is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of $y_s(i)$, and $2N+1$ is the span.

The backpropagation process calculates the gradient decent error between the desired and the predicted output considering the new weights each time, this gradient is almost always used in a simple stochastic gradient descent algorithm to find the weights that minimize the error. Different algorithms are used for training the feed forward with backpropagation neural networks, which train the NN and reduce the error values by adjusting and updating the weights and the biases of the connections that form the neural network, two kinds of training algorithms are available to slow convergence according to steepest descent methods with better generalization, and fast convergence according to newton's method, but these methods are complex because of the complex matrix calculations [19]. In our paper, we use one of the fast convergence algorithms, which is the Levenberg Marquardt Algorithm (LM) training algorithms [20], implemented by Matlab 7.1, and we use it in two steps; one is the training of time series using the time as input and the power generated by solar energy points as output, and the second step is to train the data produced by the factors that affect the energy production along the time.

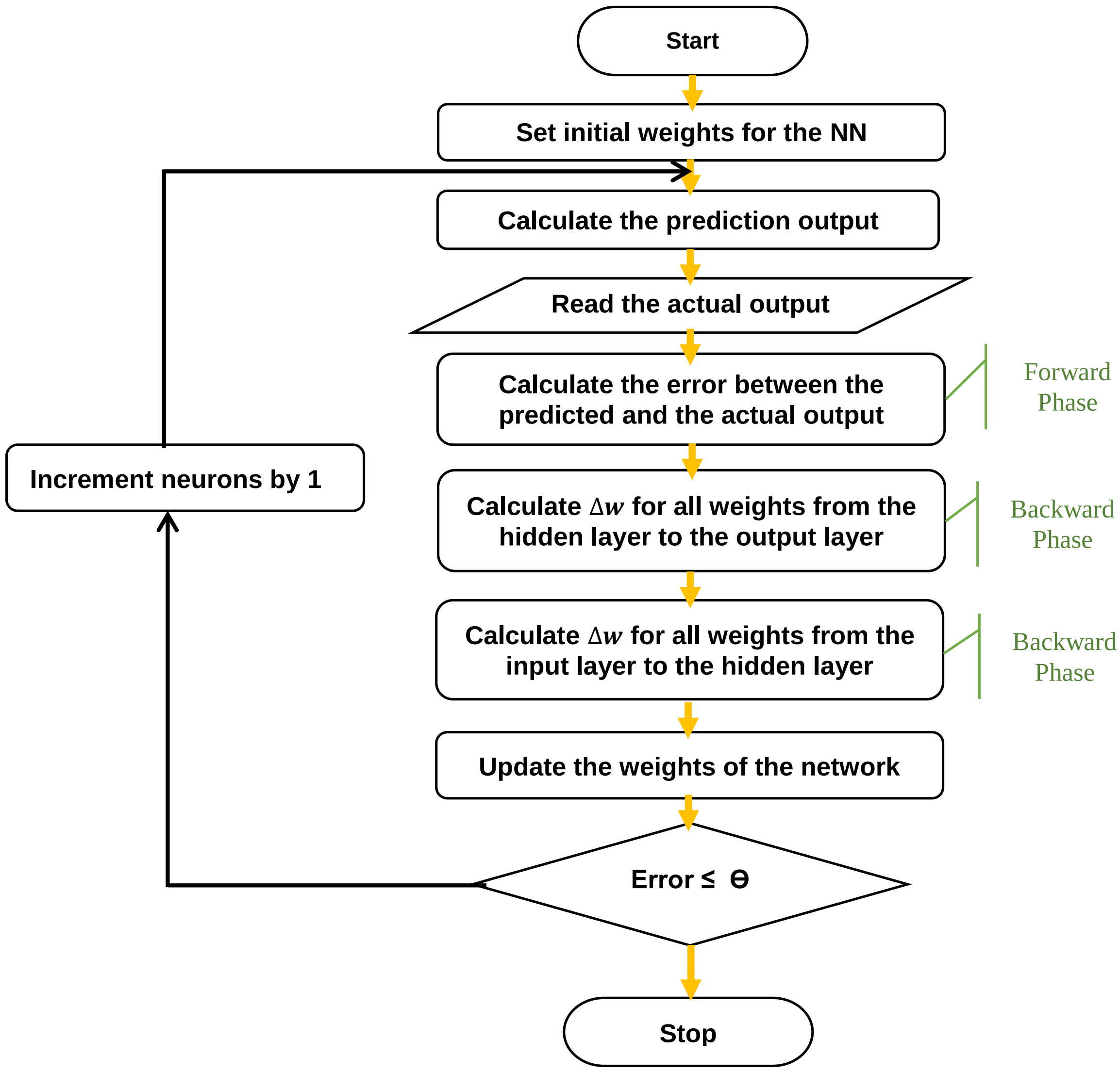

FIGURE 3: Flowchart of MFFNNBP Model.

4. RESULT AND DISCUSSION

Experiments have been performed to test the proposed prediction model. The model is simulated in MATLAB 7.1 under Windows 7 with processor i5. In this section, different examples are given to verify the procedure in the proposed model. Three different results are presented; One day, one month and one year. The results of the validity of the model in prediction samples of I/O data, compared with real results of the solar cell energy product of the last year in different areas in Palestine. The results are obtained in 5 executions; {# of neurons} the set of neurons used in each MFFNNBP. # of Epochs is the number of the execution cycle of the MFFNNBP. RMSEtest is the Root mean squared error of the training.

4.1 One Day Solar Energy Prediction

For one day prediction, we use data for each hour, which present the mean of all the read values in each 5 minutes. The day (1- Aug-2014) was selected with good climate conditions, like clear sky, long daytime, high solar irradiance, and medium humidity level, these conditions are highly effected the solar energy production. Applying the proposed model for one day of solar prediction produces the following results:

Solar prediction NN (# of neurons)	Epochs #	Train Data	Test Data	Validation Data	$RMSE_{test}$
2	11	70%	15%	15%	$7.6X10^{-5}$
4	29	70%	15%	15%	$3.16X10^{-5}$
6	19	70%	15%	15%	$1.64X10^{-5}$
8	22	70%	15%	15%	$3.3\ X10^{-6}$
10	19	70%	15%	15%	$1.8\ X10^{-6}$

TABLE 1: Results of Applying Proposed MFFNNBP in One-Day.

As seen from table 1, MFFNNBP plays a good role in solar prediction for one day, the real output for one day is a curve with some noise that are removed by using a smooth function as shown in figure 4. With one hidden layer of a small number of neurons, the proposed model predicts the future energy produced by the solar cell value in one day. This evaluated to find the RMSE of the MFFNNBP. Table 1 represents the test RMSE. In addition, figure 5 shows that the production process produces a fitting curve, with small values of RMSE.

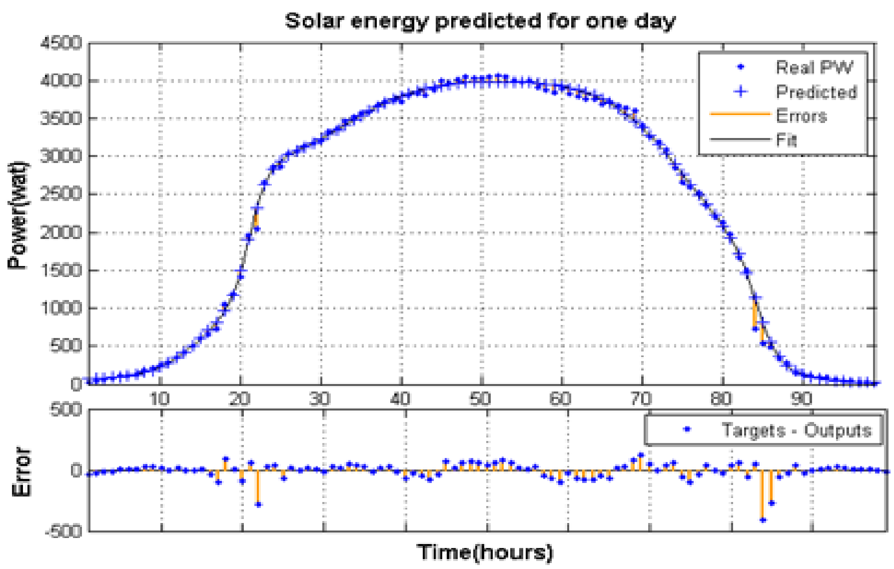

FIGURE 4: Power Generated for One Day.

4.2 One Month Prediction

To prove the process of predictions of the proposed models, we Applying the proposed MFFNNBP to predict energy that can produce in one month as the second part of the study, where July period of time was selected. Data was recorded for ALFA'A solar panel along the year 2014, and we built the training set for the July month record. The process was accomplished by taking the mean value of the generated power every 10 days with 10 readings per a day that can be illustrated in figure 5. Table 2 shows the results of applying proposed MFFNNBP for the training set which is formed of 30 examples, the results show that the best prediction result was achieved when hidden layer of 10 neurons was trained to give the following figures. According to the figure 6, the best prediction is achieved with 10 neurons in the hidden layer and 18 epoch. MFFNNBP produce small RMSE in monthly measured.

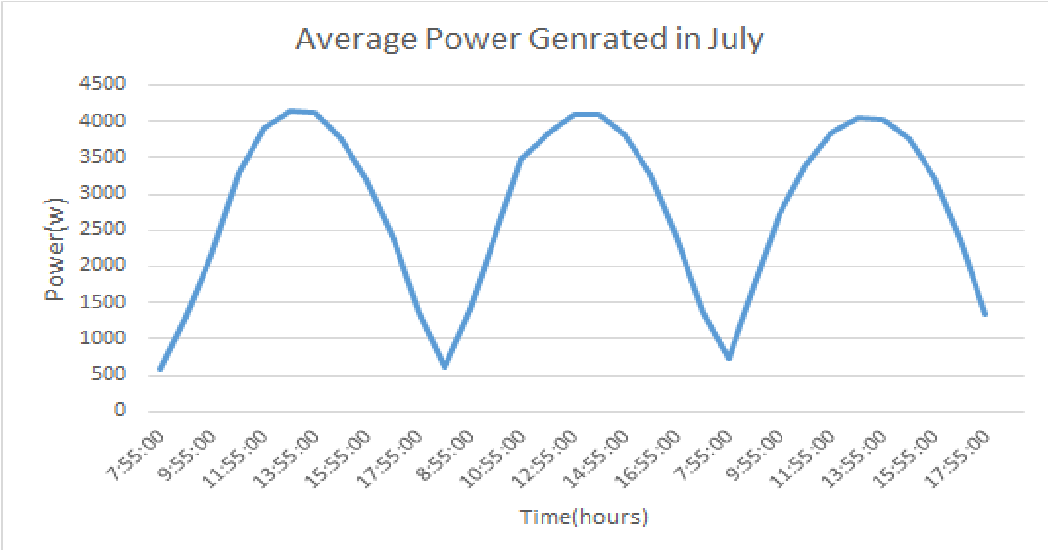

FIGURE 5: Mean Values Solar Energy Produced in July 2014.

Solar prediction NN (# of neurons)	Train	Test	Validate	Epochs #	$RMSE_{test}$
2	70%	15%	15%	8	0.091638
4	70%	15%	15%	9	0.072802
6	70%	15%	15%	11	0.000436
8	70%	15%	15%	18	0.000413
10	70%	15%	15%	18	0.000236

TABLE 2: Model Training Results for Energy Prediction at July (One-Month).

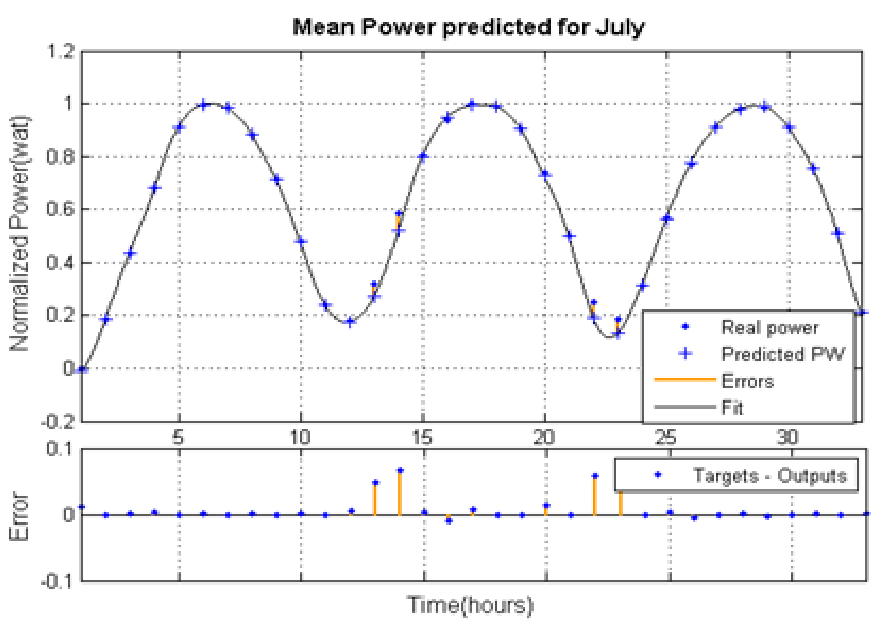

FIGURE 6: The Best Prediction Result of the Training Process for One-Month.

4.3 One Year Prediction

In order to get energy production along one year we need to deal with complex time series, figure 7 below shows the time series signal for one year [1-Jan-2014 to 1-Jan-2015], so we divided the year into four parts representing the four seasons of the year, dealing with each part as the mean value of the produced solar energy. As we see the high complexity of this signal, so we need to process it before we use it as target function to be predicted using the MFFNNBP model. This process started by; dividing the year into four parts, remove the night time where the energy produced goes to zero, reduce the large amount of data as Mean of one month = Mean [mean (1^{st} ,2^{nd} , 3^{rd} days) + mean (14 ,15 , 16 days) + mean (28 ,29 , 30 days), reduced the noise using smoothing function, normalization of the signal data, and applying the proposed model using several probabilities to get the best prediction results.

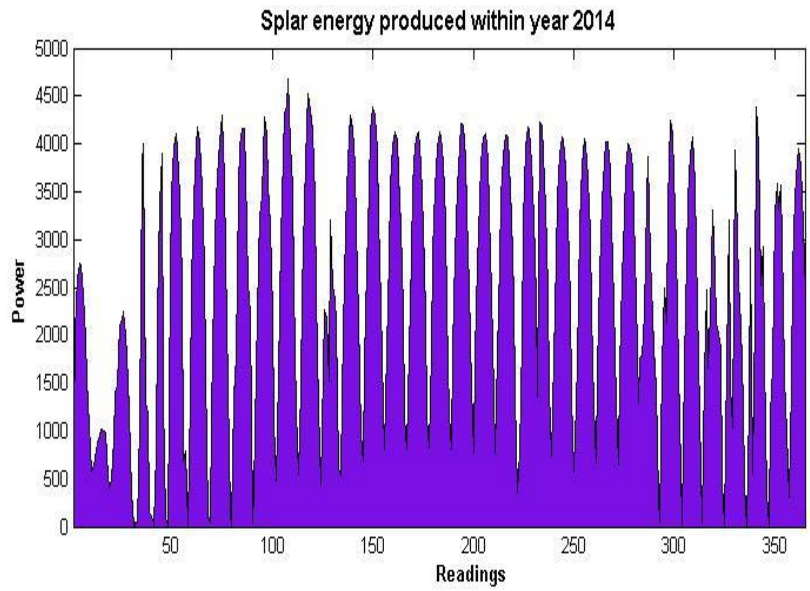

FIGURE 7: Energy Produced on One-Year.

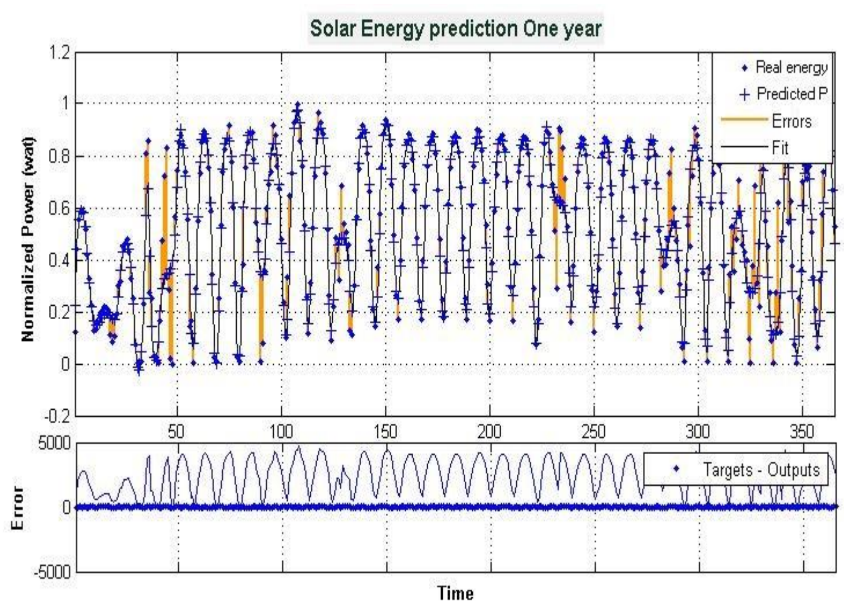

FIGURE 8: The Best Prediction Result of the Training Process for One-Year.

Figure 8 shows the best result for one-year prediction which was achieved when we applied the proposed model with 80 neurons in the hidden layer, and also shows the complexity of one-year time series solar energy prediction. As we see from figure 8 the error was at its minimum value with 90 neurons hidden layer is used [0.00564], which is the best error value, while when using more than 90 neurons the system will produce an overfitting problem. In all tables and approximation curves, we can observe the RMSE of the prediction, which clearly shows that the prediction is closest to the real value, regardless of the loss in the efficiency of the solar cells in energy production decreases by %5 in each year, all with a small number of epochs. The prediction process using the proposed model MFFNNBP was achieved using 80 neurons in the hidden layer, as shown in table 2 below:

Solar prediction NN(# of neurons)	**Train**	**Test**	**Validate**	**Epochs #**	**$RMSE_{test}$**
20	70%	15%	15%	7	0.070022
30	70%	15%	15%	8	0.067588
40	70%	15%	15%	9	0.064546
50	70%	15%	15%	22	0.039261
60	70%	15%	15%	11	0.035956
70	70%	15%	15%	11	0.01505
80	*70%*	*15%*	*15%*	*10*	*0.008242*
90	70%	15%	15%	12	0.00564
100	70%	15%	15%	12	0.008293

TABLE 3: Model Training Results for Energy Prediction for One-Year.

As we can see in the tables and figures, it is possible to observe the correlation values between real solar cell output power and power output obtained from the prediction using the proposed model MFFNNBP, that are measured in the same place. It is clear that we can consider the possibility of including other information as input to the model like, temperature, radiation, and humidity, and the time duration of the sunlight. This may perform better prediction of solar cell output power. Hence, the idea to predict more deeply the correlation between climatic parameters using NNs. The use of the MFFNNBP model for prediction of climatic variables becomes a viable solution for the knowledge of these values. The implementing of this model to solve a prediction problem is necessary to determine the optimum areas, where the solar cell panels can produce a more efficient power output. The obtained result, which use the MFFNNBP model for solar energy prediction, different attributes like training algorithm, training data, a region of study will change the values of the prediction result. This result obtained using real output data (previous data) as a measure of the prediction improvement, or prediction of the actual output using some input parameters. In the future work we will study the prediction process using the input data parameters that affect the power output of the solar cells like; temperature, radiation, and humidity, and the time duration of the sunlight. Furthermore, we will apply the model in two different types of solar cells; mono-crystalline and organic solar module, in the aim to determine the best type for our region.

5. CONCLUSION

In this paper, we used the energy produced data from solar panel located in different Places in Palestine for the year 2014, to train and test prediction technique that uses multilayer feed forward with backpropagation neural networks (MFFNNBP) trained using Levenberg-Marquardt algorithm, the model predicted the solar cells energy production for one day, one month and finally for the whole year with very high accuracy and low relatively number of processing units (neurons) to accomplish this task. The use of MFFNNBP for the prediction of solar cell energy output becomes a viable solution for the knowledge of these future values. In fact, the introducing of another meteorological system such as radiation, temperature, and sunshine hours and humidity may perform a significant improvement in prediction. From these results, we can predict the solar cell energy output for the next year, and we notice that August was the best month of the solar cell energy production, that is because of the clear sky, intermediate temperature, and long daytime which gives a long time of solar irradiation to produce energy. By looking at the figures obtained by the model you can perceive that this model predicts the future solar cell energy output in an accurate form.

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Compensated Mass Balance Method For Oil Pipeline Leakage Detection using SCADA

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Abstract

Having extracting oil from reservoir below the ground surface, and after processing, the products are transported through a network of oil pipelines to oil terminals. Thus, oil pipelines play a major role of the economic structure. However, oil pipelines could be subjected to damage due to many reasons like (i) Pipeline corrosion or wear, (ii) Operation outside the design limits, (iii) Unintentional third-party damage and (iv) Intentional damage. As a result of this damage, oil would leak from pipelines, which leads to loss of life and property, cost of lost product and line downtime, environmental cleanup cost, possible fines and legal suits.

The biggest challenge in this industry is to come up with a pipeline leak detection method that will accurately detect leaks in a timely fashion.

There are several methods which lead to detection of pipeline leakage. In most Yemeni oil fields pipeline leakage is detected by fiber optics sensing method which is expensive or by visual inspection using experienced personnel who walk along a pipeline, looking for unusual patterns near the pipeline.

In this paper, we are going to implement a different and cost effective method using Supervisory Control and Data Acquisition (SCADA) system.

Simulation has been performed using Rockwell Automation Software Products. The results so obtained are presented and discussed.

Keywords: SCADA, Leak Detection, Oil Pipeline, Mass Balance, Pump Failure.

1. INTRODUCTION

According to Yemeni Ministry of Oil & Minerals, the current average daily oil production in Yemen reached about 274,266 Barrel of Oil per Day (BOPD), from 13 producing blocks. All these products are transported through a network of oil pipelines into oil terminals [1]. These pipelines could be subjected to damage. So it is necessary to cease oil leakage by detecting it and acting to stop it as fast as possible [1].

Methods used to detect pipeline leakage are divided into two categories. External based methods which detect leaking product outside the pipeline and include traditional procedures such as right-of-way inspection by line patrols that walk along the pipeline, looking for unusual patterns near the pipeline, as well as technologies like hydrocarbon sensing via fiber optic or dielectric cables [2, 3]. However, these are quite expensive.

As an alternative, internal leak detection method that uses software algorithms and instrumentations to measure and monitor the internal pipeline parameters (i.e. pressure, flow, temperature, etc.) [2], is less expensive as compared to the external one [2, 4]. These parameters are fed to (SCADA) systems, which are computer-based systems [2]. SCADA system uses a software algorithm to calculate the inventory of the line at all times and compare this with the accurate measurements at any section in the system. The effects of pressure and temperature on line dimensions, for example, can be calculated to provide an accurate estimate of the mass of fluid in the line [4], and hence recognize hydraulic anomalies [5].

SCADA system gathers, processes, displays and controls data from field instrumentation [5]. For these reasons, most pipeline systems today employ some form of SCADA using commercially available or custom-designed software packages to monitor and recognize hydraulic anomalies and detect leakage in pipelines [2].

In block S1 in Shabwa governorate (Yemen) with daily production about 10,000 BOPD, an internal method called Pressure Point Analysis (PPA) is used for leakage detection. This paper proposes another internal method called Compensated Mass Balance method using SCADA. This method is discussed, simulated and analyzed. Comparison between the two methods is also performed.

2. PRESSURE MONITORING

When a leak suddenly occurs in a pipeline, there is a sudden change in the pipeline pressure [6]. These changes or disturbances can be useful in detecting the leakage; Pressure Monitoring method can detect the leak as following:

2.1. Pressure Point Analysis (PPA)

PPA leak detection method is based on the premise that the statistical analysis property of a series of pressure measurements taken on a pipeline is different before and after leak occurrence [7].

Pipeline pressure falls too rapidly in case of leak [8]. This leak can be detected by comparing pressure of pipeline at a single point and comparing it against the statistical pressure measurements [7]. Dedicated software will determine if the behavior of these two signals contains an evidence of leak [9], when the pressure falls below a lower limit [10].

2.2. Rarefaction Wave

When a leak occurs, there is a sudden drop in pressure at the leak followed by rapid line an increase in the pressure (re-pressurization) for a few milliseconds later. The resulting low-pressure expansion wave travels at the speed of sound through the liquid away from the leak in both directions [4]; following this wave there is a general loss of pressure in the pipeline [7].

Due to these disturbances (the sudden pressure drop, the rapid pressure increase and after that the general loss of pressure), so the pressure in pipelines can be recognized by the upstream and downstream pressure transmitters, and hence the pressures values will be below the lower limit after that will be above the higher limit which will trigger the leak alarm.

However the main drawback in pressure monitoring method is that it requires that all events other than leaks that may cause a pressure to decline and rise, such as operational changes to the pipeline (i.e. start/stop shipping pump, opening and closing valves, and flow rate increase), must be identified so that the leak detection can be inhibited until the pipeline returns to steady state operation to avoid the false alarms [8].

3. BALANCING METHODS

The mass balance method is based on the equation of conservation of mass. In the steady state, the mass entering a leak-free pipeline will balance the mass leaving it. In general, the difference in mass at the two ends must be balanced against the change of mass inventory of the pipeline [5]. Over any given period of time we can say:

$$M_{pipe} = M_1 - M_2 \tag{1}$$

Where:

M_1 is the inlet (upstream) mass flow rate (kg/s)
M_2 is the outlet **(downstream)** mass flow rate (kg/s)
M_{pipe} is the change of mass **inventory of the pipeline per unit time** (kg/s)

$M_1$and M_2 are obtained by software as (FT_1 x ρ_1) and (FT_2 x ρ_2) respectively, where FT_1 and FT_2 are respectively the upstream and down downstream flow rates measurements taken from the instruments and

ρ_1 and ρ_2 are the fluid densities at the upstream and downstream of the pipeline respectively

In principle, the mass in the pipe depends on the density of the product multiplied by the volume of the pipeline. Both are functions of temperature and pressure. The density is also a function of the composition of the product. Any addition in the mass imbalance indicates a leak. This can be quantified by rearranging Equation (1) and adding a term for leak mass flow M_{leak} gives:

$$M_{leak} = M_1 - M_2 - M_{pipe} \tag{2}$$

Where M_{leak} is the leak mass flow

Mass balance methods use the principle of mass conservation; i.e. mass is conserved if there is no leak, in general, the inventory of the pipeline for length (L) changes over time because of changes in the fluid density ρ and cross sectional area A.

By dividing the pipeline into segments (n), the temperature, pressure, and density are assumed to be uniform results in the line fill calculation as well as the uniform segment density ρ_n. The line pack equation will be as follows [11]:

$$M_{pipe} = \int_0^L \rho(x)A(x)dx \tag{3}$$

Where A is pipeline cross-sectional area (m^2)

3.1. Uncompensated Mass Balance

It is also known as Line Balance, in this method there is no compensation for the change in pipeline inventory due to pressure and temperature [7], so the fluid density (ρ) and pipeline cross-sectional area (A) are assumed to be constant [9], therefore M_{pipe} becomes negligible [5], so the leak mass flow equals the difference between the inlet mass flow rate and the outlet mass flow rate**.** Equation (2) becomes:

$$M_{leak} = M_1 - M_2 \tag{4}$$

As a result of the above assumption, the method doesn't take into account the changes in fluid density due to pressure variations, and changes in actual dimensions of pipeline due to temperature changes. Hence, it becomes a susceptible to false alarms [2].

3.2. Compensated Mass Balance

Compensated mass balance uses a bulk modulus of elasticity ε (which is a material property characterizing the compressibility of a fluid and how easy a unit of the fluid volume can be changed when changing the pressure applied on it) [2], along with an average temperature and pressure over the entire length of the pipe [11]. The inventory of the pipeline is usually calculated by dividing the pipeline into segments and assuming steady state pressure and temperature profiles from one end of the pipeline segment to the other, and calculating an average density for the segment [8].

3.3. Model of Compensated Mass Balance

Model of the compensated mass balance uses the real time transient models (RTTM) method. The RTTM uses the computational power of modern computers with the help of software algorithms for evaluation of leaks and make it possible to compute density along the pipeline [6]. Software-based method that calculates the flow balance (FB) as the difference between the M_1 and the M_2 as given below in Equation (5).

$$FB = M_1 - M_2 \quad \text{(kg/s)} \tag{5}$$

In addition, a hydraulic transient computer model is used to calculate the mass inventory of the pipeline which is referred as packing rate (PK) in Kg/s. The packing rate is calculated by the transient model from pressure and temperature or density data provided by SCADA system instrumentations. A quantity called mass balance (MB) is calculated as the flow balance minus the packing rate [9], as given in Equation (6).

$$MB = FB - PK \quad \text{(kg/s)} \tag{6}$$

Ideally, the mass balance will always be calculated as zero. A positive imbalance is interpreted as a leak [9]. The advantage of this system over PPA or uncompensated mass balance is that system transients like pump start up and shutdown will not generate alarms [9, 10].

3.2.1. Modeling Equation

The transient pipeline flow model, which is used to calculate packing rate, is the heart of a pipeline modeling system. The model computes the state of the pipeline at each time interval for which data are available. The state of the pipeline is defined as a set of pressures, temperatures, flows, and densities that describe the fluids being transported at all points within the system. These quantities are the solutions of a set of equations that describe the behavior of the pipeline system. These basic equations are the continuity equation which enforces conservation of mass, the momentum equation which describes the force balance on the fluid within a section of pipeline, and the energy equation which states that the difference in the energy flow into and out of a section equals the rate of change of energy within the section. Now the question is how to solve the above three equations. The answer is by finding a relation between the pressure, density, and temperature of the fluid [4].

Using an equation of state which relates the density of the fluid to its pressure and temperature, the density can be calculated from an average temperature and pressure over the entire length of the pipe [6].

The packing rate is calculated by assuming steady state pressure and temperature profiles from one end of the pipeline to the other, and calculating an average density of the fluid along the pipeline [8], as

$$\rho_{av} = \rho_o \left[1 + \frac{(P_2 - P_1)}{\varepsilon} + \alpha (T_2 - T_1) \right] \tag{7}$$

The density is then multiplied by the pipeline volume to find the **fluid mass inside the** pipeline

$$\text{Fluid mass} = \text{Pipeline Volume} \times \rho_{av} \tag{8}$$

Finally the **fluid mas**s is divided by the time (in seconds) to obtain the packing rate

$$PK = \text{Fluid mass}/t \tag{9}$$

Where:

ρ_{av} is the average density (Kg/m^3)
ρ_0 is the reference or real density (Kg/m^3)
P_1 , P_2 is the upstream and downstream pressures calculated by software (GPa)
ε is the bulk modulus fluid elasticity (GPa)
T_1 , T_2 is the upstream and downstream temperatures calculated by software (°C)
α is the temperature expansion coefficient (1/°C)

3.2.2. Program Algorithm

Real-time transient modeling (RTTM) is a technique that uses the full data-gathering capabilities of modern digital systems and the computational power of small computers to give accurate ‘‘snapshots’’ of the pipeline. The whole system is under the control of a SCADA package of programs, which gather data from field instrumentation, process the data, control the running of the transient pipeline model, and activate the alarm and leak location routines. The SCADA interface is responsible for acquiring the data from the SCADA system and relating them to the model representation of the line. The model provides data on the flow conditions within the line at intervals ranging from seconds to minutes, depending on operational needs. The real-time applications modules will run based on the availability of data from the measurement system and the pipeline model. These are the leak detection and location routines in the context of integrity monitoring [4].

When a leak occurs, the difference (FB - PK) become larger, but less than a set point (which is 10% of total flow), the model system does not account for a leakage. If this difference exceeds preselected set points, a leak alarm is declared.

Once the leak detection module declares a leak, the location routine is activated. The location is calculated using the upstream and downstream mass flow rates, as per Equation (10).

$$\text{Leak location} = \frac{M_2 \times L}{M_1 - M_2} \tag{10}$$

Where L is the pipeline length (Km)

4. SIMULATION AND RESULTS

In this section, simulation will be carried out with help of Rockwell Automation Software Products i.e. (RSLogix Emulate 5000, RSLinx, and RSLogix 5000 Enterprise Series) which provide SCADA hardware and software components, and ICONICS GENESIS32 family of web-enabled industrial automation software that offers applications for Human Machine Interface (HMI), SCADA and Control i.e. (real-time trending and data historian, summary viewing, logging and reporting) [12].

Simulation was done in two steps, first step by building a simulation for pipeline SCADA system, and second step by applying RTTM technique to detect the leak.

SCADA system, shown in figure 1, was build according to SCADA layers, which are:

- End devices or field instrumentation layer
- Programmable Logic Controller (PLC) layer
- Communication equipments layer
- Supervisory Station (SCADA Server) layer or Master Terminal Unit (MTU) which contains Object Process Control (OPC) software and HMI application. OPC software is a communication standard based on Object Linking and Embedding (OLE) technology provided by Microsoft windows that provides an industrial standard exchange mechanism between plant floor devices i.e. PLCs and client applications i.e. HMI

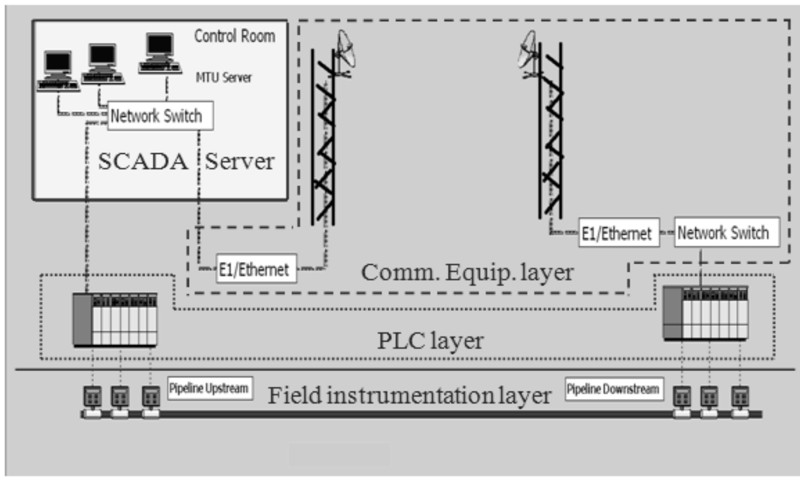

FIGURE 1: SCADA based pipeline system.

PLC layer is typically pictured as given in figure 2.

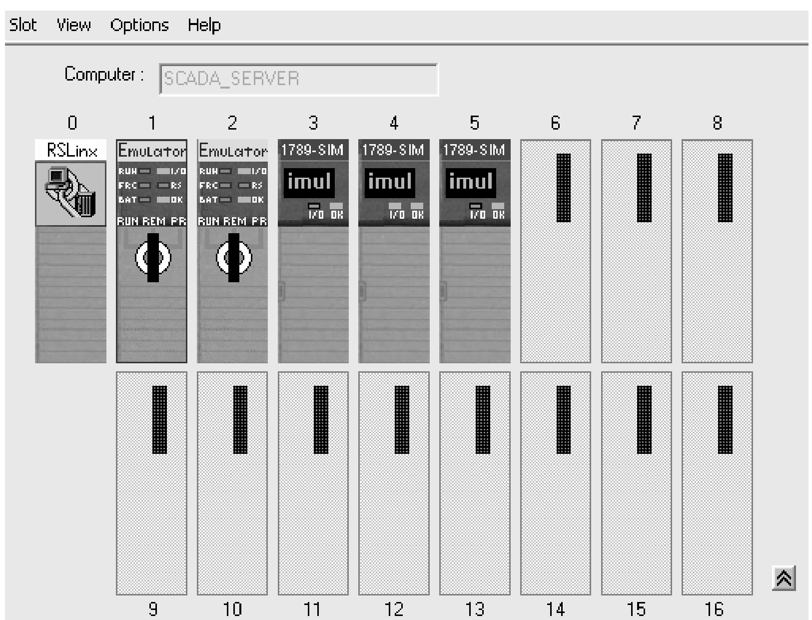

FIGURE 2: PLC layer.

The above software packages illustrate the capability of the compensated mass balanced method in recognizing the leakage of the fluid from other conditions. Some of these conditions are pump failure, flow rate increase, large leak and small leak condition.

As already mentioned, PPA method is implemented in block S1 in Shabwa governorate. With this method, all the above conditions are considered as leaks resulting, sometimes, in false alarms and unnecessary disturbances and actions.

In what follows, it will be seen that, unless the mass balance (MB) exceeds a leak set point (SP) the condition will not be considered as a leak and there will be no alarm.

The above conditions will now be simulated. However, steady state condition will first be presented to show the upstream and downstream pressures and flow rates PT_1, FT_1 and PT_2, FT_2 respectively.

PT_1 and PT_2 are the upstream and downstream pressures measurements taken from the instruments, in pound per square inch (psi) and FT_1, FT_2 are the upstream and downstream flow rates measurements taken from the instruments, in barrels of oil per hour (bbl/hr).

TT_1, TT_2 are the upstream and downstream temperature measurements taken from the instruments in (^oF**)**.

All the above measurements are transmitted to the PLC.

The steady state values presented in Table 1 are obtained by considering the actual measurements from the field as the average values for 120 days.

Upstream Data	Downstream Data
PT_1 = 310.1975 psi	PT_2 = 246.3525 psi
FT_1 = 392.4877 bbl/hr	FT_2 = 400.3265 bbl/hr
TT_1 = 100.8502 ^oF	TT_2 = 92.6744 ^oF
ρ_1 = 0.83214 Kg/m^3	ρ_2 = 0.80966 Kg/m^3

TABLE 1: Steady State Values.

During normal operation, PT_1, FT_1 and PT_2, FT_2 are found to be steady and considered as given in the above table. The leak set point (SP) is taken as 40 bbl/hr as illustrated in figure 3. As seen, MB does not exceed SP.

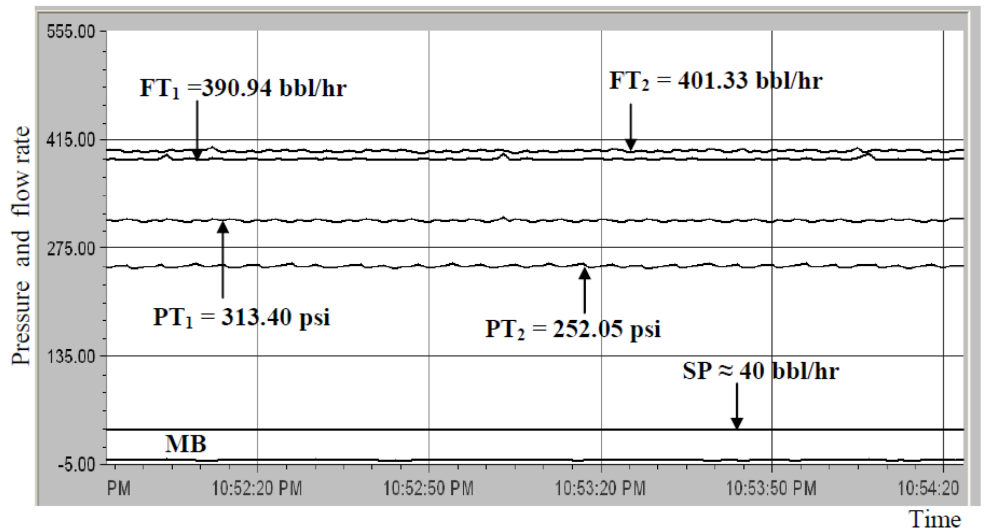

FIGURE 3: Variation of oil flow rate and pressure during steady state condition.

During normal pumping conditions a liquid will show minor transient due to pipe wall friction, reflection of pressure waves and temperature differences.

4.1. Pump Failure Condition

As long as there is no leak, the upstream and downstream flow rates drop to zero when there is a pump failure as seen in figure 4. Meanwhile, the upstream pressure falls to a value that is equal to the downstream pressure. As a result the flow rates and pressures become unsteady, for a while, in the pipeline, and hence the computed mass balance (MB) value will reduce momentarily and then comes back to its normal value. The RTTM will not trigger alarms.

In PPA method the set point is a predefined pressure value, for example 280 psi. If upstream pressure falls below this value, false leak alarm is declared.

Values of the flow rates and pressures after pump problem are indicated in the figure 4.

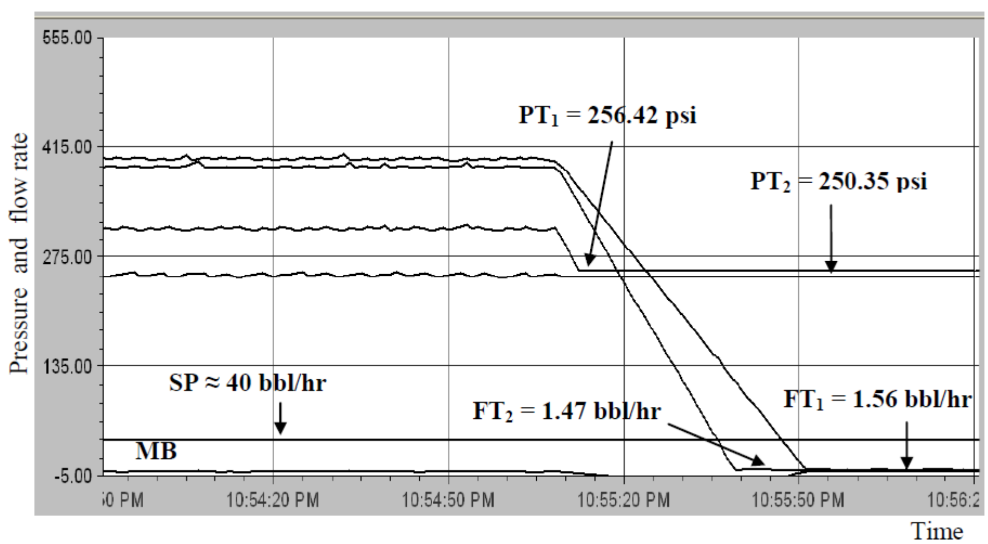

FIGURE 4: Variation of oil flow rate and pressure during pump failure condition.

4.2. Flow Rate Increase Condition

Centrifugal pumps are the most widely used in crude oil pipelines, thereby a common way to control the flow rate through the centrifugal pumps is to open/close the flow control valve which is located on the discharge side of the pump.

In this case, opening the flow control valve allows the flow rate to increase. The upstream and downstream flow rates increase to the new values and at the same time upstream and downstream pressures will increase as well. Due to these changes the mass balance (MB) value will increase for a very short time (but will not exceed the leak SP) and then comes back to its normal value and as a result there will be no leak alarm.

It is also evident that PPA method will not activate the alarm as PT_1 is more than 280 psi.

The new steady state values of the flow rates and pressures after the changes are indicated in the figure 5.

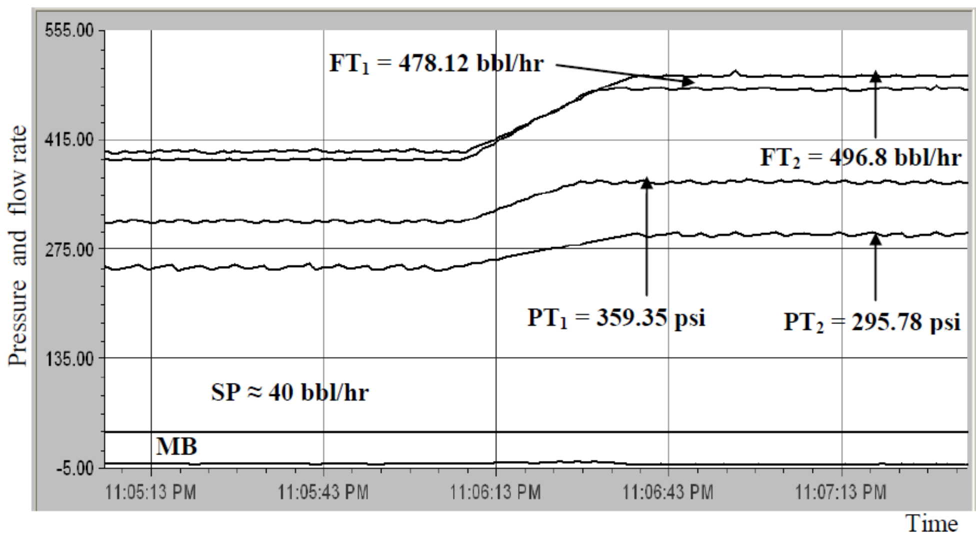

FIGURE 5: Variation of oil flow rate and pressure during flow increase condition.

4.3. Large Leak Condition

When large leakage occurs, the inlet flow rate will increase in a short time due to lower pipe flow resistance between the upstream meter and the leak, while the outlet flow will fall as mass leaves through the leak hole instead of passing through the downstream meter, see figure 6.

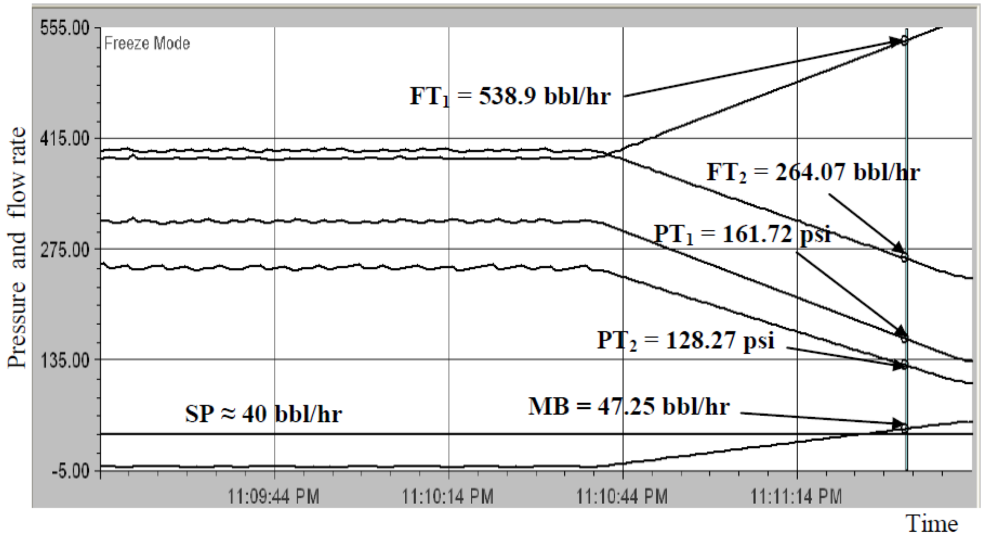

FIGURE 6: Variation of oil flow rate and pressure during large leakage condition.

The upstream and downstream pressures drop as the line is depressurized as mass leaves through the leak hole. The flow balance (FB) becomes more and more positive, at the same time the packing rate (PK) drops, and the mass balance (MB) value will increase until it exceeds the leak set point to indicate the leak rising to alarm triggering. In the figure, the indicated values are those after the leakage alarm is activated.

In PPA method the upstream pressure falls below 280 psi resulting also in a leak alarm.

Values of the flow rates and pressures after leakage occurrence are indicated in the figure 6.

It have been observed that the changes in the inlet flow rate (upstream), and the outlet flow rate (downstream) due to leakage condition in figure 6 were consistent with those changes given in figure 7 [13].

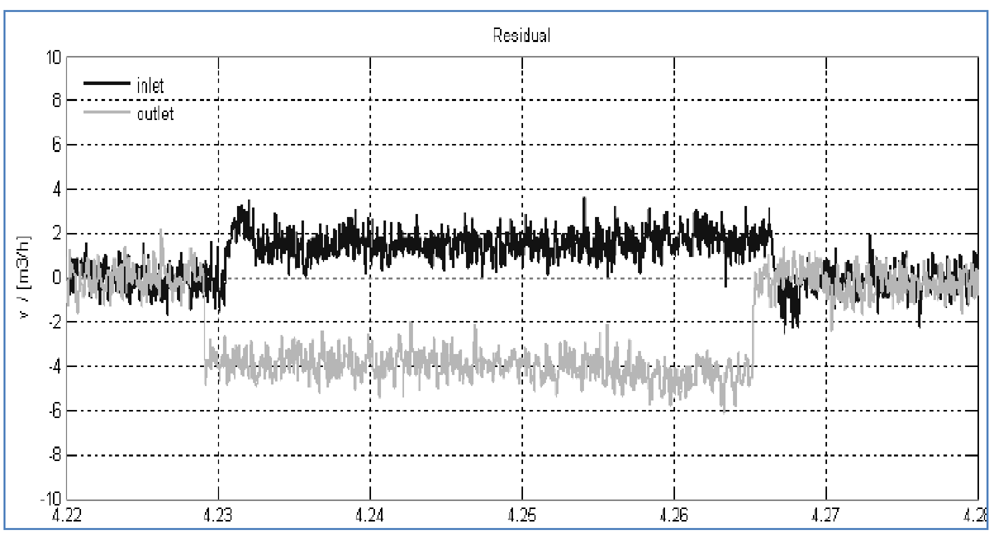

FIGURE 7: Inlet and outlet flow residual during leak trial.

4.4. Small Leak Condition

When small leakage occurs the inlet flow rate will increase slowly while the outlet flow will fall in a similar rate as shown in figure 8. The upstream and downstream pressures will also drop, which leads to an increase in the mass balance (MB) value slowly to indicate the leak. Here also, the indicated values in the figure are those after the leakage alarm is activated.

In PPA method, once the upstream pressure value drops below the set point (280 psi), the alarm will activate.

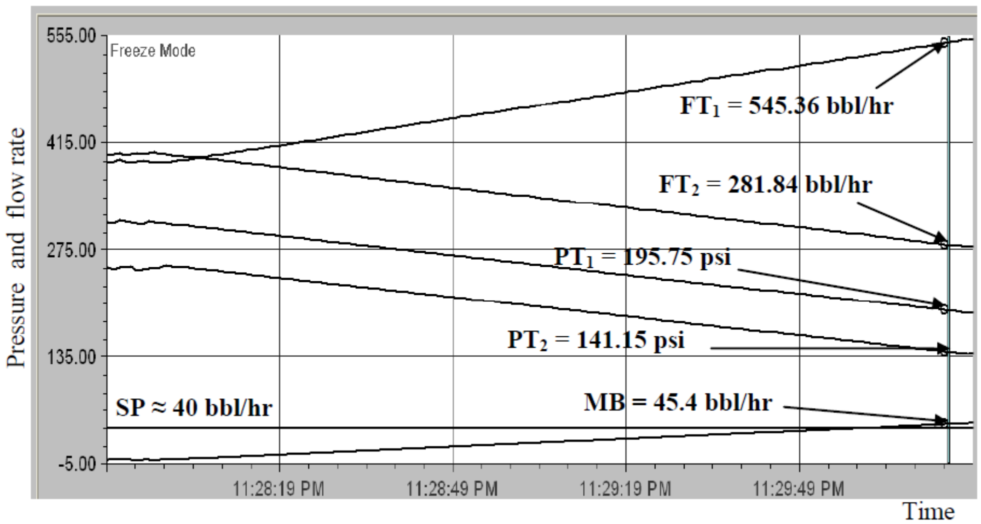

FIGURE 8: Variation of oil flow rate and pressure during small leakage condition.

As shown from the last two conditions, the time taken for the mass balance to exceed the leakage set point and declare the leakage alarm depends on the amount of the leakage.

5. CONCLUSION

In many oil fields, pressure monitoring method is used to detect oil leakage in the pipeline system based on pressure measurements. However, this method may cause false leak alarm during pump failure condition unless it is identified to inhibit the false alarm.

In this paper, For simulation, Rockwell Automation Software Products have been used. Compensated mass balance method is implemented for leak detection. This method is capable of dealing with different pipeline operating conditions and recognizes the leakage condition from other abnormal operating conditions. Since the transient model of this method uses flow rate, pressure, temperature and density to calculate the pipeline packing rate, the compensated mass balance model can deal with different operational changes of the pipeline and detects leak easily. Alarms will be activated when there is leakage only.

Different operating conditions, including leakage conditions, have been simulated, presented and discussed.

The simulation reveals that PPA method considers pump failure as a leak, while compensated mass balance method recognizes it.

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