Controlling of Artificial Neural Network for Fault Diagnosis of Photovoltaic Array

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***Abstract*--High penetration of photovoltaic (PV) systems is expected to play important roles as power generation source in the near future. One of the typical deployments of PV systems is without supervisory mechanisms to monitor the physical conditions of cells or modules. In the longer term operation, the cells or modules may undergo fault conditions since they are exposure to the environment. Manually module checking is not recommended in this case because of time-consuming, less accuracy and potentially danger to the operator. Therefore, provision of early automatic diagnosis technique with quick and efficient responses is highly necessary. Since high accuracy is the important issue in the diagnosis problems, the paper present fault diagnosis method using three-layered artificial neural network. A single artificial neural network (ANN) is not suitable to provide precise solution for this fault identification. Therefore, several ANNs are developed, then automatic control based module voltage terminal is established. The proposed method is simple and accurate to detect the exact location of short-circuit condition of PV modules in array.**

***Index Terms*--PV array, fault diagnosis, short-circuit condition, TFFN, fault location.**

I. Introduction

PHOTOVOLTAIC (PV) systems have been recently attracted more attention as prominent renewable energy sources. This phenomenon is driven by several reasons for instance mature technology development, sustainable energy provision and environmental concern. In terms of PV cell development, the conventional Silicon (Si) technologies which comprise mono-crystalline and multi-crystalline have reached their potential markets designated by high efficiency energy conversion. Meanwhile, other PV cells based thin film technology such as amorphous Silicon, Cadmium Telluride (CdTe) and Copper Indium Diselenide (CIS) have gained importance in the market penetration due to the significant cost reductions. Thanks to the excellent research and development of semiconductor and nano-technology materials. Sustainable energy provision is another reason why the PV systems become important energy sources in the future. Our power system is actually getting older where almost there is no power generation units established in the system, while the electricity demand is rapidly increased year by year. For this reason, the instant energy supply is urgently needed in our electricity grid and PV systems can be the prominent solutions to overcome the electricity shortages. About the global environmental concern, PV systems can play important roles since they are environmentally clean because no gas emission, no water or fluid, silent because no moving parts and aesthetically improved views of building architecture. The great consequences of this achievement is implicated through the huge installation of building integrated PV systems and large scale arrays of PV modules installed in rural sites in the near future.

As the size of PV array increases or the installation is remotely accessed either in open-rural sites or roof-top buildings, the quick and efficient monitoring operation of the whole PV system including the physical condition of cells will be attracted to be solved. It is due to lack of supervisory mechanism of PV system especially for the system between 1 and 10 kW. Every single module must be ensured to operate properly in order to keep the continuous power supply and to avoid potential damage. There are some potential problems that may disturb the whole PV system operation, for example short-circuit, open-circuit and shading conditions of PV modules. Short-circuit and open-circuit conditions are mainly caused by aging problems of PV modules after long term operation. On the other hand, shading problems can be from other parts of building, dirt on the top of modules or cloudy conditions. The implication of these conditions is the low output power transfer gained from PV system, potentially danger for the field engineers and let such conditions, for instance the existence of shading problems for longer time creates heating spot that can reach temperature higher than 150^{o}C and this is potentially damage the cell. For these reasons, an early fault detection system of PV array is needed, at least to provide information to the system operator about the current condition of the existing PV modules in order to provide further steps for prevention actions. In the past, any strings of PV array with one module has fault in ten series of connection, the operator performed manual checking. In fact, this traditional approach is not recommended in this task

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because of time consuming, less accuracy and potentially dangerous to the operator since the individual PV system may run at hundred of Volts or ten of Amperes.

Provision early detection system for fault diagnosis of PV system has been studied by other researchers. *Chao et. al* proposed modeling and fault diagnosis based on the extended correlation function and the matter element model [1]. However, their proposed method only accurately and promptly determines the type of faults, not the exact of fault locations. Therefore, the system operators probably need extra works to find the module that experiences fault conditions and this is not so easy and dangerous in the large size of PV system. *Chouder and Silvestre* proposed automatic supervision and fault detection of PV system using power losses analysis to generate a faulty signal [2]. In this method, the *dc* current and voltage ratio are defined as the indicators of the fault types. However, their approach is only giving the possible fault types and locations. In fact, the study about fault identification and diagnosis requires very accurate detection results. Otherwise, the information might mislead the operator. Based on these previous studies, there are still potential ways to improve the identification methods, not only the fault types but also the exact location of fault. Since the accuracy, fast computation and simplicity are the important issue in this kind of study, intelligent technique by means the artificial neural network can be a prominent solution.

In this paper, the artificial neural network (ANN) is utilized as the identification tool for the fault diagnosis of PV array. The type of ANN is the three-layered feed forward neural network utilizing tangent sigmoid (*tansig*) as the activation function. This method is simple in terms of algorithm, fast computational speed and high accuracy of validation. The only thing that might be worried about is the training process which the training results are non-repeatable as the consequence of back-propagation algorithm. However, the training process in this case is less complicated because of direct confirmation about the network structure. The accuracy of the network is improved by the *tansig* activation function; this function is noticeable more sensitive than others like *logsig* and *purelin* functions due to the wider searching output. Single ANN model is not enough to deal with this kind of task. Therefore, several developed models for specific duty are designed, and then automatic control is established based on the module terminal voltage. As the initial study, the type of fault is simply focused on the short-circuit fault condition. Short-circuit of PV module at glance does not have any significant impacts because the module is supposedly connected short-circuit. This is true if the short-circuit condition perfectly; in fact this is not the real occurrence and it is potentially dangerous to the physical condition of PV module and the people working around. All it all, the short-circuit fault condition may significantly reduce the output power delivered to the load. Our proposed method has been tested in 3x2 PV array size and shown high accuracy diagnosis on the several scenarios of short-circuit locations.

II. Configuration of Proposed System

The schematic diagram of our proposed system is shown in Fig. 1. The configuration is mainly the 3x2 PV array model integrated with dc load, three layered feed-forward neural network as the diagnostic tool and the controller to drive the artificial neural network. Unfortunately, the alarm systems are not defined in this research; however, the main idea is that the estimation results from ANN structure can be processed as the signal inputs for the alarm systems.

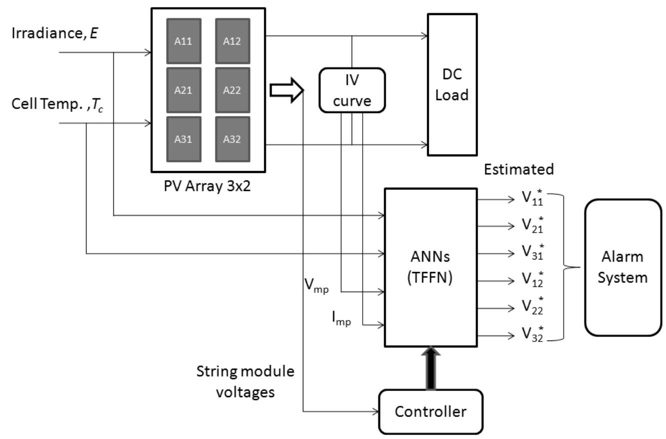

Fig. 1. Schematic diagram of proposed system

TABLE I
PV Modules Output under STC: 1000W/m^2, 25^{o}C

Maximum power	55 W
Open-circuit voltage	21.7 V
Short-circuit current	3.45 A
Voltage at maximum power point	17.4 V
Current at maximum power point	3.15 A

The type of PV module is mono-crystalline Si: Siemens SM-55 which is made up of 36 solar cells in series. The mathematical development of this module is clearly explained as in [3]. The specification of this module under standard test condition (STC) is presented in Table I. The input signals of PV array are irradiance levels (E) and cell temperature (T_c), whereas the maximum power point (MPP) voltage and current, V_{mp} and I_{mp} observed in the *I-V* curve are the output signals. These two MPPs together with E and T_c are the input signal for collective ANN models to estimate the terminal voltage of each PV module which are $V_{11}*$, $V_{21}*$, $V_{31}*$, $V_{12}*$, $V_{22}*$, $V_{32}*$. Therefore, it is necessary to have sensors to measure the irradiance level, cell temperature of module, voltage and current at maximum power points. In addition, the MPPT controller should work definitely in order to provide correct information about these two MPPs. We referred to the collective ANN models because single ANN model is not enough to determine the exact short-circuit location of module. In this study, the ANN is developed case by case, for instance different neural networks are designed for short-circuit located in the PV module A_{11} and in A_{12} and so on. To drive to which ANN works under fault condition, controller is designed based on the string module voltages.

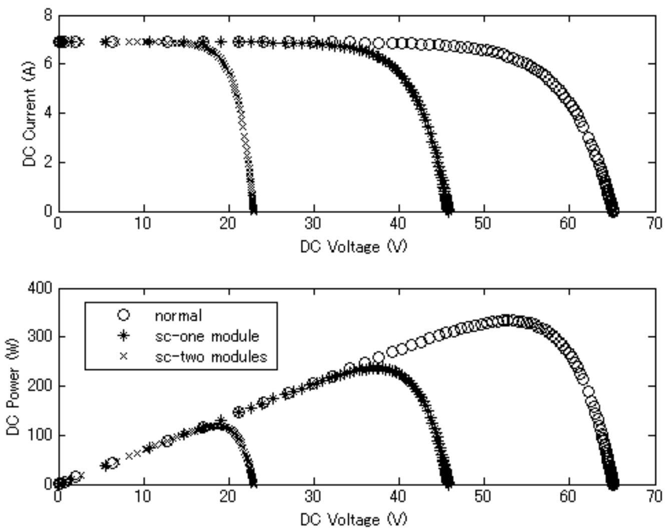

Fig. 2. *I-V* and *P-V* characteristic under short-circuit conditions

The performance of PV array under normal and short-circuit condition are shown by *I-V* and *P-V* curves in Fig. 2. These measurements were taken under irradiance of 1000 W/m^2 and cell temperature of 25^{o}C. Under normal condition by means no short-circuit fault, the voltage and current at maximum power point, V_{mp} and I_{mp}, respectively are 52.74V and 6.32A. Consequently, the maximum output power is 333.3W. However, if the module A_{11} is short-circuit, the string current does not change from the normal value; but the V_{mp} decreases and results in decrease the maximum output power to 236.1W. Much decreasing output power to 118.3W when A_{11} and A_{21} are short-circuited. In addition, the characteristic shows that there is no significant current changes when the short-circuit condition occurs in the same string. Only the operating voltage will decrease significantly as the consequence of this fault type. There are potential decreases of output power about 30% and 65% based on these two sample scenarios. In this study, the scenario to completely short-circuit all modules in one string is not performed because it is reasonable that there is no power transferred to the load and in this respect the operator will quickly identify the problem. These kinds of consideration are set for different scenarios in order to obtain set of data for training process of artificial neural network.

III. Three Layered Feed-Forward Neural Network and the Proposed Control Design

Basically, different type artificial neural networks can be utilized nowadays for different applications. In our previous works, we have investigated the performance of radial basis function (RBF), adaptive neuro-fuzzy inference system (ANFIS) and three layered feed-forward neural network (TFFN) for estimating the MPP points of PV module [4], [5]. The conclusion of these previous works is that each ANN structure has the strong and weak points, depending on the estimation tasks. Especially for the TFFN, it is probably difficult to decide the structure after the training as the consequences of back propagation and descent gradient algorithm where there are many possible structures. However, the TFFN structure is simple, high accuracy between training and validation and it is also easy to connect with other components or devices for the on-line testing. In fact, almost no problem to select the network structure because the training error is small for once trial, means the structure can be directly confirmed. Since the accuracy is the main concern in the diagnostic solving problem, the TFFN is the best option. The RBF network gives possibly small error during the training but, they are over-fitting during the validation. On the other hand, the ANFIS network has more complex network structure than the TFFN. For these reason, the TFFN structure is selected for the purpose of this study.

The three layered feed-forward neural network utilizes back propagation algorithm and descent gradient method for adjusting the weights in order to reduce the learning error [6]. The TFFN algorithm propagates the error between the estimated and actual output. In the forward pass, input vectors, actual output and error are calculated. In the reverse pass, the error gradient respect to weights is calculated by propagating the error backward through the network. Once the error gradient is calculated, the weights are adjusted. The consequence of this process that the network structure will be never obtained in the same value for one consecutive training step. Also, the number of network structure is possibly high. Therefore, the selection of network structure is based on the intuitive thinking of trainer. In this respect, the training process could take much time.

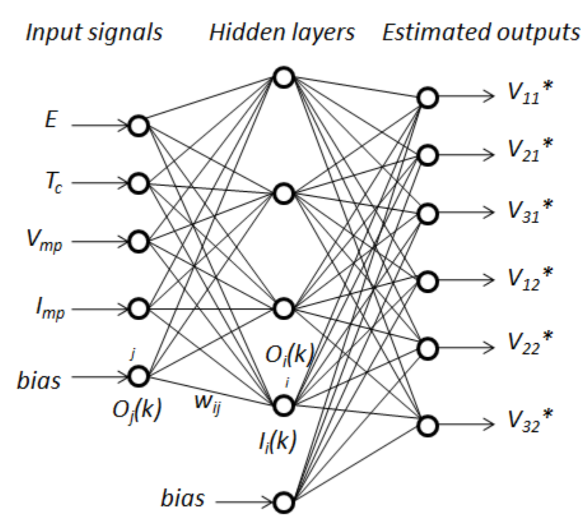

Fig.3. TFFN structure

In general, there are three important stages for developing the artificial neural network. They are training data set preparation, training process and validation or testing process. In this study, 12 cases of short-circuit will be investigated that means 12 developed ANN should be available. However, single developing process of ANN is enough to be explained, while the others are only repetitive process. To generate the training data set, it is necessary to determine the domain operating point of the ANN networks. The network structures are expected to operate in the range of irradiance level and cell temperature of 100-1000W/m^2 and 10-60^{o}C, respectively. The data pattern is taken from the observation of voltage and current at global peak in the *I-V* curve for every change in irradiance and cell temperature. Under this assumption, there are 30 combination of data pattern for training process. The basic configuration of the investigated ANN structures as shown in Fig. 3 has 4 input signals; E, T_c, V_{mp} and I_{mp} that represent the input-output signals of PV array with 6 output signals; $V_{11}*$, $V_{21}*$, $V_{31}*$, $V_{12}*$, $V_{22}*$, $V_{32}*$ that represent estimated terminal module voltages. The hidden nodes are determined after completing the training process. After the training process, the best obtained ANN structure is validated with different input scenarios.

In this study, the training process utilizes the sigmoid function as an activation function between layers. In this study, the tangent sigmoid (*tansig*) function is utilized for the input-output characteristics of the nodes. It is observed that the *tansig* function is more sensitive than other activation functions, such as *logsig* and *purelin*; therefore it can produce high accurate mapping between input-output data. For each node i in the hidden and output layers, the output $O_i(k)$ is given as:

$$O_i(k) = \frac{e^{I_i(k)} - e^{-I_i(k)}}{e^{I_i(k)} + e^{-I_i(k)}} \tag{1}$$

The term $I_i(k)$ in (1) is the input signal to node i at the k-th sampling. The input $I_i(k)$ is given by the weighted sum of the input nodes as follows:

$$I_i(k) = \sum_j w_{ij}(k) O_j(k) \tag{2}$$

where w_{ij} is the connection weight from node j to node i and $O_j(k)$ is the output from node j.

During the training process, the connection weights w_{ij} are tuned recursively until the best fit is achieved for the input-output patterns based on the minimum value of the sum of the squared errors (*SSE*); described as follows:

$$SSE = \sum_{k=1}^{N} \left(t(k) - O(k)\right)^2 \tag{3}$$

where N is the total number of training patterns, $t(k)$ is the k-th actual string module voltages of V_{11}, V_{21}, V_{31}, V_{12}, V_{22}, V_{32} and $O(k)$ is the estimated string module voltages of $V_{11}*$, $V_{21}*$, $V_{31}*$, $V_{12}*$, $V_{22}*$, $V_{32}*$. For all the training data patterns, the error function is evaluated and the connection weights w_{ij} are updated to minimize the error as in (3).

The training results are indicated by number of hidden (n_h) nodes and the training error (*SSE*) as shown in Table II. It is very surprising that the number of hidden nodes is 10 and this number is similar to all short-circuit scenarios. Again, this result confirms the simplicity of TFFN in this respected case. In terms of accuracy of training process, short-circuit in the single module has *SSE* lower than the fault occurs in two modules. The result is of course logic because of high burden for handling data training in case of two modules short-circuit.

TABLE II
ANN TRAINING RESULTS

The first string fault			**The second string fault**		
Fault locations	n_h	***SSE***	***Fault locations***	n_h	***SSE***
A11	10	$3.2\text{x}10^{-5}$	A12	10	$3.4\text{x}10^{-5}$
A21	10	$3.3\text{x}10^{-5}$	A22	10	$2.9\text{x}10^{-5}$
A31	10	$3.5\text{x}10^{-5}$	A32	10	$3.1\text{x}10^{-5}$
A11, A21	10	$4.8\text{x}10^{-5}$	A12, A22	10	$5.0\text{x}10^{-5}$
A21, A31	10	$5.1\text{x}10^{-5}$	A22, A32	10	$5.2\text{x}10^{-5}$
A11, A31	10	$5.0\text{x}10^{-5}$	A12, A32	10	$4.9\text{x}10^{-5}$

Because of there are 12 developed ANN models based on the defined task, a controller should be available to activate a certain ANN block, while the other blocks are remained unresponsive. For this purpose, a simple rule of controller based on the actual string module voltages is proposed to handle this task. For short-circuit in one module in one string:

$$\left|V_f - (V_{nf1} + V_{nf2} + \ldots + V_{nfx})\right| > m \tag{4}$$

where V_f is the terminal voltage at faulted module and V_{nf1} to V_{nfx} are the terminal voltage at non faulted modules. It is supposed to have x number of module in one string. If the value of equation (4) is fulfilled, then the input signals of E, T_c, V_{mp} and I_{mp} are processed through the ANN block means the ANN block is activated. Otherwise, the ANN block remained unresponsive. The threshold of m is the minimum voltage value of non-faulted modules. In this study, the threshold m is set equal to 34. This value is highly depending on the irradiance and cell temperature changes. We may set simply the threshold for example V_{11}=0 in the case of A_{11} short-circuits. However, this threshold will mislead to activate the ANN for the task of A_{11} and A_{21} and so on. In the case of the A_{11} module is short-circuited, the rules to drive the ANN that was trained for this task is generated as:

$$\left|V_{11} - (V_{21} + V_{31})\right| > 34 \tag{5}$$

where V_{11} is the voltage at faulted module, V_{21} and V_{31} are the voltage of non faulted module.

For short-circuit in k modules in one string:

$$\left|\frac{(V_{f1} + V_{f2} + \ldots + V_{fk})}{(V_{f1} + V_{f2} + \ldots + V_{fk}) + (V_{nf1} + V_{nf2} + \ldots + V_{nfx})}\right| > n \tag{6}$$

The nominator of the equation (6) is the total terminal voltage of faulted module, while the denominator of this equation is the submission of all terminal voltage of modules in one string. In this study, the complete short-circuit occurs in all modules of the string is not simulated because no transferred power to terminal output and this case in the real practice can be easily known by operator. The threshold of controller n is 0 which indicates that the ANN is deactivated if the condition in (6) is fulfilled. Otherwise, it is activated. To activate the ANN for the task of A_{11} and A_{21} short-circuit, the rule in (6) is modified into:

$$\left|\frac{(V_{11}+V_{21})}{V_{11}+V_{21}+V_{31}}\right|>0 \quad (7)$$

where V_{11} and V_{21} are the voltage at faulted modules, V_{31} is the voltage at non faulted module.

In other cases, there will be great number of ANN models for large size of PV array which are equal to the number potential case of short-circuit. However, the training process is very simple and accurate because the behavior of module responding to different fault cases is basically the same. Therefore, the flexibility of the proposed method in large size of PV array is guarantee with high accuracy in diagnosis of short-circuit fault occurs in different locations of PV module.

IV. Simulation Results and Discussion

Several short-circuit scenarios occurs in PV module are tested in this study under different irradiance and cell temperature conditions. In this testing, the short-circuit faults are set to occur in single module and two modules in the first string, and then followed by the second string. To ensure that the proposed method can respond in different environmental factors, the tests are performed under low irradiance and cell temperature, low irradiance and high cell temperature, high irradiance and low cell temperature, high irradiance and high cell temperature.

TABLE III
Terminal Voltgae of Each PV Module Without Short-circuit Conditions

E (W/m^2)	T_c (^oC)	V_{11} (V)	V_{21} (V)	V_{31} (V)	V_{12} (V)	V_{22} (V)	V_{32} (V)
220	20	19.66	19.66	19.66	19.66	19.66	19.66
220	60	16.17	16.17	16.17	16.17	16.17	16.17
870	20	21.87	21.87	21.87	21.87	21.87	21.87
870	60	18.68	18.68	18.68	18.68	18.68	18.68

Under normal condition by means without any short-circuit faults as shown in Table III, the terminal voltage with direct measurement is the same and balance. The fluctuation of the terminal voltage is merely due to the changes in irradiance and cell temperature. Under the same cell temperature, the terminal voltage increases slightly as the irradiance level increases due to the high photocurrent outputs. However, the terminal voltage decreases rapidly when the temperature increases due to the negative temperature coefficient of mono-crystalline Silicon cells composed the PV array. Therefore, the terminal voltage seems to be driven by the cell temperature fluctuations.

On the other hand, when the short-circuit condition occurs in any modules, then the terminal voltage of the module goes to zero. The voltage reduction of faulted module affects not only the modules located in the same string, but also the modules in the adjacent string. For instance, when the module A_{11} is short-circuited, its terminal voltage is zero. However, it makes the terminal voltage of A_{21} and A_{31} increase to 20.76V and pushes the terminal voltage of modules in the second string to be 13.84V. This behavior is more significant when two modules are short-circuited in the same string. For instance, the modules of A_{22} and A_{32} in the second string are short-circuited; the terminal voltage of these modules goes to zero and makes the terminal voltage of module A_{12} increases about 2 to 3V from its normal value. The significant effect of voltage reduction to around 6V is also undergone for the all modules in the first string. This kind of fluctuation is difficult to be tracked using other conventional techniques except the estimation results produced by artificial neural network. In addition, the direct measurement is less suitable for the on-line monitoring in the smart grid context, since delay information is less tolerable.

The estimation results of terminal voltage using three layered feed-forward neural network are shown in Table IV for the fault occurs in the first and second strings. Only typical output measurements are shown in these tables, while the others are provide the same characteristic. Our proposed method is powerful to estimate the terminal voltage of the faulted module and its neighbor modules located in the same string or in the next string. The accuracy can be achieved to around 0.001 for all measurements. These measurements were taken under different input scenarios to guarantee this method is adjustable to the variations in environmental factors. The proposed method is currently able to estimate the fault location in the same string. However, to find the multiple location of fault between strings can be achieved by increasing the number of training data and updating the control rule. The estimation results obtained in this study are very beneficial information for development of alarm systems.

V. Conclusion

This paper has proposed fault diagnosis of PV array, especially for short-circuit condition using three layered feed forward neural network. A single artificial neural network (ANN) model is less suitable since the error might be high, while in the diagnosis solving problems the high accuracy is the most important issue. Therefore, several ANN model are developed based on the estimation task, then control rule is provided to drive to which ANN can respond to the fault location. In the current form, the proposed method is able to identify the short-circuit location of PV modules in one string independently. In order to extent the task of the proposed method, for instance to find the multiple location of fault between strings, the number of data training should be increased and the control rule should be updated. The proposed method is feasible for large size of PV system because of simplicity of training process of ANN and control rule. The information gained from the estimation results is very important for the on-line system monitoring in the context of smart-grid perspectives.

TABLE IV
ANN ESTIMATION RESULTS FOR SHORT-CIRCUIT FAULT IN THE FIRST AND SECOND STRINGS OF PV ARRAY

Short-circuit locations	E (W/m^2)	T_c (^oC)	Direct Measurement						ANN Estimation					
			V_{11} (V)	V_{21} (V)	V_{31} (V)	V_{12} (V)	V_{22} (V)	V_{32} (V)	V_{11}* (V)	V_{21}* (V)	V_{31}* (V)	V_{12}* (V)	V_{22}* (V)	V_{32}* (V)
A11	220	20	0.00	20.76	20.76	13.84	13.84	13.84	0.02	20.67	20.67	13.77	13.78	13.72
	220	60	0.00	17.37	17.37	11.58	11.58	11.58	0.00	17.33	17.33	11.56	11.56	11.58
	870	20	0.00	23.02	23.02	15.35	15.35	15.35	0.01	23.08	23.08	15.38	15.38	15.38
	870	60	0.00	19.93	19.93	13.29	13.29	13.29	0.01	19.96	19.96	13.30	13.30	13.29
A11, A21	220	20	0.00	0.00	20.78	6.93	6.93	6.93	0.05	0.03	20.82	7.00	6.89	6.97
	220	60	0.00	0.00	17.45	5.81	5.81	5.81	0.03	0.02	17.43	5.77	5.85	5.78
	870	20	0.00	0.00	23.03	7.68	7.68	7.68	0.02	0.03	23.11	7.73	7.73	7.76
	870	60	0.00	0.00	20.00	6.67	6.67	6.67	0.04	0.02	20.02	6.67	6.74	6.70
A22	220	20	13.84	13.84	13.84	20.76	0.00	20.76	13.86	13.87	13.84	20.80	0.01	20.83
	220	60	11.58	11.58	11.58	17.37	0.00	17.37	11.57	11.57	11.57	17.36	0.01	17.37
	870	20	15.35	15.35	15.35	23.02	0.00	23.02	15.31	15.31	15.30	22.96	0.01	22.97
	870	60	13.29	13.29	13.29	19.94	0.00	19.94	13.29	13.30	13.29	19.94	0.01	19.97
A22, A32	220	20	6.93	6.93	6.93	20.78	0.00	0.00	6.94	6.92	6.92	20.80	0.01	0.02
	220	60	5.81	5.81	5.81	17.45	0.00	0.00	6.07	5.90	5.92	17.64	0.00	0.09
	870	20	7.68	7.68	7.68	23.03	0.00	0.00	7.56	7.65	7.64	22.99	0.01	0.05
	870	60	6.67	6.67	6.67	20.00	0.00	0.00	6.67	6.68	6.68	20.01	0.01	0.01

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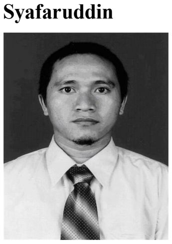
VII. BIOGRAPHIES

Syafaruddin



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