Health, Safety, Environment, and Ergonomics Analysis of Solar Power Systems Using an Adaptive Neuro-Fuzzy Inference System

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Abstract— Solar energy is recognized as a clean energy source; however, its implementation presents various challenges related to Health, Safety, Environment, and Ergonomics (HSEE) aspects that must be addressed. This study aimed to identify sub variables within the HSEE aspects and to analyze HSEE assessments using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. The identification results indicate that the health aspect comprises two sub-variables: heat stress and toxic materials. The safety aspect includes three sub-variables: electrical risk, fire hazard, and fall risk. The environmental aspect comprises three sub-variables: ecosystem damage, land use, and material recycling. The ergonomics aspect includes three sub-variables: musculoskeletal injury risk, work posture, and manual handling risk. The ANFIS model was developed from questionnaire data categorized into three risk assessment levels: good, fair, and poor. Model performance was evaluated using the Root Mean Square Error (RMSE) as an indicator of accuracy during both the training and testing phases. The evaluation results show RMSE values for the health variable of 0.0120 (training) and 0.0512 (testing); safety of 0.0232 (training) and 0.1515 (testing); environment of 0.0158 (training) and 0.0548 (testing); and ergonomics of 0.0294 (training) and 0.0327 (testing). The overall RMSE values for the health, safety, environment, and ergonomics models were 0.034, 0.140, 0.045, and 0.025, respectively. This study demonstrates that the ANFIS method can serve as a decision-support tool for systematically and adaptively assessing HSEE performance, thereby improving the health, safety, environmental, and ergonomic aspects of solar power plants.

Keywords— Health; Safety; Environment; Ergonomics; HSEE; Solar Power System; ANFIS; Adaptive Neuro-Fuzzy Inference System.

I. INTRODUCTION

Energy is a fundamental necessity of human life, and its consumption tends to increase as a nation develops. According to the 2021 Electricity Supply Business Plan, Indonesia, a developing country, was projected to experience an average annual growth rate in electricity demand of 4.9%. To meet this demand, the government targeted a total of 40.575 MW in power plant development, of which 20.923 MW was allocated to new and renewable energy (NRE). Despite Indonesia's significant NRE potential, estimated at 3686 GW by the Ministry of Energy and Mineral Resources (ESDM, 2023), the installed power capacity as of 2022 reached only 81.2 GW. In 2023, the renewable energy mix in the primary energy supply stood at just 13.1%, falling short of the 23% target set for 2025 in the National Energy Policy (KEN) [1]. To achieve net-zero emissions (NZE) by 2060, Indonesia will continue to promote the utilization of renewable energy, reduce fossil fuel consumption, and transition to low-carbon energy sources [2].

Increasing the renewable energy mix has become a global priority to support decarbonization. One potential clean energy source is solar power, particularly in countries with high levels of solar radiation [3]. Indonesia has significant solar energy potential due to its location on the equator, with an average solar radiation intensity of 4.8 kWh/m² per day or approximately 1.752 kWh/m² per year [4]. Optimizing the use of solar radiation can be achieved through the development of solar power plants. Solar power plants convert solar energy into electricity using environmentally friendly technologies. These systems offer several advantages over conventional fossil-based plants, including reduced reliance on fossil fuels, lower greenhouse gas (GHG) emissions, and lower operational costs [5]. However, the implementation of solar power plants also presents challenges related to health, safety, environment, and ergonomics that need to be addressed [6].

HSEE is a structured management system designed to identify and control risks using standards-based approaches [7]. Additionally, integrating ergonomic considerations into system design can improve worker-task interactions, thereby enhancing productivity, safety, and job satisfaction [8]. Several studies have examined the HSEE aspects of solar power plants. An experiment conducted on PV panel combustion revealed that hazardous gases, including sulfur dioxide (SO2), hydrogen fluoride (HF), and hydrogen cyanide (HCN), can be emitted [9]. Furthermore, PV technology often uses heavy metals such as cadmium (Cd) and lead (Pb) to enhance efficiency, which are carcinogenic and hazardous even at low doses [10]. The operation of solar power plants can impact the surrounding environment, leading to water quality degradation and ecosystem damage [11]. The development of solar power plants requires large land areas and GHG emissions at various stages, from production to operation [12].

Previous studies have evaluated several aspects of HSEE using various methods; however, a comprehensive assessment of these aspects remains limited. Although research on HSEE in solar power plants has been conducted, a gap remains in the holistic understanding of the variables that constitute the overall HSEE framework. Therefore, this study aims to propose a more structured and comprehensive evaluation approach to assess HSEE aspects within solar power systems. The primary

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objective is to identify and elaborate on the key variables of HSEE, thereby providing deeper insights into the factors influencing HSEE performance and supporting the development of safer, more efficient, environmentally friendly, and ergonomically sound solar power systems.

The strength of this study lies in its broad scope, which encompasses all aspects of HSEE, and its use of intelligent algorithms for the assessment process. The algorithm employed is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This method integrates the capabilities of Artificial Neural Networks (ANN) and fuzzy logic to model and control systems adaptively. ANFIS combines the advantages of fuzzy logic with the learning capabilities of neural networks, enabling it to function as an expert decision-making system for solving complex problems [13]. This method was selected for its advantages in data modelling and analysis [14] and has demonstrated superior convergence and efficiency compared to traditional fuzzy techniques. However, its performance remains slightly dependent on the quality of the training dataset [15]. The ability of ANFIS to make data-driven decisions provides a foundation for assessing HSEE aspects of solar power generation systems. Accordingly, this study is expected to advance sophisticated and effective evaluation methods for HSEE programs, particularly within the solar power generation industry.

II. Research Methodology

This study employed both qualitative and quantitative research approaches and was conducted at the Pantai Baru Solar Power Plant located in Ngentak, Poncosari, Srandakan, Bantul Regency, Yogyakarta. The data sources consisted of both primary and secondary data. Primary data were obtained directly from field workers at the power plant through interviews and questionnaires. Meanwhile, secondary data were gathered from literature and documents related to similar topics as supporting information. The research methodology is explained in detail in the sub-chapters below.

A. Literature Study

The identification and formulation of the research problem were carried out by reviewing previous studies related to the analysis of HSEE within the scope of solar power plants. Several scholars have conducted research on HSEE in solar power systems. For instance, [16] studied floating solar power plants, where workers are exposed to electrical hazards, and where fire risks in PV panels can lead to the release of toxic materials and pose a threat to workers [9]. The operation of solar power plants can also affect the surrounding environment, including ecosystem degradation and reduced water quality near the plant [11]. Additionally, the construction of solar power plants requires large land areas, and greenhouse gas emissions may occur during production, transportation, installation, and operation [12].

A study conducted by [3] comprehensively analyzed all four HSEE aspects in the context of floating solar power plants. The findings revealed that workers may be exposed to multiple risk factors, including heat stress, ergonomic hazards, electrical hazards, fire hazards, toxic materials, adverse weather conditions, and psychosocial factors. Table I presents the sub-variables identified under each HSEE aspect. However, the literature review also indicated that many previous studies tend to focus only on one or a few aspects and sub-variables, without providing a comprehensive analysis.

TABLE I
HSEE SUB VARIABLES

Papers	Health	Sub-Variable Safety	Environment	Ergonomics
[16]	-	Electrical risk	-	-
[17]	Heat stress	-	-	-
[9]	Toxic materials, fire	-	-	-
[18]	-	FIRE	-	-
[3]	Heat stress, toxic materials	Electrical risk, fire, and falling	Ecosystem damage	Musculoskeletal injuries, manual handling risks
[19]	-	FIRE	-	-
[6]	Heat stress, toxic materials	Electrical risk, falling	-	-
[20]	Heat stress,	Electrical risk, fire, and falling	-	Manual handling risks
[21]	Toxic material	-	Land use, material recycling	-
[22]	-	-	-	Musculoskeletal injuries, work posture
[11]	-	-	Ecosystem damage	-
[12]	Toxic material	Electrical risk	Land use	-

Therefore, this study aims to deepen the analysis of HSEE in solar power systems by applying an innovative approach using the Adaptive Neuro-Fuzzy Inference System. This study is proposed as a response to the limitations of prior research, which has yet to comprehensively assess and analyze all four HSEE aspects within solar power plants. One of the key novelties of this study lies in the inclusion of additional relevant sub-variables for each HSEE component, thereby providing a more in-depth understanding of the impact of solar power systems on health, safety, environmental sustainability, and ergonomics.

B. Questionnaire Design and Formulation

The questionnaire was formulated following a literature review of related topics. All selected sub-variables aligned with the literature, ensuring that the developed questionnaire comprehensively represented the HSEE conditions in Solar Power Plant systems. The questionnaire was distributed to

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several respondents working at solar power plants to assess the four HSEE variables in the Power plant system.

The assessment used a 5-point Likert scale, ranging from "Never" to "Very Often". Scoring was conducted by calculating the average score for each indicator within the respective sub-variables, as reported by the power plant workers. Each indicator had distinct characteristics, reflecting either a positive or a negative condition. To ensure consistency in risk interpretation, positively worded items representing preventive actions or safe conditions were reverse-scored. Since the questionnaire used a 5-point Likert scale (ranging from 1 = Never to 5 = Very Often), the reversal was performed using the formula Reversed Score = 6 – Original Score. The constant "6" is derived from the sum of the scale's minimum and maximum values (1 + 5), ensuring that higher scores consistently indicate higher levels of risk across all items.

For example, in a positively worded item such as "I always wear personal protective equipment (PPE)", a respondent selecting a score of 5 (Very Often) would originally indicate a low risk. To align with other items where a high score reflects high risk, this score is reversed to 1 using the formula above. This approach enables consistent risk interpretation across all questionnaire items, facilitating more accurate aggregation of total risk scores. This approach ensured that all indicator scores reflected a uniform risk scale, with higher scores indicating higher risk. After calculating the average score for each indicator, the mean score for each sub-variable was computed to obtain an overall risk level. This output value was subsequently used to develop the ANFIS model.

C. Data processing and questionnaires

The questionnaire data must first be processed to facilitate ANFIS analysis in MATLAB. The dataset consists of four input and one output HSEE variable, representing the assessment results for each HSEE aspect. Each input variable comprises several sub-variables, and each sub-variable is assessed through three indicators. However, since ANFIS in MATLAB requires a single input value per variable, the arithmetic mean is used to calculate the average score. For the output variable, a single value is determined using a risk matrix. Equation 1 illustrates the method for calculating the arithmetic mean. Where $\bar{x}$ is the sample mean, x_n is the *n*-th data, and n is the amount of data.

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \qquad (1)$$

The questionnaire data for each sub-variable were split into training and test sets. Typically, the training data comprises 70–90% of the total dataset, while the remaining 10–30% is allocated for testing purposes [23]. The selection of test data must accurately reflect the questionnaire evaluation results [8]. In this study, questionnaire data were collected from 33 respondents. A total of 23 data points (70%) were used for training, and the remaining 10 (30%) for testing.

The HSEE Assessment model design process is carried out using the toolbox function in MATLAB, which runs the neuro-fuzzy designer. The initial process begins with collecting and processing questionnaire data, which is then imported into the MATLAB workspace. After that, the data is split into training and test sets to evaluate model performance. Furthermore, using the neuro-fuzzy designer, ANFIS parameters, such as the number of membership functions, their types, and the optimization method, are determined. The model training process uses a hybrid or backpropagation algorithm until a minimum error rate is achieved.

Furthermore, validation and testing are conducted to assess the model's accuracy and predictive ability. The final results of this design are exported as an ANFIS model file, ready for use in the HSEE assessment. The data processing flowchart using ANFIS in MATLAB is explained in detail in Fig. 1 to provide an overview of the modelling stages.

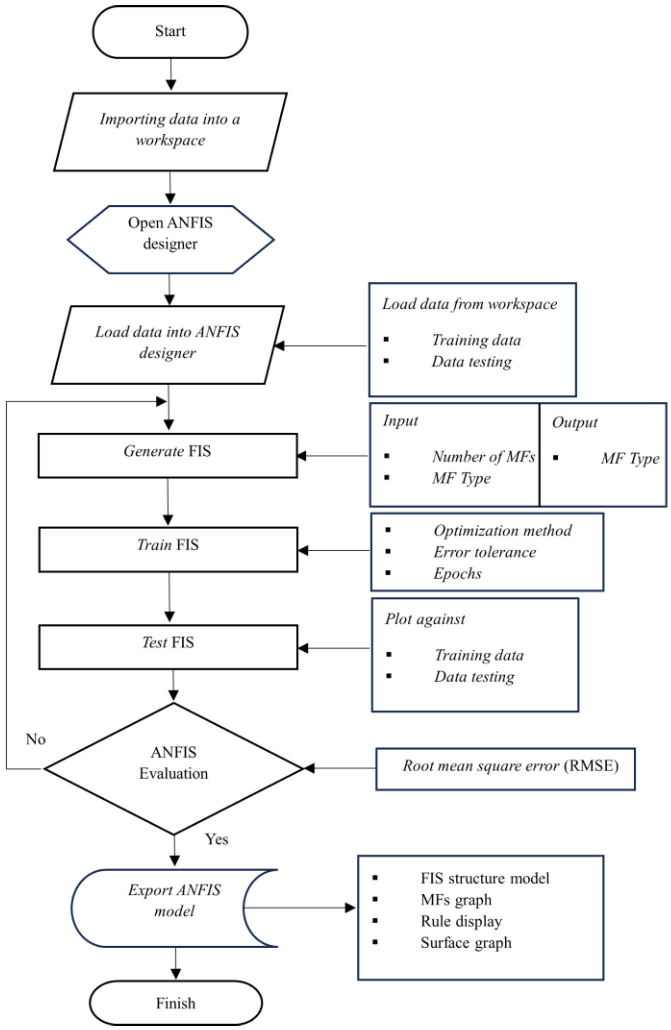

Fig.1. ANFIS-MATLAB Modelling Flowchart

D. Design of ANFIS Model for HSEE Assessment

Fig.2 shows the design of the HSEE assessment model. In this design, each HSEE variable is modelled separately using the Adaptive Neuro-Fuzzy Inference System algorithm to obtain results for each variable. Each input variable is represented by three membership functions (MFs): low, medium, and high, with overlapping ranges to capture gradual transitions. For instance, the health input variable uses the

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following numerical ranges: low (0–2.5), medium (2–4), and high (3.5–5). The output variable is similarly divided into three membership functions: less (0–2.5), sufficient (2–4), and good (3.5–5).

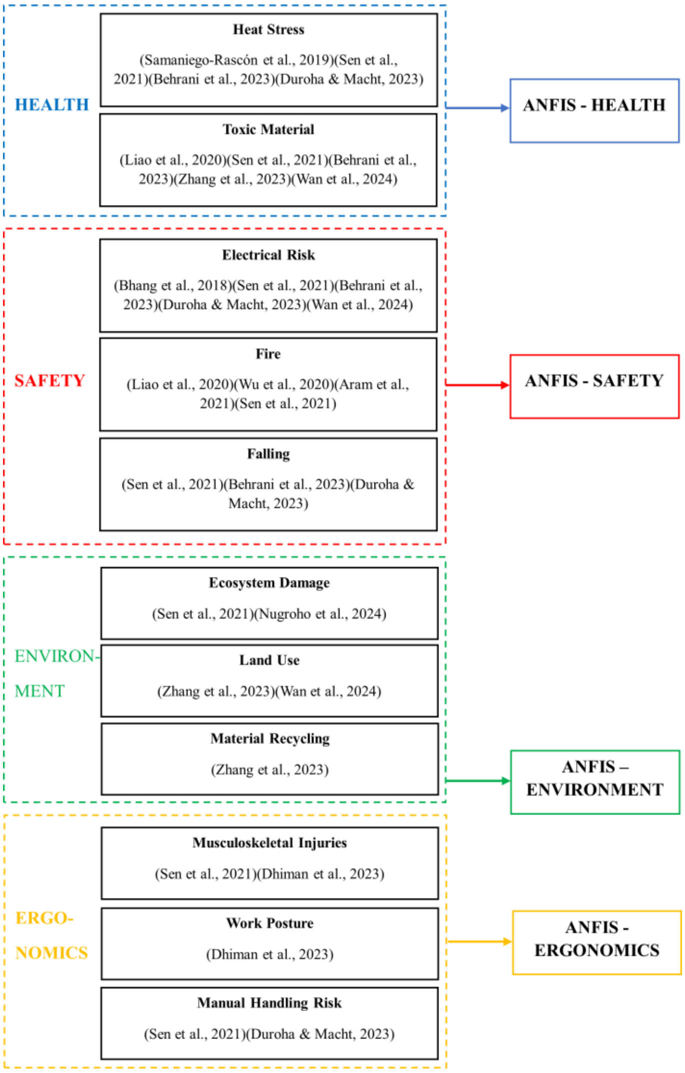

Fig.2. Structure of Variables and Sub-Variables Of ANFIS Modelling

III. RESULT AND DISCUSSION

A. *Primary and Secondary Data*

Secondary data on each HSEE variable were obtained in this study. To strengthen the validity of the secondary data, primary data were collected through questionnaires distributed to workers at the Pantai Baru Solar Power Plant to confirm their relevance to actual working conditions. The questionnaire results obtained from the workers served as a crucial element in reinforcing the HSEE risk analysis. Workers' perceptions of health, safety, environmental, and ergonomic risks provided a realistic depiction of their daily working conditions. For example, although technical data indicated high environmental temperatures with potential for heat stress, the questionnaire results showed that most workers rarely experienced heat-stress symptoms. This discrepancy indicates that adaptation mechanisms and mitigation efforts have already been put in place.

Additionally, perceptions of ergonomic risks reinforced findings related to musculoskeletal disorders (MSDs). The majority of respondents reported experiencing back pain or discomfort due to non-ergonomic working postures, particularly during the installation and maintenance of solar panels above the fish pond. This condition aligned with technical data indicating that working positions required workers to bend over, reach overhead, or maintain balance on an unstable surface.

In the health variable, two sub-variables were identified: heat stress and toxic materials. Heat stress occurs when individuals are exposed to environmental heat while engaging in physical activity, thereby increasing metabolic heat production. When heat dissipation is insufficient, the body's core temperature rises, potentially leading to health issues such as heat exhaustion and heat stroke [17]. Workers at solar power plants face a high risk of heat stress due to prolonged exposure to direct sunlight. However, the questionnaire results indicated that most workers rarely felt high ambient temperatures, despite technical data recording an increase in temperature.

Fig.3. The Ambient Temperature Around *Pantai Baru* Solar Power Plant

Fig.3 shows the recorded temperature around the solar power plant at 09:16 a.m. on September 25, 2024, which reached 34.1°C. While this value does not represent long-term trends, it captures a snapshot of the high ambient temperature during the observation period, which may contribute to heat-stress risks when sustained over time. This discrepancy suggested the need for adaptation to the working environment or mitigation efforts, such as the use of Personal Protective Equipment (PPE) and adjustments to work schedules to reduce excessive heat exposure.

Heavy metals such as cadmium (Cd) in CdTe and lead (Pb) are known carcinogens even at low concentrations [10]. If PV modules are not properly disposed of, these toxic metals can contaminate soil and water through leachate from damaged modules [24]. The risk of respiratory disorders and occupational diseases poses a significant threat to solar power

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plant workers due to exposure to these heavy metals. Therefore, proper waste management and control measures are crucial for minimizing negative impacts on health and the environment. Fig.4 shows unused and unprocessed PV modules.

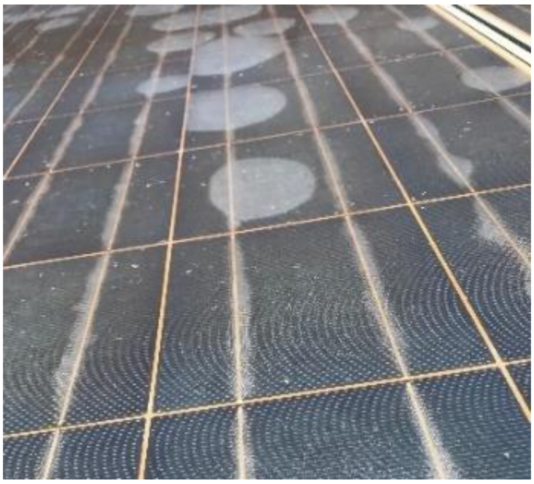

Fig.4. Damaged PV Modules.

The safety risks in solar power plant operations, under the safety variable, included three sub-variables: electrical, fire, and fall hazards. Electrical hazards can occur during installation, maintenance, and operation; therefore, the use of Personal Protective Equipment (PPE), such as helmets, gloves, and safety shoes, is necessary, as electric current can remain present even when components are temporarily deactivated.

At the Pantai Baru solar power plant, 40 battery units were utilized to store energy generated by the solar panels. One of the observed hazards was the 2018 explosion of a battery unit. Based on field observations and information from plant personnel, the explosion was suspected to be caused by overcharging, which may have led to gas accumulation inside the battery due to inadequate ventilation. Fig.5 shows the damaged battery as recorded during the site visit.

Fig.5. Exploded Battery

Although no direct measurement of overcharging was available, visual evidence and operational reports suggest that poor charging control and ventilation may have contributed to the incident. Additionally, installation errors, such as using cables that do not meet specifications, can cause electrical short circuits, leading to current surges and excessive temperature increases in the battery. Physical damage to solar cells, including cracks, broken solder joints, and internal circuit short circuits, has also been identified as a potential cause of fire [19].

Slip-and-fall accidents are the second most common type of nonfatal injuries in the construction industry [6]. The installation of solar panels at the Pantai Baru solar power plant was considered to have a high risk of falling due to the unique structure of the facility, which was elevated 2 meters above the ground with a fish pond located 1 meter above it, as shown in Fig.6 shows the position of the solar panels above the pond increased the risk of workers falling either into the pond or from a height. To minimize the risk of slip-and-fall accidents, installing safety equipment, such as protective railings, is recommended.

Fig.6. *Pantai Baru* Solar Power Plant Building

The environmental impacts of solar power plants include ecosystem degradation, land use, and material recycling. Floating solar power plants offer greater benefits than conventional land-based installations, such as the Pantai Baru solar power plant [11]. The main difference was the placement of the panels. The Pantai Baru plant was installed above a fish pond, whereas the floating solar power plants used buoyant systems directly on the water surface.

The cooling effect of water was observed in both the Pantai Baru and floating solar power plants, enhancing the solar panel efficiency. However, the cooling effect at installations above the fish ponds was optimal. Both types of installations could disrupt aquatic ecosystems by reducing water quality and dissolved oxygen levels, thereby limiting sunlight exposure needed by aquatic organisms. Additionally, land use in the solar power industry is expanding as energy demand grows. Another environmental impact was the generation of electronic waste from solar panels and batteries with short lifespans, which required proper management and recycling to prevent environmental pollution.

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The ergonomics variable in solar power plant operations included three sub-variables: manual handling risks, musculoskeletal disorders (MSDs), and working posture. The workers at the *Pantai Baru* solar power plant faced MSD risks due to non-ergonomic working positions, such as bending, reaching overhead, or maintaining balance on unstable surfaces. These conditions can lead to disorders affecting nerves, joints, and other body parts. The installation of solar panels and the use of heavy equipment also contributed to poor working posture, increasing the risk of lower back pain and musculoskeletal disorders [3]. These tasks include lifting and positioning solar panels at elevated heights, fastening bolts while crouching or twisting, and working for extended periods on narrow, unstable platforms above the water surface.

Fig.7. Solar Panel Maintenance

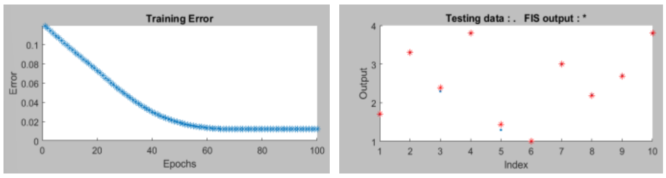
MSDs are among the most common types of occupational injuries and diseases worldwide [25]. The questionnaire results obtained from the workers at the *Pantai Baru* solar power plant reinforced these findings. Most respondents reported experiencing back pain or discomfort due to non-ergonomic working postures, especially during the installation and maintenance of solar panels above the fish pond, as illustrated in Fig.7. This condition was consistent with the technical data, which indicated that workers frequently had to bend, reach overhead, or maintain balance on unstable surfaces. The consistency between the technical data and workers' perceptions highlighted the need for ergonomic improvements, such as training on proper working postures and the provision of assistive tools to reduce physical strain.

B. Design of ANFIS Model for HSEE Assessment

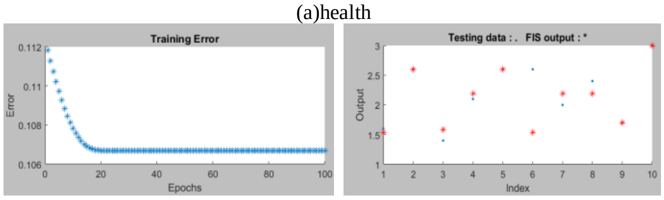
To assess the level of risk associated with Health, Safety, Environment, and Ergonomics in the solar power plant system, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed. This model was designed to predict risk categories based on the total questionnaire scores obtained for each HSEE component. The ANFIS model was designed and trained in MATLAB, which provides a graphical interface for constructing and evaluating fuzzy inference systems. The ANFIS modelling process begins by defining the FIS structure in the Command Window by typing "anfisedit", then selecting "load data" to import the training and testing datasets from the workspace. The FIS structure can be viewed by selecting the structure column in the ANFIS Designer. Once the data is loaded, the number of MFs and types of MFs for each input and output are specified.

The ANFIS training process continues by selecting the hybrid optimization method, setting the error tolerance, and determining the number of epochs, which was set to 100 in this study. The epoch process trains the model until it reaches the lowest, most stable Root Mean Square Error (RMSE), ensuring the model avoids performance degradation or overfitting. In this study, 100 epochs were selected because preliminary tests indicated that the RMSE values for each MF type did not significantly decrease beyond this point. Therefore, 100 epochs were considered the optimal stopping point to prevent unnecessary overtraining and inefficiency.

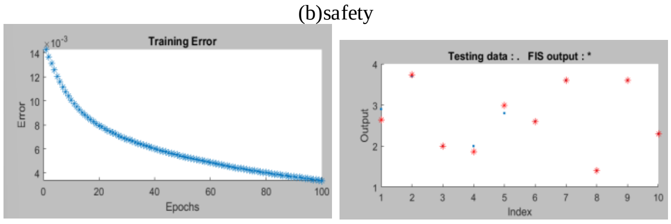
After training, the ANFIS prediction model was evaluated for accuracy by applying the trained FIS to the testing data. The results of the training and testing phases are presented in Fig.8, which shows the prediction performance for each HSEE variable: (a)health, (b)safety, (c)environment, and (d)ergonomics. For the health variable, the best-performing MF was gauss2mf, with RMSEs of 0.0120 (training) and 0.0512 (testing). The safety variable showed the best results with the gbellmf type, yielding RMSE values of 0.0232 (training) and 0.1515 (testing). The environment variable achieved its best performance using trimf, with RMSE values of 0.0158 (training) and 0.0548 (testing). Lastly, for the ergonomics variable, the gaussmf type produced the most accurate results, with an RMSE of 0.0294 (training) and 0.0327 (testing).



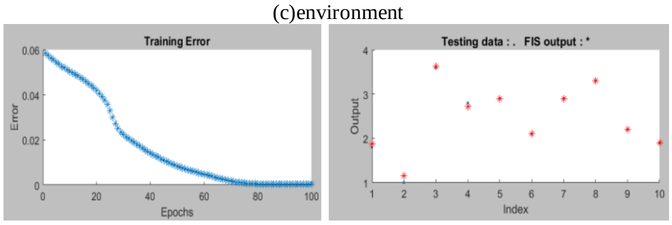
(a)health



(b)safety



(c)environment



(d) ergonomics

Fig 8. Training And Testing Graphs of Variables

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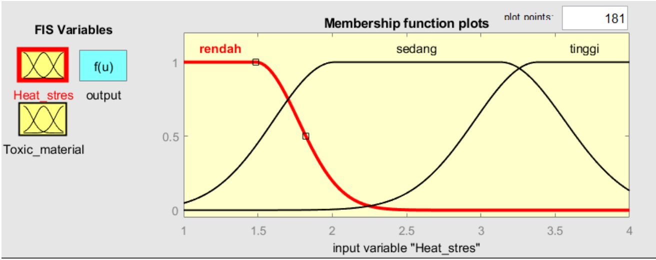
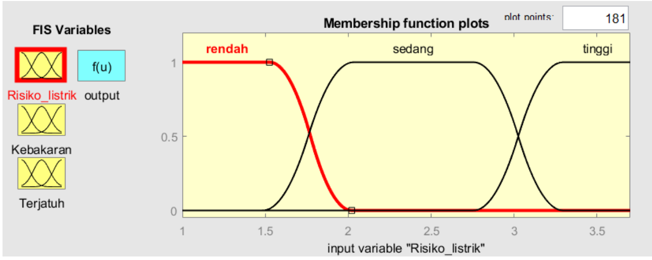
C. Export ANFIS Model

Upon completing ANFIS training in MATLAB, several key outputs are generated, including the FIS model structure, membership function (MF) plots, rule-base display, and surface plots. The resulting FIS model represents the predictive system for assessing HSEE.

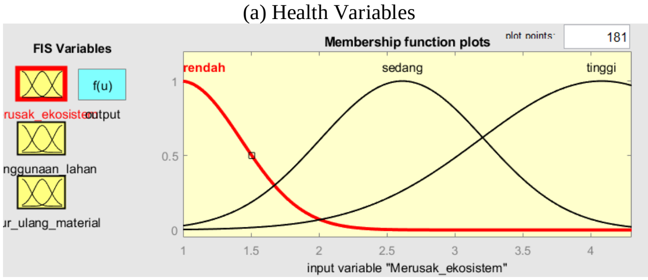
This predictive model comprises four main variables, each with its respective type of membership function and input sub-variables. For the health variable, the gauss2mf type is used, with two input sub-variables (heat stress and toxic material) and one output variable representing the health assessment. This structure is illustrated in Fig.9(a). For the safety variable, the PIMF type is used, with three input sub-variables: risk of electric shock, fire, and falling, as shown in Fig.9(b). For the environment variable, the gaussmf type is employed, with three input sub-variables: damaging the ecosystem, land use, and material recycling, as depicted in Fig.9(c). Finally, for the ergonomics variable, the Gauss2MF type is used, with three input sub-variables: musculoskeletal injury, work posture, and manual handling risk, as shown in Fig.9(d).



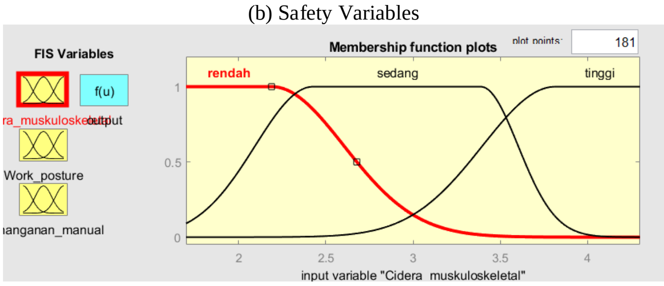
(a) Health Variables



(b) Safety Variables



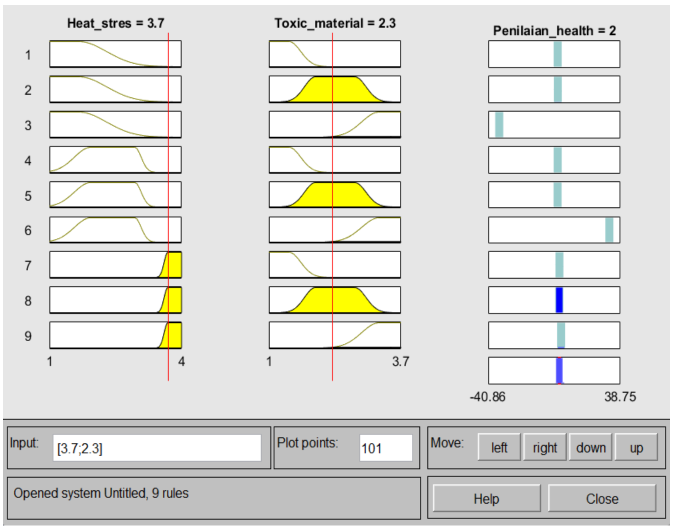
(c) Environment Variables



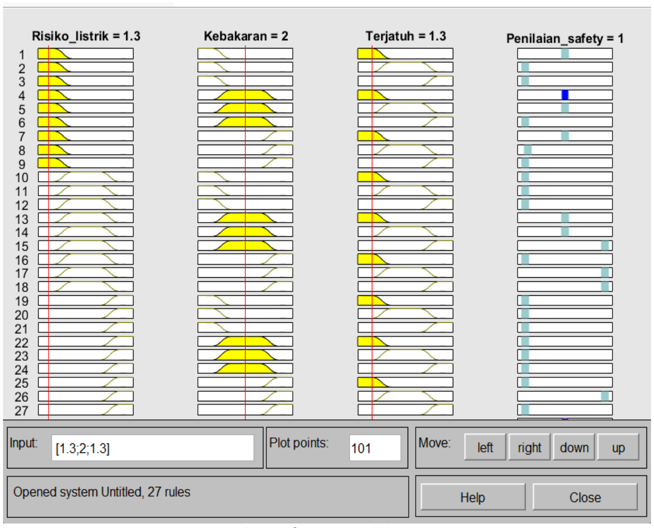
(d) Ergonomics Variables

Fig. 9. FIS Graph

The ANFIS rule displays a tabular interface that allows users to enter values for each model variable. These input values are then processed using the Sugeno-type fuzzy inference rules that were generated during the training phase. As a result, the system produces a numerical output corresponding to the specific combination of input values entered. This rule display plays an important role in validating the ANFIS model developed. The validation process is essential to ensure that the FIS system performs accurately and logically, in alignment with the data characteristics learned during training. It helps verify whether the rule base produces consistent, reasonable outputs across various input scenarios. The rule-based visualizations for each HSEE component are presented in Fig. 10, which illustrate the rule bases for the health, safety, environment, and ergonomics variables, respectively.



(a) Health Variables



(b) Safety Variables

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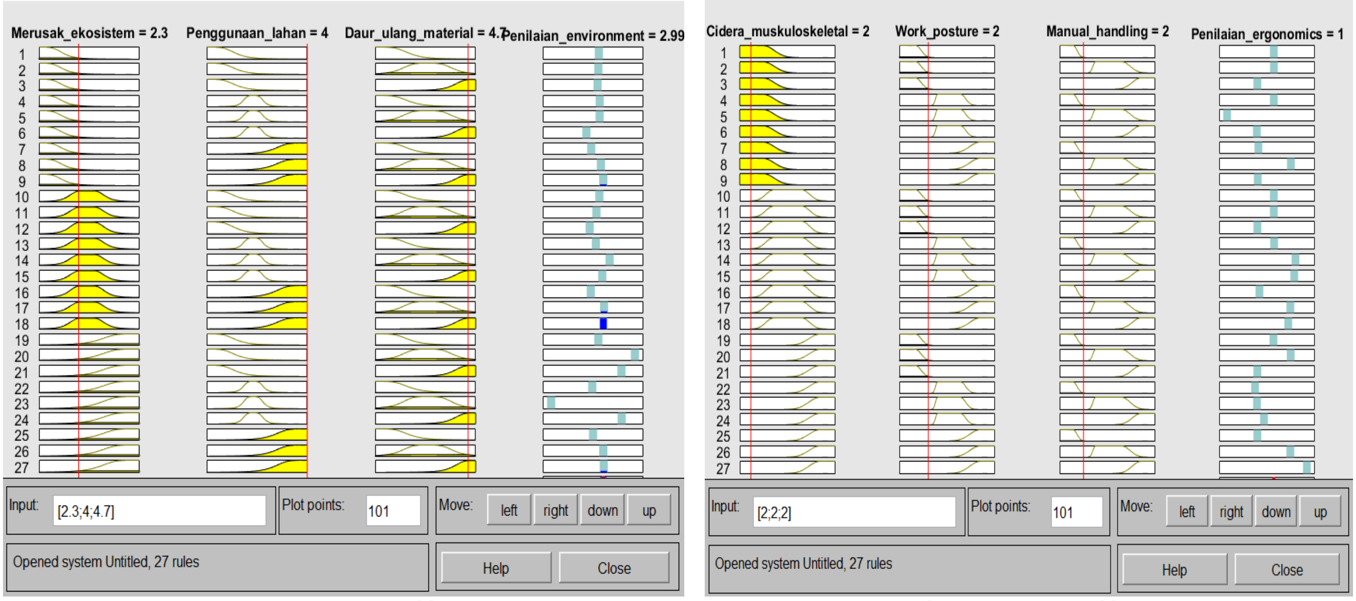

(c) Environment Variables (d) Ergonomics Variables

Fig. 10. ANFIS Rule Base Display

D. Calculation of RMSE Values for Each Health, Safety, Environmental and Ergonomic Assessment Model.

In evaluating the performance of a predictive model, error metrics are used to assess how accurately the model represents the data. Various metrics are used to evaluate the performance of a predictive model, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). This study uses the Root Mean Square Error metric to evaluate model fit because RMSE can be a better indicator for evaluating fit. After all, it explains the model's prediction accuracy[26]. RMSE is used to assess model performance by comparing measured and predicted values. A model with a lower RMSE is considered to perform better than one with a higher RMSE. RMSE is always positive and ideally zero for perfect estimation [27]. RMSE measures the average squared difference between actual data points and predicted values, where the difference is squared to avoid cancellation of positive and negative values and then summed [28]. RMSE is expressed in Equation (2). Where, y_t is the actual value at the t-th data point, $\hat{y}_t$ is the estimated value at the t-th data point, and n is total number of data points.

$$
\begin{aligned}
RMSE &= \sqrt{\sum_{i=1}^{n} \frac{(y_t - \hat{y}_t)^2}{n}} \\
RMSE_{\text{Safety}} &= \sqrt{\frac{0.6411}{33}} = 0.140 \\
RMSE_{\text{Environment}} &= \sqrt{\frac{0.0670}{33}} = 0.045 \\
RMSE_{\text{Ergonomics}} &= \sqrt{\frac{0.0208}{33}} = 0.025
\end{aligned}
\tag{2}
$$

IV. CONCLUSION

The study identified four main HSEE variables relevant to solar power plants. The identification process was based on a literature review of previous studies and adjusted to actual field conditions. Each main variable consists of several sub-variables. The health variable has two sub-variables: heat stress and toxic materials. The safety variable has 3 sub-variables: risk of electrical hazards, fire, and falling. The environment variable has 3 sub-variables: ecosystem damage, land use, and material recycling. The ergonomics variable comprises three sub-variables: risk of manual handling, musculoskeletal injury, and work posture.

The ANFIS model developed in this study evaluates the performance of HSEE in Solar Power Plants using questionnaire data categorized into three risk levels: good, sufficient, and poor. The results of the model testing demonstrate that ANFIS can classify risk levels with high accuracy, producing a total risk score that accurately reflects the field conditions. The performance evaluation used the Root Mean Square Error (RMSE) as an indicator of model accuracy at the training and test stages. The evaluation results show that all tested membership functions yield relatively small RMSE values, indicating low prediction error. The evaluation results for various MF types show that each variable has an optimal MF type that yields the lowest RMSE in both the training and test sets. For the Health variable, the best MF type is gauss2mf, with RMSE values of 0.0120 on the training data and 0.0512 on the test data. The Safety variable showed the best performance with the gbell MF type, producing RMSEs of 0.0232 (training) and 0.1515 (testing).

Meanwhile, for the Environment variable, the trimf MF type yielded the best results, with RMSEs of 0.0158 (training) and 0.0548 (testing). The Ergonomics variable was most

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optimal with the gaussmf MF type, yielding RMSEs of 0.0294 for training and 0.0327 for testing. These findings suggest that selecting the appropriate MF type significantly improves the model's accuracy in representing the data.

Overall, the ANFIS model demonstrated good performance in assessing and predicting HSEEs, particularly in health and safety aspects, with high accuracy. However, the results on environmental and ergonomic specifications indicate that the model still has limitations in generalizing from the test data; thus, improvements are needed in data quality and quantity, as well as in model optimization methods. This study demonstrates that the ANFIS method can be utilized as a decision-making tool to systematically and adaptively assess HSEE performance, thereby improving safety, health, environmental, and ergonomic aspects in the workplace.

References

[1] A. P. Sisdwinugraha, A. Hapsari, F. Wijaya, and H. M. Padhilah, "Indonesia Energy Transition Outlook 2025," Dec. 2024.

[2] A. H. Yafi, A. Bagaskara, A. P. Sisdwinugraha, and A. Hapsari, "Indonesia Energy Transition Outlook 2024 IESR Institute for Essential Services Reform," Jakarta, Dec. 2024.

[3] A. Sen, A. S. Mohankar, A. Khamaj, and S. Karmakar, "Emerging OSH Issues in Installation and Maintenance of Floating Solar Photovoltaic Projects and Their Link with Sustainable Development Goals," *Risk Manag Healthc Policy*, vol. 14, pp. 1939–1957, 2021, doi: 10.2147/RMHP.S304732.

[4] A. M. Ismail, R. Ramirez-Iniguez, M. Asif, A. B. Munir, and F. Muhammad-Sukki, "Progress of solar photovoltaic in ASEAN countries: A review," August 01, 2015, *Elsevier Ltd*. doi: 10.1016/j.rser.2015.04.010.

[5] K. Ukoba, K. O. Yoro, O. Eterigho-Ikelegbe, C. Ibegbulam, and T. C. Jen, "Adaptation of solar energy in the Global South: Prospects, challenges and opportunities," April 15, 2024, *Elsevier Ltd*. doi: 10.1016/j.heliyon.2024.e28009.

[6] P. Behrani, A. Shahrul Nizam Isha, R. Salleh, and A.-B. Abdulrahman Al Mekhlafi, "Determination of Occupational Health and Safety Risks in Solar Energy," *KnE Social Sciences*, Dec. 2023, doi: 10.18502/kss.v8i20.14599.

[7] V. Hajipour, H. Amouzegar, A. Gharaei, M. S. Gholami Abarghoei, and S. Ghajari, "An integrated process-based HSE management system: A case study," *Saf Sci*, vol. 133, Jan. 2021, doi: 10.1016/j.ssci.2020.104993.

[8] A. Azadeh, M. Rouzbahman, M. Saberi, and F. Valianpour, "An adaptive algorithm for assessment of operators with job security and HSEE indicators," *J Loss Prev Process Ind*, vol. 31, no. 1, pp. 26–40, 2014, doi: 10.1016/j.jlp.2014.05.004.

[9] B. Liao, L. Yang, X. Ju, Y. Peng, and Y. Gao, "Experimental study on burning and toxicity hazards of a PET laminated photovoltaic panel," *Solar Energy Materials and Solar Cells*, vol. 206, Mar. 2020, doi: 10.1016/j.solmat.2019.110295.

[10] I. Haq, "Environmental Impact Assessment Study: Leaching Of Chemical Contaminants From A Municipal Dump Site Hastsal, DELHI (Capital Of INDIA)," *International Journal of Environmental Studies*, vol. 60, no. 4, pp. 363–377, Aug. 2003, doi: 10.1080/00207230304732.

[11] A. Nugroho, J. Santoso, I. A. Nugroho, and M. Kom, "Environmental Impact Evaluation of Floating Solar Power Plant in Cirata Reservoir, West Java Article Info ABSTRACT," 2024.

[12] M. J. Wan, Z. X. Phuang, Z. X. Hoy, N. Y. Dahlan, A. M. Azmi, and K. S. Woon, "Forecasting meteorological impacts on the environmental sustainability of a large-scale solar plant via artificial intelligence-based life cycle assessment," *Science of the Total Environment*, vol. 912, Feb. 2024, doi: 10.1016/j.scitotenv.2023.168779.

[13] E. Çakıt, A. J. Olak, W. Karwowski, T. Marek, I. Hejduk, and R. Taiar, "Assessing safety at work using an adaptive neuro-fuzzy inference system (ANFIS) approach aided by partial least squares structural Equation modeling (PLS-SEM)," *Int J Ind Ergon*, vol. 76, Mar. 2020, doi: 10.1016/j.ergon.2020.102925.

[14] M. F. Sidiq and M. A. Rohman, "A review on safety knowledge and skills for reducing human error and accidents in construction," in *E3S Web of Conferences*, EDP Sciences, Sep. 2023. doi: 10.1051/e3sconf/202342901006.

[15] S. R. Revathy *et al.*, "Design and Analysis of ANFIS - Based MPPT Method for Solar Photovoltaic Applications," *International Journal of Photoenergy*, vol. 2022, 2022, doi: 10.1155/2022/9625564.

[16] B. G. Bhang *et al.*, "Design methods of underwater grounding electrode array by considering inter-electrode interference for floating PVs," *Energies (Basel)*, vol. 11, no. 4, Apr. 2018, doi: 10.3390/en11040982.

[17] D. Samaniego-Rascón, M. C. Gameiro da Silva, A. D. Ferreira, and R. E. Cabanillas-Lopez, "Solar energy industry workers under climate change: A risk assessment of the level of heat stresss experienced by a worker based on measured data," *Saf Sci*, vol. 118, pp. 33–47, Oct. 2019, doi: 10.1016/j.ssci.2019.04.042.

[18] Z. Wu, Y. Hu, J. X. Wen, F. Zhou, and X. Ye, "A Review for Solar Panel Fire Accident Prevention in Large-Scale PV Applications," 2020, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2020.3010212.

[19] M. Aram, X. Zhang, D. Qi, and Y. Ko, "A state-of-the-art review of fire safety of photovoltaic systems in buildings," July 25, 2021, *Elsevier Ltd*. doi: 10.1016/j.jclepro.2021.127239.

[20] J. C. Duroha and G. A. Macht, "Solar installation occupational risks: A systematic review," *Saf Sci*, vol. 160, Apr. 2023, doi: 10.1016/j.ssci.2022.106048.

[21] H. Zhang, Z. Yu, C. Zhu, R. Yang, B. Yan, and G. Jiang, "Green or not? Environmental challenges from photovoltaic technology," March 01, 2023, *Elsevier Ltd*. doi: 10.1016/j.envpol.2023.121066.

[22] B. Dhiman, D. Zindani, D. Chakrabarti, and G. Singh, "A user-centric assessment of solar-photovoltaic-home-lighting systems in rural parts of Assam, India," *Energy for Sustainable Development*, vol. 76, Oct. 2023, doi: 10.1016/j.esd.2023.101290.

[23] J. L. Aznarte M., J. M. Benítez Sánchez, D. N. Lugilde, C. de Linares Fernández, C. D. de la Guardia, and F. A. Sánchez, "Forecasting airborne pollen concentration time series with neural and neuro-fuzzy models," *Expert Syst Appl*, vol. 32, no. 4, pp. 1218–1225, May 2007, doi: 10.1016/j.eswa.2006.02.011.

[24] P. Nain and A. Kumar, "Ecological and human health risk assessment of metals leached from end-of-life solar photovoltaics," *Environmental Pollution*, vol. 267, p. 115393, Dec. 2020, doi: 10.1016/J.ENVPOL.2020.115393.

[25] A. Afsharian *et al.*, "Work-related psychosocial and physical paths to future musculoskeletal disorders (MSDs)," *Saf Sci*, vol. 164, Aug. 2023, doi: 10.1016/j.ssci.2023.106177.

[26] D. L. J. Alexander, A. Tropsha, and D. A. Winkler, "Beware of R2: Simple, Unambiguous Assessment of the Prediction Accuracy of QSAR and QSPR Models," *J Chem Inf Model*, vol. 55, no. 7, pp. 1316–1322, Jul. 2015, doi: 10.1021/acs.jcim.5b00206.

[27] B. Jamil and N. Akhtar, "Comparative analysis of diffuse solar radiation models based on sky-clearness index and sunshine period for humid-subtropical climatic region of India: A case study," 2017, *Elsevier Ltd*. doi: 10.1016/j.rser.2017.04.073.

[28] L. Bi, A. Feleke, and C. Guan, "A review on EMG-based motor intention prediction of continuous human upper limb motion for human-robot collaboration," May 01, 2019, *Elsevier Ltd*. doi: 10.1016/j.bspc.2019.02.011.