

Article

Infrastructure Diagnosed by Solar Power Supply in an Intelligent Diagnostic System in Five-Valued Logic

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Abstract: This article discusses the issue of diagnosing low-power solar power plants using the five-valued (5VL) state evaluation {4, 3, 2, 1, 0}. We address in depth how the 5VL diagnostics built upon 2VL, 3VL, and 4VL—two-valued diagnostics, three-valued logistics, and four-valued diagnostics. Logic (5VL) assigns five state values to the range of signal value changes, and these states are completely operational ({4}), incomplete ({3}), critical efficiency ({2}), and pre-fault efficiency ({1}). For the identical ranges of diagnostic signal values, all three of the applied state valence logics interpret failure as changes outside of their permitted ranges. Diagnostic procedures made use of an AI-based DIAG 2 system. This article’s goal is to provide a comprehensive overview of the DIAG 2 intelligent diagnostic system, including its architecture, algorithm, and inference rules. Diagnosis with the DIAG 2 system is based on a well-established technique for comparing diagnostic signal vectors with reference signal vectors. A differential vector metric is born out of this examination of vectors. The input cells of the neural network implement the challenge of signal analysis and comparison. It is then possible to classify the object components’ states in the neural network’s output cells. Based on the condition of the object’s constituent parts, this approach can signal whether those parts are working, broken, or urgently require replacement.

Keywords: neural networks; intelligent systems; servicing process; diagnostic process; expert system; knowledge base; low-power solar plant devices; diagnostic information



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1. Introduction

The use of five-valued logic (5VL) to work out diagnoses about the investigated state in the diagnosis of complex technical objects is new and has not yet been presented in publications. The implementation of object diagnosis in 5VL diagnostics required the additional training of the SSN precisely to teach the network to recognise state “1”—the state of pre-damage fitness. The theoretical principles developed by the research team for diagnosing and distinguishing the ‘1’ state are new to the literature, which we are already effectively implementing. The diagnostic condition labelled “1” is new to diagnostic research. The condition ‘1’ is already recognised and described is called the ‘pre-injury condition’. This condition is the team’s original idea. It is also an important and significant scientific achievement of ours. This new “1” state has already been fully developed theoretically, is also trained by the SSN, and is put into practice in the intelligent diagnostic

system DIAG 2. The technical ability to recognise the pre-damage state in an object is particularly important for reliability reasons for sensitive objects. This is particularly true of such objects, where their efficiency and continuity of use is decisive, such as passenger aircraft, medical systems, energy systems, etc. If a pre-damage condition is recognised in a technical facility, it means that technical refurbishment must be initiated, resulting in the facility being restored to a serviceable condition. Therefore, the knowledge of the time of occurrence of the “1”—pre-damage state in the object is the basic diagnostic information due to the possible use in the developed strategy of restoration of the object in the literature called the “state by state strategy”. This fact underlines the novelty and innovation of this article in relation to other studies on the diagnosis of complex technical objects. The term “object renewal strategy by condition” was already known in the literature. What was lacking, however, was a diagnostic tool such as the DIAG 2 system that would effectively recognise the “1” state—the pre-damage state. Such a capability was not provided by diagnostics in logic: 2VL; 3VL; and 4VL diagnostics—four-valued due to the state of critical fitness. The above-mentioned diagnostics ensure, with some approximation, the realisation of the renewal of an object with a “strategy by state”. Thus, as presented in the article, the diagnostics of each object allow the recognition of current states in the object. Especially states that are related to non-critical damage.

Our research confirms the thesis, and it can be concluded with high probability that technical diagnostics (5VL) is an effective tool to identify the occurrence of a pre-damage state. The ‘1’ condition information produced indicates that the technical facility will experience a state of unfitness (sudden and critical damage) in the near future, as a result of which, the facility will cease to be used.

Studies [1–7] in particular offer a plethora of material regarding AI systems, neural networks included. All things considered, the findings from these studies lay a firm groundwork for comprehending the inner workings of artificial neural networks. In addition, they contain the scientific and mathematical foundations for understanding the brain and its networks. The authors laid out the theoretical foundations of static neural network training, instruction, and design in great depth. Research into radial basis function artificial neural networks may shed light on their development, training, and deployment. Efforts were also made by the authors to incorporate sections on dynamic neural networks, covering topics such as training methods, teaching methodologies, and construction concepts. Artificial neural network operation has been the focus of multiple investigations into sets and fuzzy knowledge [8–11]. The references begin with the publications [12–18].

The text covers the fundamentals of how technological devices function. It includes equations that spell out how a technological object’s model works and how reliable it is. An approach to structuring the operation process according to the object models is also part of the study. The authors have substantial experience in this field, and their prior work describes the outcomes of diagnostic tests on technological devices. Recent years have seen a dramatic acceleration in the development of technical diagnostics thanks to the utilization of AI systems, particularly artificial neural networks. Many variables have been considered in earlier research on technical and technological process control and diagnosis, such as the difficulty of controlling different kinds of industrial robots and the necessity to modify technological systems [19–21].

Investigations conducted might significantly affect the design of a diagnostic system that makes use of artificial neural networks. Based on the results of the technical diagnostics, these studies outlined a method for constructing an operating system for technological objects. A theory on how the status of a technological item evolves was suggested in the study. This causes it to undergo a transformation or lose some of its useful properties. As a result, you need a solid diagnostic for this item’s following state. Preventative procedures, including regenerating the object, are the way to go when the recognized state is partially operable or non-operable. The author of the aforementioned study outlined an ANN’s architecture and explained how it functions, down to the theoretical dependencies that determine the ANN’s operation by the approach given. The trivalent logic also laid

the theoretical groundwork for identifying technological goods using an artificial neural network. The results were supported by a case study of the diagnostic information base setup of the device that was evaluated [22,23].

The focus of the diagnostic procedure is the technical component. The method of diagnosis is determined by its structure, function, and target application. This document explains a diagnostic problem with a complex technical item. Specifically, the paper describes the construction and operation of this solar power plant equipment. One particularly innovative aspect of this work is the method it presents for creating diagnostic knowledge bases for solar low-power plant devices (L-PPD). Analysing distance measurements produced by comparing diagnostic signal vector images with their patterns, the authors of this article painstakingly improved the object's condition testing technique, which improved the reliability of condition testing of technical devices. We completed this task by utilizing AI and solutions based on expert systems.

The result of this work is the DIAG 2 diagnostic program [24–28]. Discover the results of tests and research on solar low-power plant devices in the following articles [29–32]. A study by Hwang et al. [33] detailed the application of multilayer neural networks (MNN) in the diagnosis of solar streetlamps. Adaptive Responsiveness Theory 2 was the basis for the selected network type. The duty cycle voltage applied to unloaded panels was inputted into two neural networks. In their study, Ganeshprabu et al. [34] utilized a distributed online monitoring system based on an XBee wireless sensor network to track crucial performance indicators of solar panels. Module insolation, temperature, voltage, output current, and ambient insolation are some of these indicators. Jing et al. [35–40] describe a method for PV system fault detection and diagnosis that can operate independently. It uses a combination of an ANN and a more conventional analytical method to identify and fix errors. An ANN with two layers was used for electricity forecasting. By analysing the power differential, the difference between predicted and actual power, the open-circuit voltage and short-circuit current of a string of PV modules, and other similar variables, the authors were able to identify as many as six distinct failure types. In their papers, Duera et al. [41] explain the diagnostic system (DIAG 2) for devices used in low-power power substations and discuss research topics related to logical diagnoses with two, three, or four values. The article not only details the testing but also gives a quick rundown of the intelligent diagnostic system (DIAG 2) that was used.

The diagnostic system (DIAG 2) functions by comparing a set of actual diagnostic output vectors with their respective primary vectors. The comparison produces the diagnostic output vectors' elementary divergence metrics that were determined by the neural network. Using difference-trial distance measurements, elementary divergence metrics determine the condition of the test object's basic components as input (DIAG 2). Projecting future output power from various solar cell types was the principal goal of the ANN model. The process was carried out on all three types of cells: monocrystalline, multicrystalline, and amorphous. According to the findings, multi-, mono-, and high-crystalline cells are the most effective. Most of the essay was devoted to explaining how to identify damaged photovoltaic (PV) panels. The suggested method examines the ideal features of the fault by analysing current–voltage (I-V) curves from various fault types, including hybrid faults. To standardize the fault features, we also proposed a metaheuristic approach to particle swarm optimization (PSO) and a deterministic technique for the reflective confidence region. In addition, we used AdaBoost, an adaptive multi-class method that models stage-wise with the multi-class exponential loss function (SAMME) and depends on the classification and regression tree (CART).

2. Ranges of Changes in Object's Conditions in Five-Valued Logic Used in the DIAG 2 Diagnostic System

The technical features of each complicated technical entity are determined by the values of the physical quantities that define it (Figure 1). These quantities are referred to as features that indicate the specific conditions which the object can be located in. The output

signals of the object are contingent upon the input signals and the state of its fundamental components. Let us establish the definition in the subsequent manner:

$$Y_i = f(X_1, X_2, \dots, X_m; p_1, p_2, \dots, p_n) \tag{1}$$

where p_1, p_2, \dots, p_n are parameters that describe the object’s status and Y_i is the output diagnostic signal of the i th functional element and X_1, X_2, \dots, X_m are the input signals given to the m th inputs of the object’s elements.

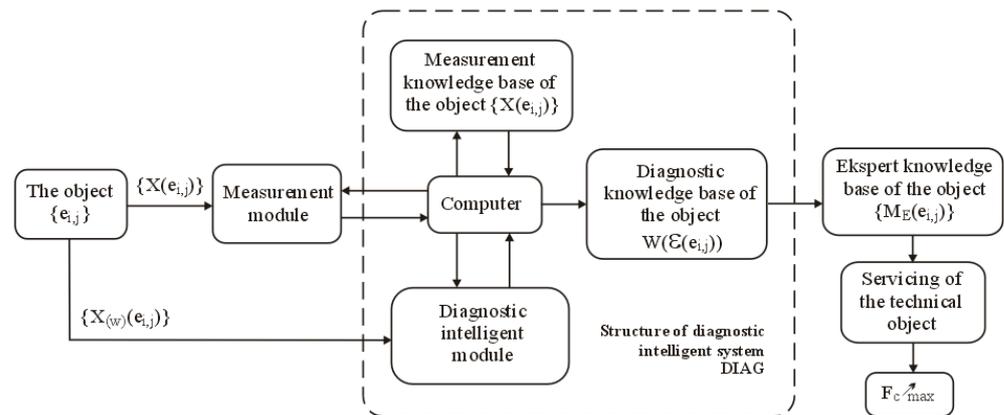


Figure 1. Schematic representation of a sophisticated diagnostic system for a technical device, where $X(e_{i,j})$ is the diagnostic signal is present; j th is an element of i th set; $X_{(w)}(e_{i,j})$ is an exemplary signal for $X(e_{i,j})$ signal; $F_C \max$ is the max. worth of the purpose for which the object is used; $W(\epsilon(e_{i,j}))$ is the importance of state assessment reasoning for the j th element within i th module, which is a part of the recognised five-valued logic of state evaluation; and $\{M_E(e_{i,j})\}$ is a specialist knowledge base that refers to a collection of maintenance information specific to an object.

The technique of comparing diagnostic signals with their corresponding model signals is frequently employed in the diagnostics of technical objects (see Figure 2). The diagnostic approach is described in the literature by the following equation:

$$\forall_{e_{i,j} \in \{E_i\}} \exists X(e_{i,j}) \in X \rightarrow \forall_{e_{i,j} \in \{E_i\}} \exists X_{(w)}(e_{i,j}) \in X_{(w)} \Rightarrow W(\epsilon(e_{i,j})) \tag{2}$$

where the abbreviations below represent the following: variables $W(\epsilon(e_{i,j}))$ and $W(\epsilon(e_{i,j}))$ represent the value of state assessment logics for the j th element in the i th module, the diagnostic signal in the j th element of the i th assembly of the object, the model signal for the $X(e_{i,j}) \rightarrow$ signal, and the symbols a and E_i , which denote diagnostic activities and \Rightarrow comparison, respectively.

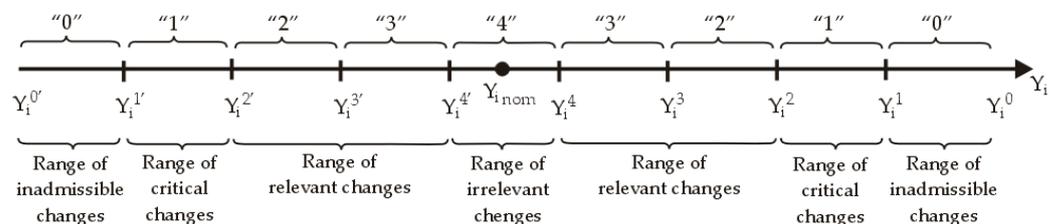


Figure 2. Changes within the feature value range of the i th diagnostic signal. “4”—the state of full operation; “3”—the state of an incomplete usability; “2”—a critical operable condition; “1”—pre-damage condition; “0”—the state of non-operation (defect).

A determination is made by the network regarding which of the three distinct states {4, 3, 2, 1, 0} a particular element of the object that computed the signal should be classified into, as a result of this activity (comparison of signals).

Assuming that the nominal values of the input signals' characteristics are provided, we may determine the signal's value at the object's output, which represents its current state. The process of analysing the output signal Y_i involves measuring its k th features and comparing the measurement result with the feature of the i th modular signal $Y_{(w),i}$. It is much easier to determine whether the values of diagnostic signals fall within their range of allowable changes rather than comparing the output signal with the model. Figure 3 displays the ranges of the value variations of the i th diagnostic signal feature for five-valued logic.



Figure 3. View of the solar power plant system experimental research and measurement stand.

Figure 2 identifies five distinct categories of changes, namely:

- variety of inconsequential signal alterations $(Y_i^{4'}, Y_i^4)$; this specifies the state of the characteristic of the entity at level "4";
- extent of the pertinent signal alteration $(Y_i^{3'}, Y_i^{4'}) \cup (Y_i^4, Y_i^3)$; this refers to the state or status of a specific characteristic of the object at a particular level "3";
- range of the crucial signal variation $(Y_i^{2'}, Y_i^{3'}) \cup (Y_i^3, Y_i^2)$, which describes the state of the characteristic of the item at level "2";
- extent of signal alteration in the pre-damaged compartment $(Y_i^{1'}, Y_i^{2'}) \cup (Y_i^2, Y_i^1)$; describes the state of the characteristic of the item at level "1";
- range of unacceptable signal variations $(-\infty, Y_i^{1'}) \cup (Y_i^1, +\infty)$ to determine the state of the feature of the object at level "0", if there is a requirement to analyse multiple features of the output signal Y , one must check if each of these characteristics falls within an acceptable range of change.

The establishment of ranges for variations in the diagnostic signals relative to the reference signal facilitated the formulation of diagnostic guidelines for the functioning of the RBF artificial neural network as follows:

$$R_{w1} : \bigcap_{Y_k \in Y} \{Y_k \in (Y_i^4, Y_i^{4'})\} \Rightarrow (\varepsilon_i = \varepsilon_i^4) = \{4\} \quad (3)$$

where R_{w1} is the first guideline for diagnostic inference, $(Y_i^4, Y_i^{4'})$ is the range of changes that are of no significance to the signal features' values, \Rightarrow is a comparison symbol, and $\{4\}$ is the operable condition.

$$R_{w2} : \bigcap_{Y_k \in Y} \{Y_k \in (Y_i^{3'}, Y_i^{4'}) \cup (Y_i^4, Y_i^3)\} \Rightarrow (\varepsilon_i = \varepsilon_i^3) = \{3\} \quad (4)$$

where the second rule of diagnostic inference is denoted as R_{w2} , the range of changes for the relevant values of the signal characteristics is $(Y_i^{3'}, Y_i^{4'}) \cup (Y_i^4, Y_i^3)$, \Rightarrow is a comparison symbol, and {3} represents the state of imperfect operability.

$$R_{w3} : \bigcap_{Y_k \in Y} \{Y_k \in (Y_i^{2'}, Y_i^{3'}) \cup (Y_i^3, Y_i^2)\} \Rightarrow (\varepsilon_i = \varepsilon_i^2) = \{2\} \quad (5)$$

where R_{w3} represents the third rule of diagnostic inference. $(Y_i^{2'}, Y_i^{3'}) \cup (Y_i^3, Y_i^2)$ represents the range of changes for the critical values of the features of the signal. The symbol \Rightarrow denotes a comparison, and {2} represents the critical operable condition.

$$R_{w4} : \bigcap_{Y_k \in Y} \{Y_k \in (Y_i^{1'}, Y_i^{2'}) \cup (Y_i^2, Y_i^1)\} \Rightarrow (\varepsilon_i = \varepsilon_i^1) = \{1\} \quad (6)$$

where R_{w4} is the diagnostic inference rule, which states that the range of modifications for the pre-damage compartment values of signal characteristics is $(Y_i^{1'}, Y_i^{2'}) \cup (Y_i^2, Y_i^1)$, with \Rightarrow as a comparison symbol and {1} as the critical operable condition.

$$R_{w5} : \bigcap_{Y_k \in Y} \{Y_k \in (-\infty, Y_i^{1'}) \cup (Y_i^1, +\infty)\} \Rightarrow (\varepsilon_i = \varepsilon_i^0) = \{0\} \quad (7)$$

where the fourth rule of diagnostic inference is known as R_{w5} , the allowable range for the values of the signal's features is $(-\infty, Y_i^{1'}) \cup (Y_i^1, +\infty)$, \Rightarrow is a comparison symbol, and {0} denotes the inoperability condition.

The four-valued evaluation of conditions in technical diagnostics allows us to determine the genuine condition of the object's states during the diagnosing process. We assign one condition from a collection of conditions to represent the actual condition of the object.

- {4}: the object is said to be in an operable condition when it has the whole capability to carry out the duties it was specifically built for;
- {3}: an item is said to be in an incomplete operable condition when it can only fulfil its functions to a limited extent. In such cases, it is necessary to initiate preventive operations in order to restore the object's full functionality;
- {2}: a critical operable condition refers to a state when an object is capable of performing its functions, but only within a very limited scope. This condition occurs before any harm occurs and it necessitates taking pre-emptive measures to restore the object;
- {1}: the term "pre-damage compartment operable condition" refers to a state in which the object is able to execute its tasks, but only to a very limited extent. This condition occurs before any damage ensues and necessitates adopting preventive measures to restore the object;
- {0}: an inoperable condition refers to a state when the object has lost its ability to function and is unable to accomplish the tasks it was built for.

3. Diagnostic Model of Devices in the Solar Power Plant System

The low-power solar plant devices were diagnosed using the DIAG 2 system, which is a patented intelligent system that operates based on an artificial neural network of the RBF type. The descriptive section of the article outlines the algorithm used in the DIAG 2 intelligent diagnostic system for implementing the diagnostic approach. The diagnostic approach employed in the DIAG 2 system employs a methodology described in the literature. This methodology involves comparing diagnostic signals with their corresponding standard diagnostic signal vector, as indicated in Equation (1). The DIAG 2 system utilizes a diagnostic information format that is represented by a five-valued state evaluation {4, 3, 2, 1, 0}. The diagnostic information obtained from the DIAG 2 program is presented in a tabular format, specifically referred to as the "Table states of objects". To conduct the approved experiments in a small solar power plant system, an experimental setup was created, as depicted in Figures 3 and 4.

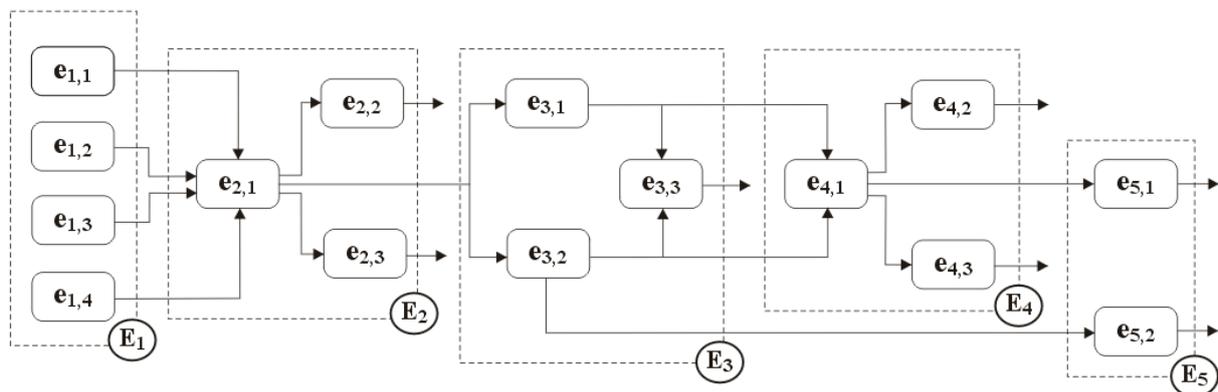


Figure 4. Diagram of functional and diagnostic structure of low-power solar plant devices: E_1 —photovoltaic system, E_2 —voltage regulator (controller) system), E_3 —electrical energy storage system, E_4 —DC/AC converter, E_5 —receiving system.

Prior to conducting diagnostic tests using the DIAG 2 diagnostic system, it is necessary first to perform a diagnostic analysis of the object being inspected. The reader will discover illustrations and the approach to implementing this diagnostic objective in the subsequent sections: the following text is a functional and diagnostic study of devices in low-power solar plant devices which was conducted for research purposes. The outcome of this analysis is a specified collection of i th functional units $\{E_i\}$. During the subsequent stage of the research, the collection of j th fundamental components was identified within each i th group $\{e_{i,j}\}$. The DIAG 2 diagnostic system displays the functional units of the item, which are labelled as “units”, and the basic elements are labelled as j th “elements”. The subassemblies within the i th assemblies of the facility are regarded as third-level components, referred to as “Modules” which function as intermediate elements. The modules facilitate the conversion of an object’s hierarchical form into an internal matrix structure, as depicted in Figures 4 and 5. This conversion can be performed in both directions.

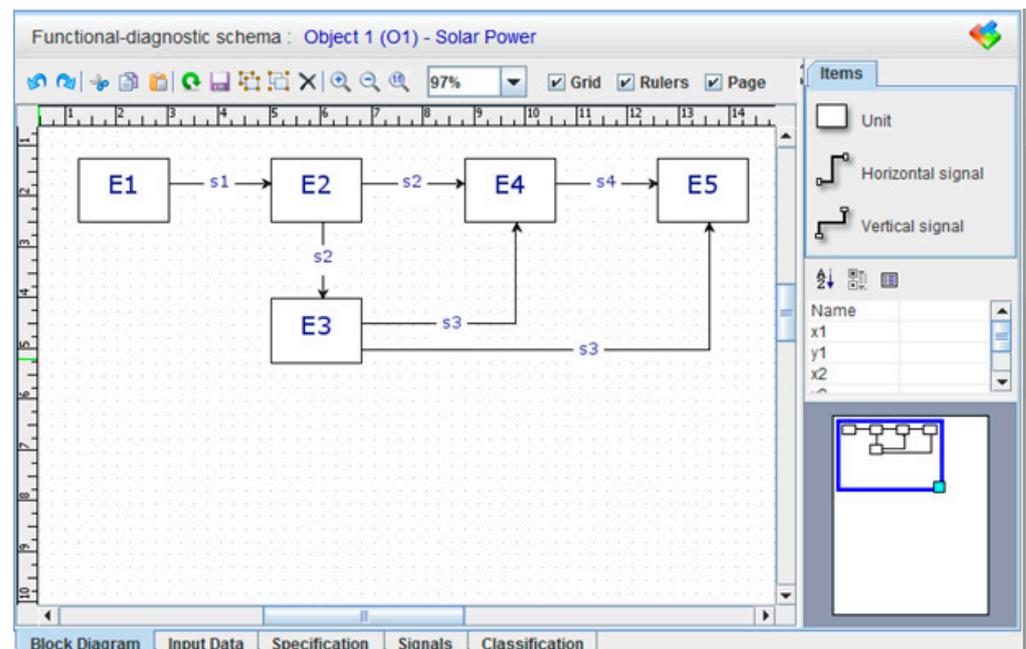


Figure 5. DIAG 2 program results for the “Structure” module.

To initiate the DIAG 2 diagnostic system, it is necessary to connect and store the diagnostic measurement knowledge base created in the program memory. The measure-

ment base comprises diagnostic signals $\{X(e_{i,j})\}$ obtained from the output of the j th object elements, along with the corresponding diagnostic standard signals $\{X_w(e_{i,j})\}$. The measurement base set produced for the DIAG 2 program is depicted in Figure 6.

Specification : Object 1 (O1) - Solar Power

A set of basic elements and their diagnostic signals

Object units		Basic elements of the object		Diagnostic signals		
Symbol	Name of unit	Symbol	Name of element	Symbol	Value	Max
E1	PV modules	e1,1	Panel PV1	X(e1,1)	11.98	12.0
		e1,2	Panel PV2	X(e1,2)	12.06	12.0
		e1,3	Panel PV3	X(e1,3)	11.96	12.0
		e1,4	Panel PV4	X(e1,4)	12.12	12.0
E2	Regulator	e2,1	Controller	X(e2,1)	12.2	12.0
		e2,2	Voltage measurement circuit	X(e2,2)	12.4	12.0
		e2,3	Current measurement circuit	X(e2,3)	2.84	3.0
E3	Wiring system	e3,1	Accumulator 1	X(e3,1)	11.8	12.0
		e3,2	Accumulator 2	X(e3,2)	12.25	12.0
		e3,3	Current measurement circuit	X(e3,3)	2.0	3.0
		e4,1	Power inverter	X(e4,1)	224.0	220.0

A set of basic elements and their diagnostic signals

Block Diagram | Input Data | Specification | Signals | Classification

Figure 6. Panel for classifying technical objects in the “Signal values” module.

The DIAG 2 system determines the diagnostic status of the object by examining and analysing the set of output diagnostic signals and comparing them with the reference signal (nominal) (Figure 7).

Diagnostic signals : Object 1 (O1) - Solar Power

Table of signals (Diagnostic) Sign Color

Unit	e1	e2	e3	e4
E1	11,98	12,06	11,96	12,12
E2	12,2	12,4	2,84	
E3	11,8	12,25	2	
E4	224	223,1	4,72	
E5	226	11,7		

Number signals 15 Number 5 DFT 75%

Table of additional computations

Signal	Diagnostic	Nominal	Metric	Deviation	Variance	N-metric
s11	11,98	12	0,02	1	1	0,003
s12	12,06	12	0,06	1	1	0,008
s13	11,96	12	0,04	1	1	0,005
s14	12,12	12	0,12	1	1	0,015
s21	12,2	12	0,2	1	1	0,025
s22	12,4	12	0,4	1	1	0,05
s23	2,84	3	0,16	1	1	0,02
s31	11,8	12	0,2	1	1	0,025

Diagnostic

The data that determine the technical condition the survey object and allow you to specify

Name of signal

s14

Probability density

Cumulative distribution

Block Diagram | Input Data | Specification | Signals | Classification

Figure 7. “Diagnostic signals table” format on DIAG 2 programme screen.

4. Investigations and Outcomes of an Artificial Neural Network-Based Determination of Diagnostic Information for Low-Power Solar Plant Devices (L-PSPD)

The DIAG 2 diagnostic system utilizes two-, three-, four- or five-valued logic to generate the conclusive diagnostic information regarding the condition of the object. The conclusive compilation of diagnostic information regarding the states of the object studied is shown in the state table for 2VL—a two-valued state assessment. The states determined are established based on the values from the $\{1, 0\}$ set (Figure 8).

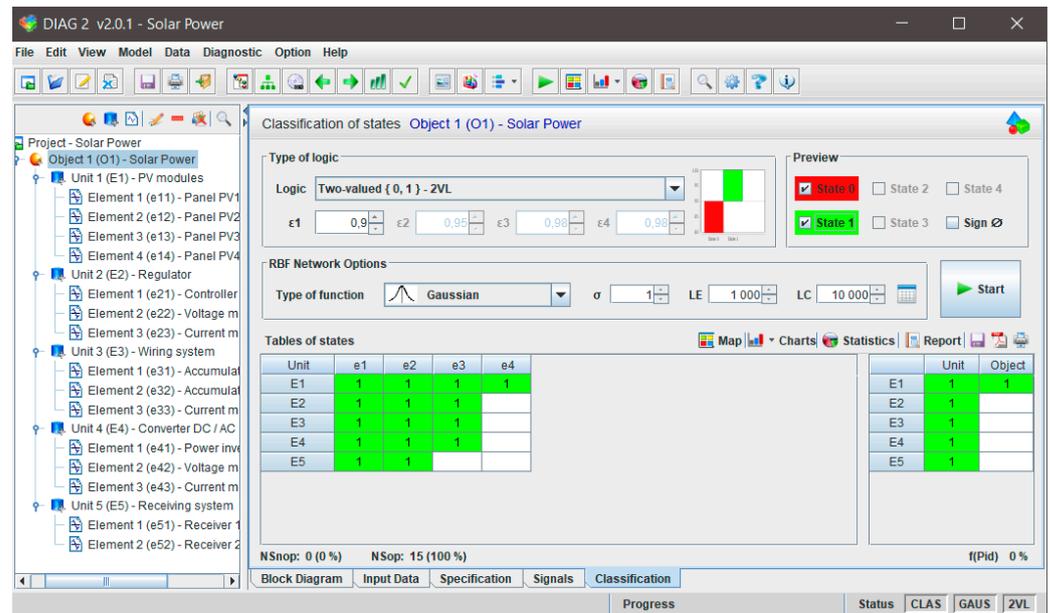


Figure 8. The output format of the DIAG 2 program, specifically the “Table of states of L-PSPD”, for a two-valued logic system.

The diagnostic outcome of the bivalent evaluation of 2VL conditions in low-power solar power plant equipment is depicted in Figure 8. The diagram illustrates that the j fundamental components in the subset $\{e_{1,1}; e_{1,2}; e_{1,3}; e_{1,4}; e_{2,1}; e_{2,2}; e_{2,3}; e_{3,1}; e_{3,2}; e_{3,3}; e_{4,1}; e_{4,2}; e_{4,3}; e_{5,1}; e_{5,2}\}$ all have the state of “1”, i.e., the state of fitness.

The diagnostic information regarding the states of the object examined is consolidated in the state table for 3VL: three-valued state assessment. The calculated states are based on values from the $\{2, 1, 0\}$ set (Figure 9).

The diagnostic results of the low-power solar plant equipment in the three-valued 3VL state assessment are depicted in Figure 9. Figure 9 illustrates that the fundamental components of the subset $\{e_{1,1}; e_{1,2}; e_{1,3}; e_{2,1}; e_{3,1}; e_{4,1}; e_{4,2}\}$ exhibit the state of “2”: the condition of fitness. Nevertheless, the fundamental components of the item belonging to the collection $\{e_{2,2}; e_{2,3}; e_{3,2}; e_{3,3}; e_{4,3}; e_{5,1}; e_{5,2}\}$ exhibit the “1” state, indicating an unfinished state.

The examination of Figure 9 demonstrates that the DIAG 2 system, developed in three-valued logic (3VL), exhibits enhanced informativeness in terms of reasoning and informationally. This is due to the fact that the DIAG 2 system not only acknowledges the $\{1\}$ condition but also recognizes it as the state of incomplete compliance. Thus, it is evident, as already established in the literature, that in three-valued logic, the presence of the determined state “1”—representing an incomplete condition—renders this 3VL logic more informative than 2VL two-valued logic.

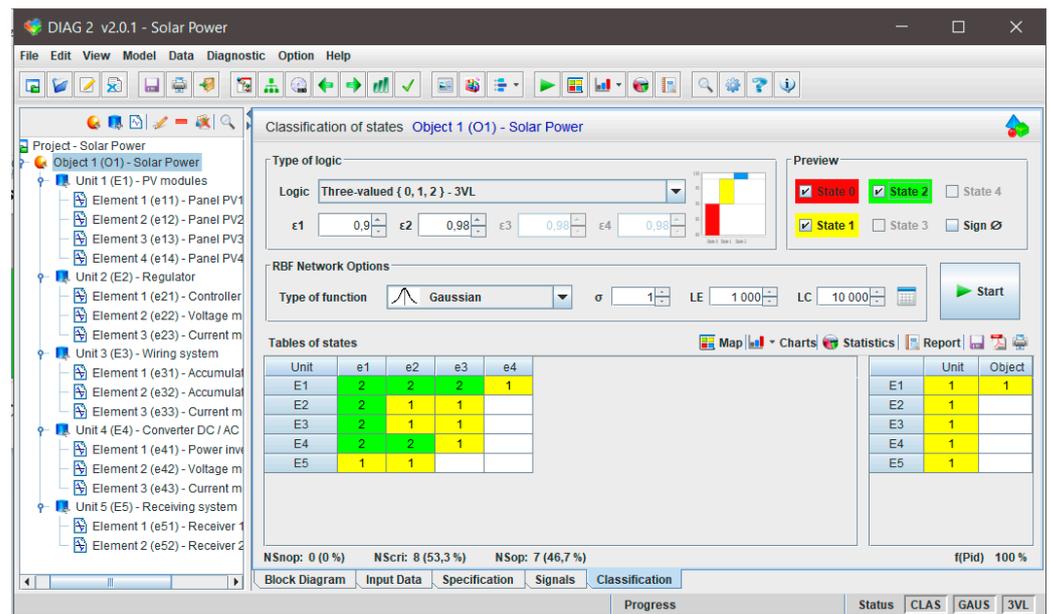


Figure 9. The output of the “Table of states of L-PSPD” DIAG 2 software for 3VL.

Figures 10 and 11 display diagnostic information for four-valued and five-valued logic. The ultimate form of diagnostic information on the states of the item investigated, in which the $15j$ th basic elements (modules) found in the i th functional units, are identified by their internal structure. Figure 10 demonstrates that the basic components in the subset $\{e_{1,1}; e_{1,2}; e_{1,3}; e_{2,1}; e_{3,1}; e_{4,1}; e_{4,2}\}$ possess state “3”: fitness. The basic components of the element belonging to the collection $\{e_{1,4}; e_{2,2}; e_{2,3}; e_{3,2}; e_{5,1}; e_{5,2}\}$ show the state of ‘2’, indicating a state of partial fitness. The remaining components of the collection $\{e_{3,3}; e_{4,3}\}$ element show the status of ‘1’, indicating a critical performance condition.

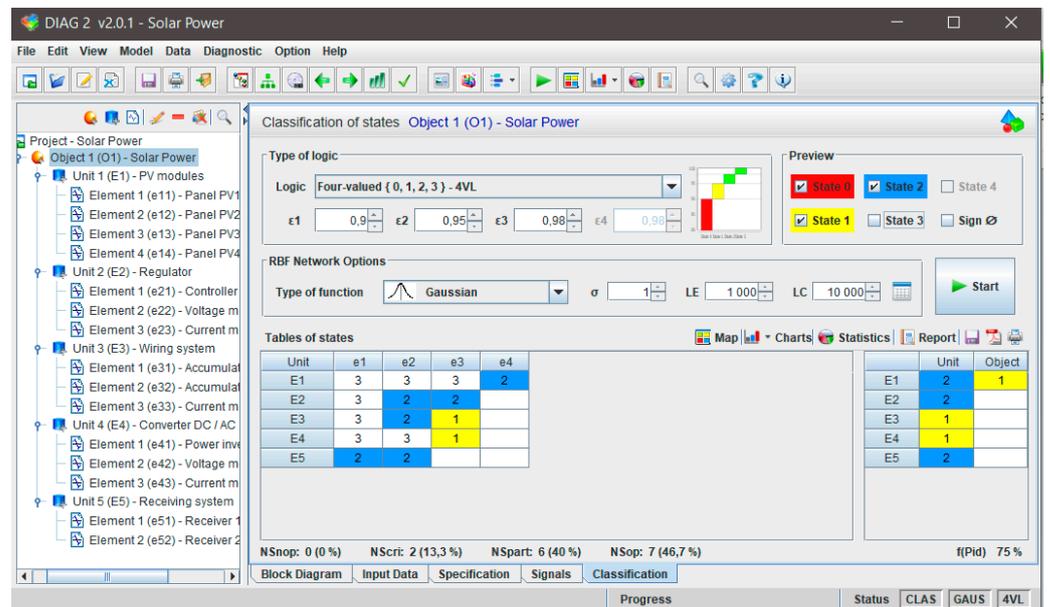


Figure 10. The resulting form of the DIAG 2 programme “Table of states of L-PSPD” for 4VL.

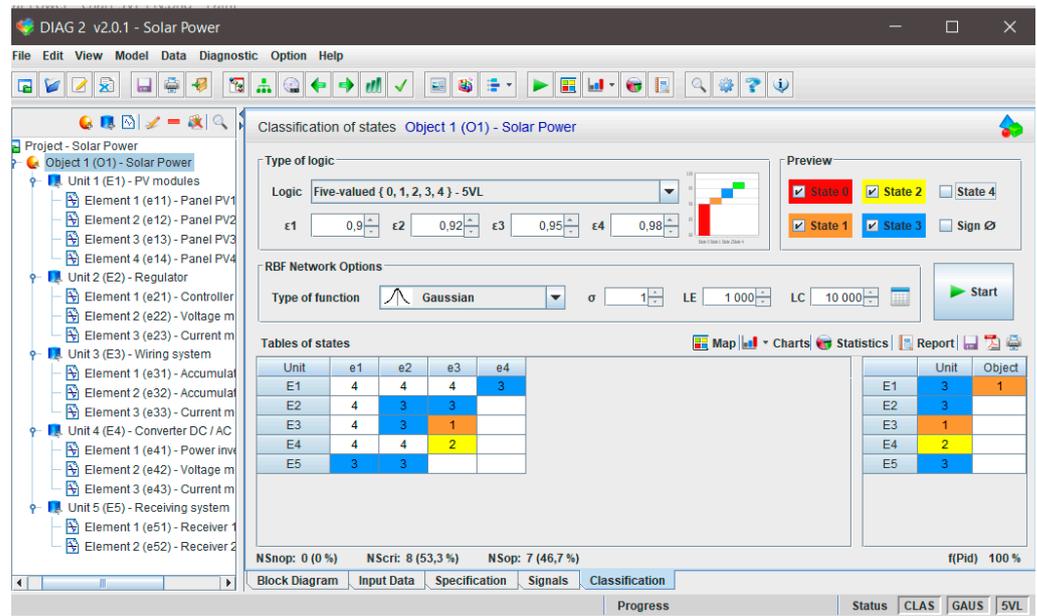


Figure 11. The output format of the DIAG 2 program, namely the “Table of states of the EHPSS”, is designed for assessing states using a five-valued system known as 5V: “4”—the state of full operation; “3”—the state of an incomplete usability; “2”—a critical operable condition; “1”—pre-damage condition; “0”—the state of non-operation (defect).

In the case of five-valued logic, tests showed that only one basic element $\{e_{3,3}\}$ has state ‘1’: pre-fault, which is 3%. The basic elements $\{e_{1,1}; e_{1,2}; e_{1,3}; e_{2,1}; e_{3,1}; e_{4,1}; e_{4,2}\}$ have state ‘4’: fitness. Other core components assessed from the subset $\{e_{1,4}; e_{2,2}; e_{2,3}; e_{3,2}; e_{5,1}; e_{5,2}\}$ have state ‘3’: partial fitness. The remaining subset of core components from the set $\{e_{4,3}\}$ have state ‘2’, which indicates critical fitness. The percentage of these j th components with the state of critical condition in the structure of the object assessed is 3%. The information gain from five-valued logic to four-valued logic is 16%, relative to three-valued logic at 26%, and relative to basic logic at 58%. Tests have shown that the use of five-valued logic is an optimal solution for the diagnosis of technical objects, providing a lot of information about the state of the object.

Here you may obtain the final version of the diagnostic data pertaining to the object’s condition. With these data, we can pinpoint exactly where in the object’s internal structure each of the fifteen fundamental components (modules) located in the functional units sit. Figure 8 shows the DIAG 2 program’s output form, the “Object states table” for 2VL: the bivalent state evaluation. In terms of the technical condition of the item under investigation, this is the pinnacle of diagnostic information. Each functional unit had fifteen separate fundamental pieces, or modules, that together formed the object’s underlying structure. The basic components from the subset $\{e_{1,1}; e_{1,2}; e_{1,3}; e_{1,4}; e_{2,1}; e_{2,2}; e_{2,3}; e_{3,1}; e_{3,2}; e_{3,3}; e_{4,1}; e_{4,2}; e_{4,3}; e_{5,1}; e_{5,2}\}$ (Figure 8) using three-, four-, or five-valued logic tend to have a decreasing fitness condition for the basic element, leading to more accurate object diagnosis, as shown in Figures 12 and 13.



Figure 12. Display of the “map of the states of elements in EHPSS” on DIAG 2 software.

We reach the meat of the matter with low-power solar plant devices in Section 3. Any technological item’s diagnostic procedure is an intricate organizational and technical activity. Included in that operation are the following elements: The first step is to test the item’s functionality and diagnose any problems. The second is to create a diagnostic system, which is essentially a computer program. The third is to establish a measurement database. Conducting a functional and diagnostic investigation of the examined object is necessary before making a diagnosis. This investigation is based on a generally recognized technique for segmenting the object’s internal structure, such as a three- or four-level division. This leads to the identification of the object’s structural elements, which in turn define the object’s diagnostic state, which in turn indicates the states of the object’s separate units, or functional systems. The object’s functional systems identify its state, which in turn determines the object’s state under investigation.

For things assessed as low-power solar plant equipment in particular, the DIAG 2 diagnostic system’s usage of an artificial neural network is a powerful research and analysis tool. An efficient measuring system that builds a measurement knowledge base is the bedrock for diagnostics implementation. Along with this specific database of measurement information, which includes a subset of diagnostic signal values, it is necessary to include a subset of standard diagnostic signal values (Figure 7).

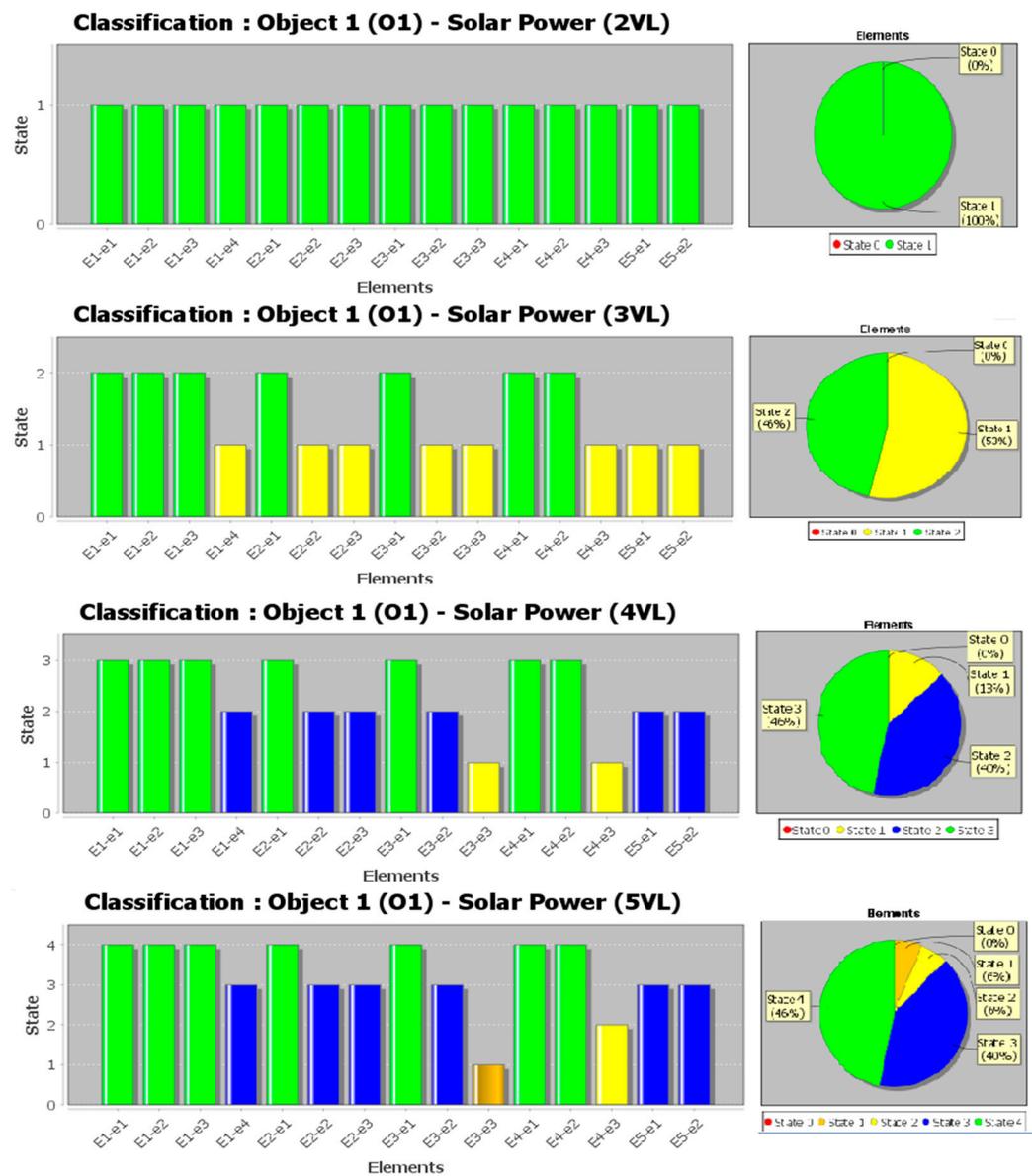


Figure 13. Screen of “State-by-state diagram of elements within EHPSS”.

The authors of this research provide a technique for assessing comparable photos that they used to troubleshoot equipment in low-power solar plants. The DIAG 2 software and an algorithm for artificial neural networks were both built on top of that approach. The article lays forth a comprehensive method for identifying technological items and systems. The diagnostician’s work model is crucial for establishing the object’s condition. That is why we used this three-tiered technique to partition the object’s internal structure. Object System Function: The object’s fundamental component or module. Graphs depicting these diagnostic signals and a collection of fundamental components are the end product of this process.

5. Discussion

The DIAG 2 diagnostic program, created by the author and shown in this paper, works as a result of using an artificial neural network with an RBF-like architecture. The effectiveness of the artificial neural network’s operation and training determines how well the DIAG 2 system performs. For the SSN’s training process to work, training signal vectors had to be made for each of the recognized states.

The SSN was initially trained to identify (classify) the fundamental states of 2VL logic. The recognized states in 2VL logic are “1” states, which denote the state of fitness, and “0” states, which denote unfitness. In contrast, the SSN has been trained to detect the additional states present in five-valued 5VL logic, such as the “3” state, which stands for the state of incomplete fitness; the “2” state, which stands for the state of crucial fitness; and the “1” state, which stands for the pre-damage state. The EHPSS diagnosis findings in the 2VL and 5VL logics, which are shown in Figure 14 clearly demonstrate that the DIAG 2 system detects the “0” unfitness state in both diagnosis logics applied. Both logics tested share the unfitness condition, sometimes known as the “0” condition. The DIAG 2 system detected an unsuitable state in one element, e1,6 when used in 2VL and 5VL logics. This leads to the conclusion that the DIAG 2 diagnostic system is quite powerful and that the SSN in the system is well-trained. Additionally, it may be inferred that the training vectors developed for instructing and training the SSN to identify an unfit state were ready. All the diagnoses in the investigation were made using the same DBW diagnostic knowledge base. The size of the DBW matrix was initially anticipated to be small during the system testing stage due to the speed of the research being undertaken. After performing test runs and looking at how well the developed diagnosis worked, it was possible to state that the initial limits on the size of the DBW were not very significant.

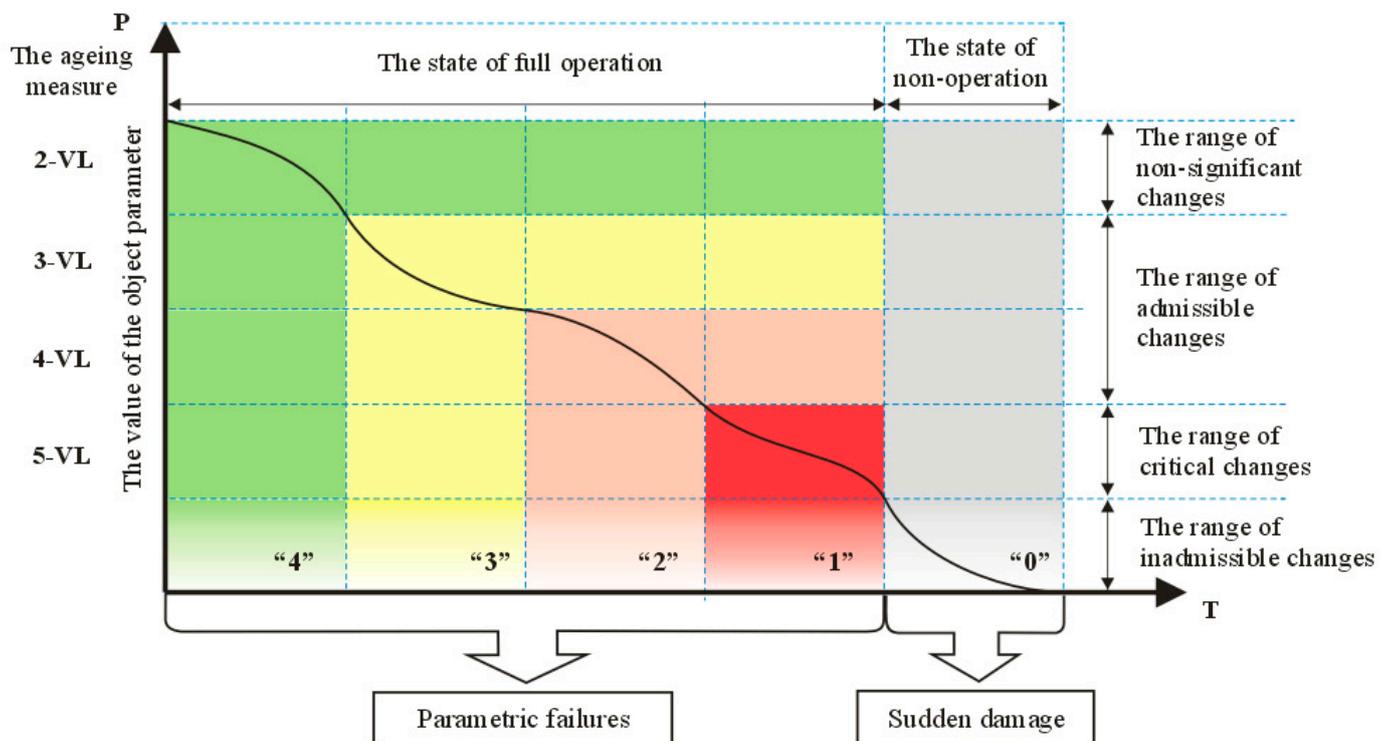


Figure 14. An artificial neural network (SBM) in the program of the DIAG 2 intelligent diagnosis system: “4”—the state of full operation; “3”—the state of an incomplete usability; “2”—the critical operable condition; “1”—pre-damage condition; “0”—the state of non-operation (defect).

The same DBW diagnostic knowledge base is used by the 2VL and 5VL implementations of the EHPSS diagnostic tests that are based on the DIAG 2 system at logic. As a result, diagnostic tests are applied to the same test object and the same test conditions. When we wish to compare how accurate and useful the diagnoses we performed in the 2VL and 5VL logics are, it is important that the same conditions in the diagnostic test plan are met.

A study that describes the diagnostics of a technical object in four-valued logic is included in the papers cited in the article. This article is unique in comparison to other works, such as the study, because it presents a diagnosis utilising 5VL five-valued logic for the first time.

Technical objects sustain damage while in use due to internal and external forces acting on them as well as aging processes. Any damage to a technical object may have little or a lot of effect on how it can be used in the future.

In accordance with:

Definition 1. *The damage is a state in which a technological object is unable to carry out its intended functions (the object ceases to carry out its functions). The two types of damage include critical and non-critical based on their nature.*

Definition 2. *Critical (sudden) damage is any harm that causes the technical item to be in the “0” condition, which denotes the state of unfitness. The object’s capacity to carry out its necessary functions is suddenly completely lost in this state. Critical damage can be caused by huge material losses or other issues that could bring harm to both to the facility and the people who use it.*

Definition 3. *Non-critical (parametric) damage is the kind of damage that occurs slowly over time to a technical object while it is being used. It can be caused by aging, the effects of internal factors (like pressure, temperature, etc.) on the object’s structural parts, and other things.*

When a technological facility is in use, there is a circumstance that causes the level of operational characteristics to gradually (parametrically) decline. The object’s capacity to carry out its necessary functions in a parametric manner also gradually declines. Non-critical damage does not always mean property loss or other risky situations for the facility and the staff that work there.

Technological diagnostics, when used in a technical facility, have the responsibility of continuously observing (diagnosing) and monitoring any state inside (Figure 14).

When analysing the figure, it can be observed that non-critical (parametric) damage is continuously recognised, regardless of the diagnosis rationale applied during the diagnosis procedure. The DIAG 2 system continuously recognises variations in the level of exploitation characteristics that occur in the technical object as it is being used. The DIAG 2 system detects negative changes in the object’s level of exploitation characteristics when they deteriorate over time in the form of interpreted states that are appropriate to the inference logic applied, such as “3” for incomplete serviceability, “2” for critical serviceability, and “1” for pre-damage. It needs to be noted that only fit objects possess the state of “4”, which is the state of fitness. A new item possesses a state that it is present after it is put into use.

It has not yet been documented in publications how 5VL logic can be used to diagnose intricate technical objects. The SSN needs more training to implement object diagnosis in 5VL diagnostics. The “1” state, or the pre-damage state, is used to train the network to recognise a new state for this diagnosis. My research team is already using principles that are novel in the literature as well as developed theoretical rules for diagnosing and separating the “1” condition. The concept of the diagnostic condition, which my team developed, is known as the “pre-rupture state” in diagnostic research. It represents our significant scientific accomplishments. This new condition “1” has already been created in theory, taught by SSN, and put to use by the DIAG 2 intelligent diagnostic system. Due to their operability and continuous usage, sensitive objects such as passenger aircraft, medical systems, energy systems, etc., require the technical ability to identify a pre-damage condition in the object. If the pre-damage status of the technical facility is acknowledged, technical renewal should be commenced, leading to the facility’s return to the state of fitness. The primary diagnostic information is the knowledge of the object’s time of occurrence in the “1”—pre-damage state, owing to the potential restoration plan for the object described in the literature as “strategy by condition”. This finding highlights how unique this article is in comparison to other studies on the diagnostics of complex technical objects. In the literature, the idea of the “object’s renewal strategy by condition” is already well known. However, there is no diagnostic device like the DIAG 2 system that could accurately identify the “1” state or the pre-damage state. The logic diagnostics do not point to such a possibility: due to the condition of critical fitness, 2-VL, 3-VL, and, to a certain extent, 4-VL diagnostics

are given with some approximation so that the “strategy by state” renewal of the object can be performed.

When compared to four-, three-, and two-valued diagnostics, and five-valued diagnostics are new because they can more accurately identify the pre-damage condition. Before the occurrence of an inoperable condition in the object, the “0” condition: the pre-damage condition in the object under study occurs in the process of its use. Experience with the application of 5VL logic to the diagnosis of EHPSS equipment shows how crucial it is for a facility’s operational procedures to be able to identify the facility’s pre-damaged state. If the technological facility exhibits a pre-damage condition, it means that there is a possibility that a failure (unfitness) may happen there soon.

The structuration of technical object restoration utilizing a “strategy by state” approach will be the main topic of our upcoming research.

6. Conclusions

Based on the results obtained, it appears that the diagnoses occurring in five-valued logic in terms of informativeness are greater (richer) than those occurring in two-value, three-value, and four-valued logic. On this basis, the percentage information efficiency of five-valued logic (5VL) diagnoses was calculated, which is 16%, four-valued logic (4VL) to two-valued logic (26%), and three-valued logic (3VL) diagnoses, which is 58% higher than two-valued logic (2VL) diagnoses (Table 1).

Table 1. Amount of additional information that can be obtained when introducing the k -th condition into the diagnostic evaluation of the object.

k	$P(A)$	$I_k(A)$	$I_k(A)$ [%]
2	0.5	-	-
3	0.33	1.5849	58.5
4	0.25	1.2618	26.2
5	0.2	1.1609	16.1

Where: k —number of states; $P(A)$ —probability of the occurrence of state A ; $I_k(A)$ —amount of possible additional information for the k -th number of states.

The DIAG 2 diagnostic system is based on an artificial neural network, which is a powerful tool for research and analysis, particularly when dealing with test objects like equipment for low-power solar power plants. An efficient measuring system that builds a measurement knowledge base is the foundation for diagnostics implementation. We will build the measurement knowledge base from these values of the diagnostic signals. The establishment of a consistent set of diagnostic signal values is an additional requirement for this body of information (Figure 7).

The necessity to employ the data generated by the DIAG 2 system in the course of arranging maintenance (repair and renewal procedures) increases the diagnostic utility of technical objects in five-valued logic. In order to use an appropriate strategy for arranging the technical maintenance (renewal) in the item under consideration, it is necessary to interpret (recognize) the incomplete state of the object and the reliability status of its components. In complicated technological items, the diagnostic process using a five-value condition evaluation is predictive. Because of the frequent and brief outages experienced by such sophisticated technological facilities, this issue is of paramount importance when it comes to their usage and operation.

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Abbreviations

E_1	photovoltaic system
E_2	voltage regulator (driver) system
E_3	electric energy storage system
E_4	DC/AC converter
E_5	receiving system
$X(e_{i,j})$	diagnostic signal in j th element of i th set
$X_{(w)}(e_{i,j})$	model signal for $X(e_{i,j})$ signal
$F_C \max$	max. value of the function of the use of the object
$\Delta X_{(n)i}$	standardized vector of the distance metric of j th signal
D_{Mi}	standard deviation of i th vector of signal metric
$W(\varepsilon(e_{i,j}))$	valued of state assessment logics for j th element within i th module (from the set of the accepted three-valued logic of states' assessment)
$\{M_E(e_{i,j})\}$	specialist knowledge base (a set of maintenance information of the object)
$D_M(X_i, X_{(w)i} \alpha)$	standard deviation of the vector signal metric, ($\alpha = 2$)
X_n	n th diagnostic signal in j th element of i th set
$w_{i,n}$	weight coefficient
$\sigma_{i,j}$	coefficients of weights
$w(\varepsilon^{(0)}(e_{i,j}))_{i,j}$	compliance coefficient of the similarity of the input signal vector to its standard vector for the diagnostic signal in j th element of i th set
(4VL)	four-valued state rating
DIAG 2	invented name of the Intelligent Diagnostic System
ANN	artificial neural network
RBF	radial basis function (type of ANN)
SBM	similarity-based method (type of ANN)
(5VL)	five-valued state assessment
{4}	set of performance states
{3}	set of incomplete states
{2}	set of critical condition states
{1}	set of pre-damage states
{0}	set of unfitness states
(4VL)	four-valued state assessment
{3}	set of fitness states
{2}	set of incomplete states
{1}	set of critical fitness states
{0}	set of states of unfitness
(3VL)	three-valued state assessment
{2}	set of states of fitness
{1}	set of incomplete states
{0}	set of states of unfitness
(2VL)	two-valued state assessment
{1}	set of states of fitness
{0}	set of states of unfitness

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