DOCTORAL THESIS

Photovoltaic Modules, Design and Manufacturing

Pavel Tšukrejev

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Pavel Tšukrejev

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PAVEL TŠUKREJEV

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Contents

List of publications

The list of author’s publications, on the basis of which the thesis has been prepared:

I Tšukrejev, P.; Karjust, K.; Majak, J. (2021). Experimental evaluation and numerical modelling of the quality of photovoltaic modules. Proceedings of the Estonian Academy of Sciences, 70 (4), 477–483.

II Herranen, H.; Majak, J.; Tšukrejev, P.; Karjust, K.; Märtens, O. (2018). Design and Manufacturing of composite laminates with structural health monitoring capabilities. In: Wang, L. (Ed.). Procedia CIRP (647−652). Elsevier. DOI: 10.1016/j.procir.2018.03.128.

III Tsukrejev, P.; Kruuser, K.; Gorbachev, G.; Karjust, K.; Majak, J. (2020). Real-Time Monitoring of Solar Modules Manufacturing. International Journal of Engineering Research in Africa, 51, 9−13. DOI: 10.4028/www.scientific.net/JERA.51.9.

IV Tšukrejev, P.; Kruuser, K.; Karjust, K. (2019). Production monitoring system development for manufacturing processes of photovoltaic modules. Proceedings of the Estonian Academy of Sciences, 68 (4), 401−406. DOI: 10.3176/proc.2019.4.09.

List of publications not included in this thesis

V Herranen, H.; Majak, J.; Tšukrejev, P.; Karjust, K.; Märtens, O. (2018). Design and Manufacturing of composite laminates with structural health monitoring capabilities. In: Wang, L. (Ed.). Procedia CIRP (647−652). Elsevier. DOI: 10.1016/j.procir.2018.03.128.

VI Väer, K.; Anton, J.; Klauson, A.; Eerme, M.; Õunapuu, E.; Tšukrejev, P. (2017). Material Characterization for Laminated Glass Composite Panel. Journal of Achievements of Materials and Manufacturing Engineering, 81 (1), 11−17. 10.5604/01.3001.0010.2032.

Author’s contribution to the publications

Contribution to the papers in this thesis are:

I First author. Methodology. Design of experiments. Conducting experiments. Formal analysis. Data analysis. Manuscript preparation.

II First author. Methodology. Design of experiments. Conducting experiments. Formal analysis. Data analysis. Manuscript preparation.

III First author. Methodology. Design of experiments. Conducting experiments. Formal analysis.

IV First author. Methodology. Design of experiments. Conducting experiments.

Introduction

The world is moving more and more to the sustainable energy usage and development of the products and technology, which support the sustainable energy use in transport, heating and power systems (Benda and Cerna, 2020). Renewable energy sources like solar, wind, hydroelectric power and geothermal energy are generally more sustainable than traditional fossil fuel sources. Together with the growth of development of the new sustainable energy technologies and products, it is crucial to focus on the energy storage and conversion; energy efficiency and distribution; and policy and economics topics and tasks (Ritchie and Roser, 2020). One of the products which support sustainable energy usage in heating and electricity manufacturing are Photovoltaic modules. Volumes of the Photovoltaic (PV) modules manufacturing and installations are rapidly growing not only in the service and manufacturing sector, but also household and private sector (see Figure 1).

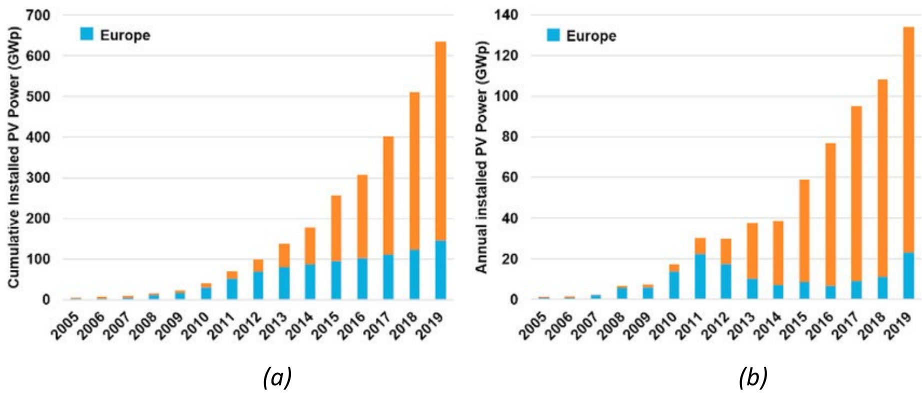


Figure 1. Globally cumulative installed PV power (a) and annually cumulative installed PV power (b) [2].

The Photovoltaic modules are utilizing the PV effect, which generates the flow of the electrons inside the materials, which are exposed to the light. Due to the high efficiency, low manufacturing price and good manufacturability the most popular way to manufacture the PV modules are using the silicon-based solar cells. For manufacturing the PV modules in a lower price level and higher productivity, it is needed to get the real time feedback from the manufacturing processes to be able to act the system changes quickly, because of that the production monitoring system implementation and usage is needed.

This thesis is focused on application of the real time measurement of temperature, pressure and duration, during the PV module lamination process, representing those parameters in a graphical view with possibility to analyze lamination conditions in accordance with further cross-linking results of Ethylene/Vinyl-Acetate (EVA) for developing a module lamination quality prediction algorithm and visualize the overview of the process in real time.

Ensuring quality of the encapsulant is a challenging due to lack of the possibilities to assess and evaluate the quality of lamination on chemical composition level just after the lamination cycle is done. In order to define the crosslinking level laboratory tests are needed. The production monitoring system for the manufacturing process of photovoltaic modules is proposed (Herranen, 2013). In the current problem there is a number of inputs having impact on the quality of the lamination process: temperature, duration, pressure/vacuum time, which are examined in the thesis.

The experimental evaluation of the gel content (degree of cross-linking) of EVA material is time consuming process [4]. In order to reduce the number of experiments needed for evaluation of the value of gel content the response surface between the gel content and its two main impact factors (duration of the process and temperature) is developed. Two advanced mathematical modelling techniques are implemented for composing response model. First, the feedforward artificial neural network model (ANN) is developed. Due to its hierarchical structure, the feedforward ANN model used is powerful tool for function approximation. However, in the case of limited dataset, available in the current study, this stochastic approach does not provide stable results. The Haar wavelet-based function approximation technique is introduced as alternate recent and deterministic approach (preferred in the case of limited dataset).

The two mathematical models developed are found to be in good agreement. Utilizing the response surface composed provide fast evaluation the value of gel content in desired points and form basis for further design optimization.

List of abbreviations

Abbreviation	Full description
AI	Artificial Intelligence
ANN	Artificial Neural Network
BOM	Bill of Materials
CFS	Completely Fair Scheduler
DoE	Design of Experiments
EAM	Enterprise Analyses Model
ERP	Enterprise Resource Planning
EVA	Ethylene/Vinyl-Acetate
FMEA	Failure Mode and Effects Analysis
GA	Generic Algorithm
I4.0	Industry 4.0 (fourth industrial revolution)
IoT	Internet of Things
KPI	Key Performance Indicator
MSE	Mean Square Error
OEE	Overall Equipment Efficiency
PID	Potential Induced Degradation
PV	Photovoltaic
P&S	Production Planning and Scheduling System
QA	Quality Assurance
QC	Quality Control
QFD	Quality Function Deployment
QM	Quality Management
RFID	Radio Frequency Identifications
SPC	Statistical Process Control
TEEP	Total Effective Equipment Performance

1 The review of the literature

Manufacturers are trying to improve production by applying different monitoring systems and using the Key Performance Indicators (KPIs). KPIs are showing the level of performance compared with the existing systems or in the field generally through measurable attributes, like the amount of material, energy, or time consumed in the process. With the high amount of the Internet of Things (IoT) and the increasing availability of data (from the product parameters and process parameters) in real time, manufacturers have availability to calculate a broad range of KPIs and their usage in certain processes and product specific parameters.

1.1 Background

Current trends in smart manufacturing show the direction to stay competitive on the market and to deliver the maximum return on assets for production related companies. To achieve this, companies have to continuously search for innovative ways to improve their production and quality control processes, to optimize manufacturing processes using new I4.0 based technologies and perform work in a faster and better way (Sell et al., 2008; Kuts et al., 2018). Production processes should be effectively monitored and controlled to avoid malfunction and unplanned downtime.

Quality is becoming an increasingly important function for the company due to the increased customer demands and product quality requirements. Manufacturing companies apply modern quality control techniques to improve the production line and its processes quality. A range of techniques are available to control product or process quality (Judi et al., 2011). These include seven statistical process control (SPC) tools, acceptance sampling, quality function deployment (QFD), failure mode and effects analysis (FMEA), six sigma, and design of experiments (DoE). Quality Control (QC) and Quality Assurance (QA) can be defined as fulfilling specification or customer requirements, without any defect. A product is said to be high in quality if it is functioning as expected and is reliable. Quality control refers to activities to ensure that produced items are fulfilling the highest possible quality.

The smart factory concept is closely tied to decentralized decision-making; that is, the system itself adapts, optimizes, evolves and makes changes independently and automatically. This is where the use of Artificial Intelligence comes in and it enables entire CFS to make decisions entirely without human intervention. The companies are in different level with implementing the different possibilities of Industry 4.0. The companies also have different processes and different production with the needs for quality QC, QA and QM.

For fulfilling different functions of QC, QA or QM different methods, tools and systems are needed depending on the needs of current company (with its production system, processes and products). For developing these instruments, one is clear. These must be intelligent, cognitive, equipped with different sensors and having the possibilities for monitoring and control functions in the production lines, gathering different data from the production and making validation and decision-making procedures. The objective is to achieve the comprehensive quality control with zero defect manufacturing possibilities.

In each company the main objective is to guarantee the required quality of the product (product specification), which is achieved by the technology and used equipment. There for having product we need the production process (production line) in which there is certain number of workplaces, where are quality control according to the technology.

Volumes of PV modules installations are rapidly growing annually. Global Compound Annual Growth Rate of cumulative photovoltaic installations during period from year 2010 to 2019 was as much as 35% [4]. Photovoltaic modules are utilizing the Photovoltaic effect that generates flow of electrons inside the materials which are exposed to the light. There are different materials that are possible to use for achieving photoelectric effect. At the moment the most popular way of manufacturing (due to efficiency, price and manufacturability) PV modules is using the silicon-based solar cells. According to (Fraunhofer Institute for Solar Energy Systems, 2020) 95% of manufactured modules are built on silicon-based solar cells. The simplified cross-section of solar cell and the PV principle are represented in Figure 2.

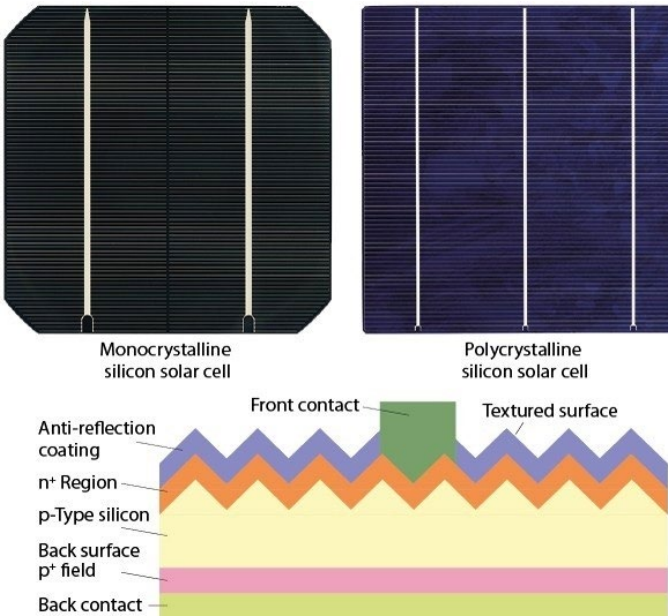


Figure 2. Schematic cross-section of c-Si silicon solar cell.

The main goal of the study is to develop the concept of the real time monitoring system for manufacturing processes of PV modules. Driven by reduced costs of the solar power generation, which is growing rapidly and the number of the photovoltaic modules being delivered to the customer increases. Automatic and earlier detection of defects/shortcomings will reduce the production cost and increases the productivity. One of the topics in this study is to detect main issues, influencing the performance of the manufacturing process of PV and determining the quality of the product produced. There will be proposed and analyzed the key parameters to be monitored in order to eliminate the faults and optimize the manufacturing processes.

The photovoltaic module is composed of different layers of different materials such as glass, encapsulant, photovoltaic cells, back-sheet laminated together. In this study encapsulant used is Ethylene/Vinyl-Acetate as this is the material mainly used by the PV manufacturer (and the one mainly used in the industry) who helped with the research. Other encapsulant possibilities are not in the focus of the study.

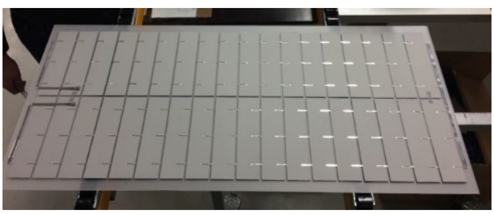
This thesis is considered to be further development of study started by authors in (Tšukrejev et al., 2019). Initial study focused on examining the possibility and need in measuring temperatures of lamination process by external sensors, need for further research with employing laboratory cross-linking test was defined.

There are several factors that are both, impacting the final quality of the photovoltaic module and could be tuned during manufacturing process. According to (Tšukrejev et al., 2019) these factors are considered as input/design parameters:

- lamination temperature of the module;
- pressure and vacuum time during the process;
- duration of the process (time).

Same factors are influencing the level of cross-linking of the EVA after it has been cured. These are the main parameters to follow and tune in order to achieve a desired gel content level of the encapsulant. At the same time, it is challenging to manufacturer to balance between duration time of the process, temperature and getting to the acceptable level of gel content. Every tuning of the process recipe can bring additional issues as appearing of trapped bubbles of EVA fumes or EVA gel content percentage exceeding desired levels.

All factors considered separately and as well as their combination plays role. The considered parameters have impact to the gel content (degree of cross-linking) of Ethylene/Vinyl-Acetate. This is something that is complicated to monitor in real time as there is need to define it during laboratory tests. There are several of different procedures for defining gel content, but those do not vary a lot. Determining of the fact that the gel content is a time-consuming process (Jaunich et al., 2016), this study uses cross-linking measurement by dissolving encapsulant samples in toluene solution for 24 hours. The gel content percentage is important to the further performance of the module during operation. The good cross-linking of encapsulant material is one of the key points to ensure structural health of the module. It is found that encapsulant and back-sheet failures are responsible for nearly 22 % of PV modules returns (Hasselbrink, et al., 2013). This thesis focuses on application of real time measurement of temperature, pressure and duration, during the lamination process, representing those parameters in a graphical view with possibility to analyze lamination conditions in accordance with further cross-linking results of EVA for developing a module lamination quality prediction algorithm and visualize the overview of the process in real time.



(a)

(b)

Figure 3. PV module cells layout and electrical circuit is ready (a) and finished PV module.

To build a PV module, there are also other materials used in order to ensure maximization of light gathering, structural health as well as electric and climate insulation. The structure of PV module considered includes (Amrani et al., 2007):

- Front-sheet – usually glass or other transparent material for light transparency as well as climate and mechanical protection;
- Photovoltaic cells – for electrical current generation;
- Ribbon connections – for electrical circuit;
- Back-sheet – for electrical and climate insulation;
- Encapsulant – for laminating everything all together, protection from moisture and air as well as being transparent for light.

On Figure 3 the view of single PV module during the manufacturing stage is shown (a) with one of the EVA sheets laid onto the glass and solar cells soldered together into the electrical circuit on top of the EVA. The finalized ready and framed module represented on Figure 3 (b).

During lamination process due to thermal activation the polymer chains inside the encapsulant are being linked together. Cross linking level is having impact on different material properties and can define reliability and performance of the material during service time. In order to define the degree of cross linking inside EVA encapsulant the gel content parameter is used. Lower degree of gel content referring to the lower level of cross linking which brings the mechanical properties of the encapsulant to insufficient level. Also the higher level of gel content refers to the higher level of cross linking which can cause mechanical properties to be over necessary levels.

Current study aims to gather the experimental data and based on these data, to build mathematical model(s) for prediction the quality of the encapsulant gel content. The obtained results will allow manufacturers to predict the crosslinking level instantly at place on the basis of real-measured parameters. The response surfaces, built on mathematical models, allow to predict unknown values of the functions. In the current study are employed two recent techniques.

First is utilized artificial neural network technique – one of the most widely used modelling technique in engineering covering various engineering problems (Fathi et al., 2021; Montesinos et al., 2021; Kazi et al., 2022; Teharia et al., 2022; Zarringol et al., 2020; Kumar et al., 2022; Sada et al., 2021; Mondal et al., 2020; Hein et al., 2019). In (Fathi et al., 2021) the intelligent maximum power point tracking for photovoltaic panels is developed using a novel fuzzy logic and artificial neural networks. In (Montesinos et al., 2021) the ANN model is developed to estimate atmospheric horizontal extinction in central solar tower power plants. In (Kazi et al., 2022) the crashworthiness performance of composite rectangular tubes is studied to achieve the given values of the load carrying capacity and energy absorption. In (Teharia et al., 2022) is performed optimization of additive manufacturing process for producing PLA based tensile specimen. In (Kumar et al., 2022) and (Zarringol et al., 2020) the ANN models are developed for predicting micro-hardness during electric discharge machining of cryogenically treated titanium alloys and the ultimate strength of rectangular and circular concrete-filled steel tubular columns, respectively. In (Sada et al., 2021) the modeling ability of the ANN and adaptive neuro-fuzzy inference system in the prediction of AISI 1050 steel machining performance are evaluated. In (Mondal et al., 2020) the ANN model is utilized for optimization of drilling burr. In (Jaanuska et al., 2019) the ANNs and the random forests are applied to predict the location and severity of a crack in Euler–Bernoulli cantilever beam. In (Hein et al., 2019) the parameter identification is performed in vibrating nano-beams as a classification problem using different machine learning methods.

The development of ANN based prediction models and combining ANN models, etc. AI tools with gradient based and evolutionary optimization algorithms are subjects of the study of the workgroup during several decades covering optimal material orientation problems (Majak et al., 2010) design of car frontal protection systems, 2008, 2012); technology route planning of large composite parts (Karjust et al., 2010), modelling reprocessing of the glass fiber reinforced plastic (GFRP) scrap (Aruniit et al., 2011), prioritization of key performance indicators (Kaganski et al., 2017, 2018), design of composite laminates with structural health monitoring capabilities (Herranen et al., 2013, 2018), development of production monitoring system with predictive functionality (Eiskop et al., 2017, 2018, Snatkin et al., 2015). The accuracy and configuration of the ANN is studied in (Gnana Sheela et al., 2013) and (Hecht-Nielsen, 1989).

The second recent mathematical modelling approach used herein is based on Haar wavelet expansion. The Haar wavelet-based techniques for function approximation is used over decade. According to commonly used approach the functions are expanded directly into Haar wavelet series (Babolian et al., 2009; Lepik and Hein, 2014). It has been proved by (Babolian et al., 2009) that in latter case the rate of convergence with respect to mesh is equal to one. The obtained convergence rate value is obviously poor for wide use in engineering design. The higher order Haar wavelet-based function approximation has been introduced in (Majak et al., 2018). According to (Majak et al., 2018) the derivatives of the function are expanded into Haar wavelets. The order(s) of derivative(s) are considered as method parameter(s), which can be adopted for particular problems. Latter method provides principal increase of the accuracy and the rate of convergence in comparison with widely used Haar wavelet expansion-based approach keeping the increase of the computational and implementation complexity reasonable (Majak et al., 2021; Tšukrejev et al., 2021; Haavajõe et al., 2019).

1.2 Objectives and activities of the research

The main objective of the research is to improve the manufacturing processes of photovoltaic modules by developing real time monitoring system concept and prototype, performing measurements of key parameters and composing mathematical models for prediction of quality characteristics. This thesis is focused on detecting main issues, influencing the performance of manufacturing process of photovoltaic modules and considering key parameters in modelling the quality of encapsulant.

The main activities of the research are:

- Development of Photovoltaic Module Production Monitoring System Concept;
- Prototype development and real time testing;
- Mathematical modelling of the quality of encapsulant.

1.2.1 Scope and limitations of the research

The scope of the particular research is to define the most important parameters that are influencing the quality of the PV module and to compose mathematical models allowing to predict the behavior of quality characteristics. To develop the procedure for tracking those parameters in real time as well as the concept of the tool which would process the gathered data and bring suggestions regarding the quality of the module. Limitations are coming from the limitations of the manufacturing facility of the company, which is the partner of particular study. Limiting factors are as follows:

- Existing machinery;
- Existing materials used in production process;
- Existing module structure.

In order to understand better practical manufacturing process, the theoretical development and numerical modeling is implemented on basis of particular manufacturer (monitoring system built, gathered data, etc.). However, the research results and findings can be utilized also by other PV modules producers as the challenges faced by manufacturers who are using the same or similar materials are very alike. Cross-linking level determination process and principles used by different manufacturers is the same. The main difference is that some of the companies can use their in-house laboratory capabilities and the others have to seek for an outsourced laboratory service. Topic of optimization of the PV module design is studied by Chen et. Al, 2015, hence it is not mainstream research.

The research was applied mainly to the standard 60-cell PV module with the Low-iron structured 3,2 *mm* thick glass, two layers of EVA and a backsheet. Dimensions of the laminate are 981x1618 *mm*. As a final step laminate is framed with aluminium frame and junction box installed. This type of module is the main product and takes share of 90% of production output of the manufacturer.

1.2.2 The research questions

The encapsulant cross-linking level is essential to the photovoltaic module's structural health and performance during operation in the future as well as it is one of the major parameters for the quality assessment of the module. The fact that it is not possible to perform such kind of tests in real time without destructing the product makes it highly complicated to assess this parameter on a module level. The tests are performed for different batches of EVA. At the same time there could be a difference inside one batch caused by different settings of the machinery or different performance of the machinery. Considering that there is a need to develop a prediction tool which would use existing real-time measurable parameters to evaluate the quality of encapsulant and give a suggestion regarding product quality during the production run.

The research questions can be formulated as:

Q1. What are the basic functionalities and features of the real-time production monitoring system featured for manufacturing of photovoltaic module's?

Q2. Which key performance characteristics are important for the quality assessment of the module?

Q3. How can mathematical modelling help to evaluate performance characteristics? What kind of advanced prediction tools can be utilized?

Q4. What is the practical outcome? How the results obtained can be applied?

2 Theoretical Concepts

In the following the theoretical concepts of manufacturing and quality evaluation of the photovoltaic modules are discussed. Two mathematical models are introduced for response surface modelling.

2.1 General Structure and Manufacturing Process of the Photovoltaic Modules

Burning fossil fuels is in charge for the big part of atmosphere pollution and the greenhouse effect in general (Graus et al., 2009). According to Clover et al., 2018 in Europe (including Turkey) countries newly installed photovoltaic systems capacity was of 28% growth in 2017 in yearly comparison. The main technology for manufacturing solar modules, with market share over 90%, is the silicon-based photovoltaic cells (Fraunhofer Institute for Solar Energy Systems, 2020; Silvestre et al., 2018). Fraunhofer ISE report notes that the efficiency of the silicon cells hitting the laboratory efficiency of 26.7% and 22.3% depending on technology used: respectively monocrystalline or polycrystalline. The efficiency of cells available in the market is about 21.5% and growing on annual basis. Additionally, to the traditional silicon-based solar cells, there are different perspective materials used. One example is to use Perovskite instead of crystalline silicon inside the solar cells, as it is considered to be cheaper material reaching the efficiency of 22.1% (Shi et al., 2018). Another example of future material to use as a solar cell is to be the “black silicon”, which have the significant laboratory efficiency of over 90% (Juntunen et al., 2016). The solar modules with silicon cells are consisting of different layers, composing a sandwich structure (Amrani et al., 2007): shown in Figure 4.

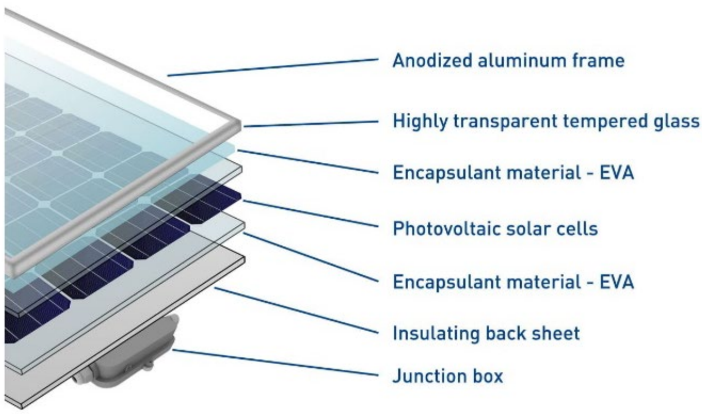


Figure 4. Layers of solar module.

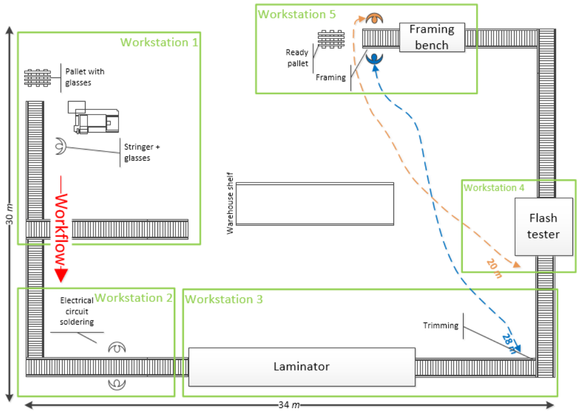
This paper addresses the manufacturing process of photovoltaic modules with silicon-based cells and focuses on the lamination part of it. The lamination step is essential to the manufacturing process and placed in the middle of it, after lamination nothing can be changed as the whole module is already encapsulated.

2.2 Photovoltaic module manufacturing process

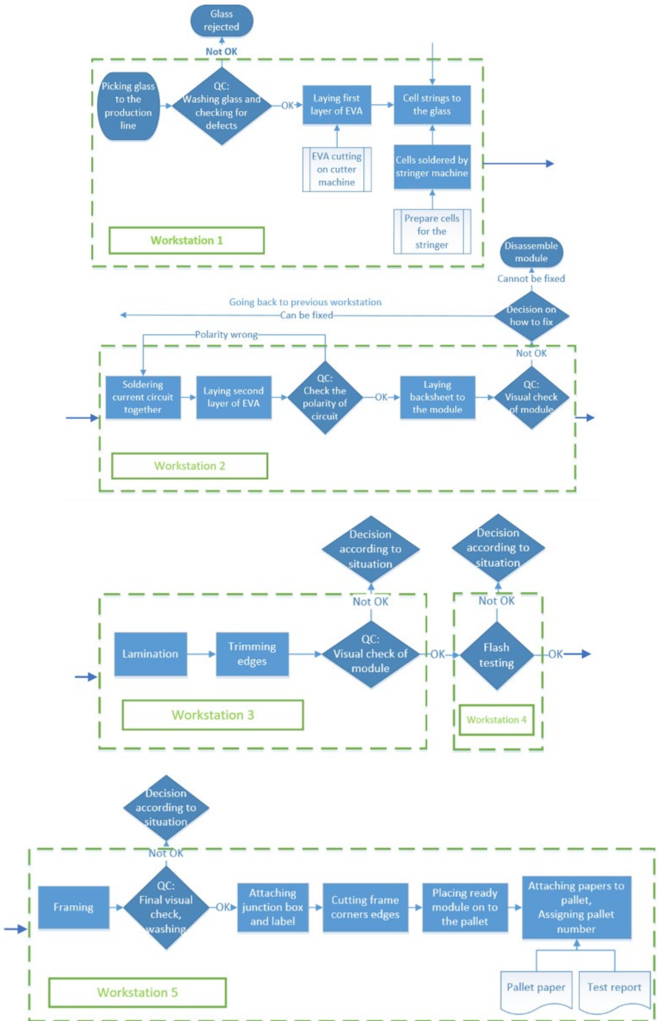
The production process in the particular facility is not having any special differences with generic widely known Si-c PV modules manufacturing process. The work of automated machines (cell stringer, laminator) as well as manual labor of skilled operators is used. To ensure the working condition of module, electrical parameters to be in accordance with specifications as well as cosmetic appearance of the product the quality control station (Workstation 4) is integrated into the process. Special flash-light and measurement equipment setup is used in this workstation. Manufacturing process consists of the number of steps:

- **Workstation 1**
    - Preparation of the glass
    - Soldering of the solar cells into the cell strings
    - Layering the encapsulant cell strings onto the glass
- **Workstation 2**
    - Soldering the cells and ribbon connectors into the electrical circuit
- **Workstation 3**
    - Lamination process
    - Cooling down process
    - Module cleaning and visual inspection
- **Workstation 4**
    - Flash testing
- **Workstation 5**
    - Final assembly of the module
    - Packing

Production technological steps mentioned above can be found also on the Figure 5 (a). Figure represents the physical layout of the workstations and machines as well as staffing and the way of workflow. Figure 5 (b) represents the main processes taking place during the manufacturing cycle.



(a)



(b)

Figure 5. Layout of production line and technological steps of the manufacturing process (a) and workflow detailed description (b).

Particular thesis focuses on the lamination process. The flow chart of the lamination steps is represented on the Figure 6, showing the sequence of operations. Lamination process consists of diferent steps and starts when the PV module is ready to be laminated (meaning that all layers are placed to the glass and connections are soldered into proper electrical circuit). Laminator machine operates in semi-automatic mode, as feeding of the modules and taking those from the machine is manual work. All other steps: taking into the chamber, lamination and going out of the chamber are automated and happening according to the recipe.

During the lamination process the module is fed into the lamination chamber. After the laminator lid is closed the chamber is sealed and no air can go inside there. The module is curing under certain temperature inside the chamber in accordance with the recipe. At the same time as a first lamination step the under pressure is applied and air is being pumped out of the chamber. Lamination chamber consists of two sections separated by silicone membrane, the pressure can be different in the chamber sections. The one with the module inside usually is being under pressurized to ensure no air or EVA fumes will be left in between the material layers of PV module and no bubbles will be appearing. The other section "behind" the membrane can be over pressurized (depending on the recipe) in order to apply pressure to the PV module being cured. This is in order to glue all of the layers together as well as helps to extract leftovers of air or fumes.

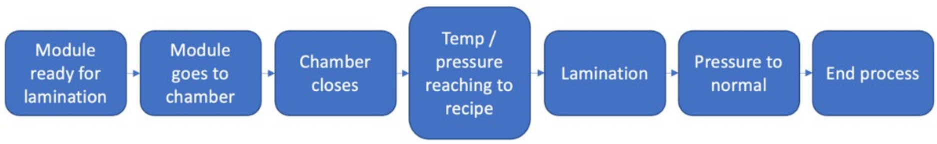


Figure 6. Flow chart of lamination process.

2.3 Main Issues in Photovoltaic Modules Manufacturing Processes

As noted in (Meyer et al., 2017; Zhu et al., 2012), the major faults of solar modules because of the wrong design or troubles during production could be brought as follows:

- air bubbles inside modules;
- broken cells;
- microcracks;
- hot spots;
- potential induced degradation (PID);
- snail trails.

The photovoltaic modules production issues are analyzed and the results are brought out in Table 1. It is explained how those types of issues and faults appear inside module and what are the reasons. Certain suggestions, how it is possible to overcome these issues, are proposed in last column of Table 1.

Table 1 Different issues in PV modules.

Issue	How it looks like in product	Why is it bad	What is causing it	How to avoid it
Air bubbles	Bubbles laminated inside module – in different spots.	Bubbles are risk of delamination. Impossible to repair.	1. Trapped air 2. Fumes of EVA 3. Cooling process. (Meyer et al., 2017)	Fine tuning for lamination cycle is the only possibility to avoid the bubbles.
Broken cells	Cells are broken inside the laminated module. Either there is a crack or a whole piece of cell is apart.	Can impact power performance. Cannot be repaired.	1. Microcracks in cells 2. Transportation issues 3. Production handling 4. Issues in production process itself	Ensure that handling during manufacturing and process does not damage cells.
Microcracks	Not visible by eye. The crack is not through the whole thickness of cell (ca 200 micrometers).	Impacting performance of cell. Risk of a real crack. Growing due to weather influence.	1. Transportation issues. 2. Supplier ships faulted cells 3. Handling during production	Electroluminescence picture of every single cell that is going to be used in production.
Hot spots	The burnt spot under the glass on the surface of cell.	Spots that become warmer inside the module. Leading to short circuit.	Issues in soldering of ribbon to the cell. Structural defects of cell.	Ensure the quality of soldering the interconnectors.
PID	Does not visually appear.	Accelerated aging of modules. Solar modules could lose performance.	Potential difference between solar module, and the earthing. Caused a lot due to encapsulant itself or the way of encapsulation.	Improve design of the module, and the choice of materials used. Improve lamination technology for avoiding humidity penetration into the module
Snail trails	"Browning" of contact fingers of cell in a form of trails. Appearing after some years.	Appearance of module. Can cause loss of power output.	Moisture penetrating into the module because of poor EVA encapsulation causing oxidation of components of cells on the trails of microcracks.	Ensuring quality of EVA encapsulation. Avoiding different types of crack in cells.

In understanding the nature of those faults brought out in Table 1, it is possible to follow the set of selected parameters in order to prevent the issues listed above. Most of the issues in photovoltaic modules appear during lamination process. This process is very important to the success of module but very complicated to be tuned. Settings depends on used materials. Laminator has to perform the whole cycle (up to 25 minutes) in order to produce a module. During lamination the chamber is closed and it is not possible to see if something going wrong there. After every smallest change in program there is need to wait for whole cycle. In case of wrong settings modules will be scrapped.

There are different steps in lamination process with different temperatures and pressures. The encapsulant material EVA is becoming liquidous during lamination, which makes possible for cells to float inside and is causing undesirable displacements.

EVA is a mildly transparent thermoplastic, soft, easily can be deformed, melting range for EVA is in the range of 60–70 degrees *C*. EVA is a copolymer of ethylene and vinyl acetate. The percentage of vinyl acetate for PV use is usually in the range of 28-33%. In order to fulfill the encapsulation requirements EVA needs to go through thermally activated crosslinking which is possible with a help of radical reaction of peroxide or peroxycarboxylic acid as an initiator (crosslinker). This crosslinker is cleaved into two radical species, by the creation of a chemical bond between the polymer chains, the initial thermoplastic EVA is transformed into a "cured" three-dimensionally crosslinked elastomer. During the lamination at temperatures around 150 °C. The rate of crosslinking is modulated mainly by the temperature and duration of the lamination process (Hirschl et al., 2013).

2.3.1 Measurable Parameters

The manufacturing process is often highly automated by the various IT/software systems and production lines with combination of robots. The production is planned and scheduled by a Production Planning and scheduling System (P&S). The efficiency and effectiveness of the resources in the production plant can be estimated through KPIs.

The study of lamination process allows selecting of the parameters that need to be tracked:

Table 2 Process parameters relationships between input and output parameters.

Parameter		**Explanation**
Pressure	Input	essential during lamination process (impact on the cross-linking level of encapsulant and appearing of air bubbles)
Temperature	Input	main parameter for photovoltaic module lamination. Impacting the cross-linking level of encapsulant
Duration	Input	lamination time. Influences EVA cross-linking level and appearing of bubbles inside of the laminate
Displacements	Output	essential to understand if module's structure is right. By finding displacements that are not seen by eye and understanding when those happened it is possible to improve modules overall

EVA gel content (degree of crosslinking)	Output	important parameter to be followed, but it is hard to track by sensors in real time, as it is determined during chemical processes. Highly dependent on process duration time and temperature
Cracks	Output	finding different types of cracks before laminating process allows to replace the cell
Measured temperature	Output	the temperature data gathered from additionally installed sensors could be considered as an output as it could be used further in making decisions according how to measure temperature in a right way

In order to track those parameters (please see Table 2), the main idea is to embed a sensor inside the photovoltaic module body on the production stage and by this track parameters noted.

As it is marked in Table 2 all three of considered inputs are having an impact on the quality of encapsulant through the cross-linking level of EVA.

2.4 Experimental Evaluation of the Quality of Encapsulant

Quality of lamination is a general focus of the series of papers and emerging problem for solar companies. Encapsulant under study is Ethylene/Vinyl-Acetate (EVA), as it is mainly used by the partner PV manufacturer of this study. In terms of particular research assessment of lamination success could be divided into two main branches, represented in Figure :

1. Visual component (aspect) – all possible visual fault that leading to bigger issues in the future;
2. Quality of encapsulant (crosslinking level) – Gel content of the EVA material, should be defined during time consuming process (Jaunich et al., 2016).

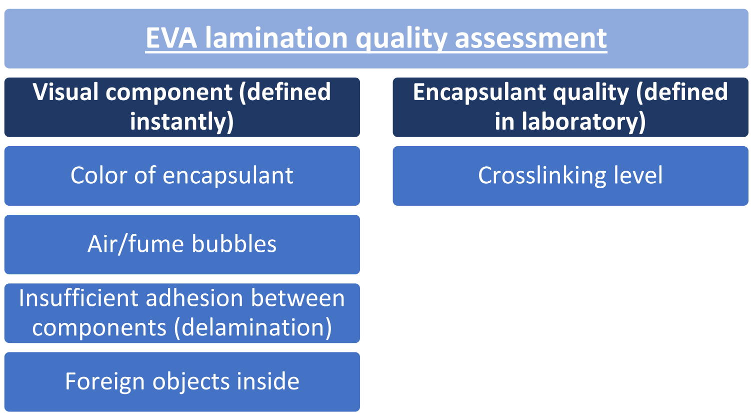


Figure 7. Quality assessment of cured Ethylene/Vinyl-Acetate.

Ensuring quality of the encapsulant is a challenging due to lack of possibilities to assess and evaluate quality of lamination on chemical composition level just after the lamination cycle is done. In order to define the crosslinking level laboratory tests are needed. Good cross-linking level is considered to be 65% (Eiskop et al., 2017). Supplier of EVA suggesting target value for PV modules to be between 70% and 80%. Sample gathering is something that is making a PV module not usable anymore.

The production monitoring system design and implementation issues are discussed in (Eiskop et al., 2018; Shiva Prasad et al., 2016; Kaganski et al., 2017; Kaganski et al., 2018; Sell et al., 2008; Kumar et al., 2021; Sada et al., 2021). Particularly, the production monitoring system for manufacturing process of photovoltaic modules is proposed in (Eiskop et al., 2018).. In the case of current problem, here is a number of inputs having impact on quality of the lamination process: temperature, duration, pressure/vacuum time (Meyer et al., 2018). As temperature and duration of the process are considered by the authors to make the biggest impact on the quality of encapsulation it was decided to measure the temperature from the edge of the module during the real manufacturing lamination cycle. Previous experience showed that measuring from the surface of the module is damaging back sheet and module is becoming visually defected and not usable.

2.5 Mathematical modelling of the quality of encapsulant

In general, the mathematical model will be developed with an aim to predict the values of the function in points, where experimental data or numerical analysis data are not present with an aim to save/reduce expenses for experiments and/or computing time.

In engineering design one of the recent and most popular modelling technique used is artificial neural network (Kazi et al., 2022; Teharia et al., 2022; Zarringol et al., 2020; Kumal et al., 2022; Sada et al., 2021; Mondal et al., 2020). Main application areas of the ANN in engineering design can be listed as

- function approximation;
- pattern recognition;
- classification, etc.

The response modelling allows to save time and other resources in engineering applications. Especially can be pointed out stochastic optimization algorithms, which need commonly huge number of evaluations of the objective functions. The workgroup has long time experience with development and adaption of ANN and artificial intelligence tools for wide range of engineering design problems like modelling car frontal protection system, optimal material orientation problems, design of composite laminates with structural health monitoring capabilities, prioritization of key performance indicators, design of sandwich panels, modelling reprocessing of the glass fiber reinforced plastic (GFRP) scrap, etc. (Majak et al., 2008, 2010, 2012; Karjust et al., 2010, Aruniit et al., 2011, Kaganski et al., 2017, 2018; Herranen et al., 2018; Eiskop et al., 2017, 2018).

2.5.1 Artificial Neural Network model

The general structure of the feedforward ANN employed in the current study is shown in Figure 8. It has been shown by several authors that in the case of function approximation the feedforward artificial neural network (ANN) model with one hidden layer can approximate any continuous function accurately on a compact space (closed real interval) (Gnana et al., 2013; Hecht-Nielsen 1989). For that reason, only one hidden layer is considered. In the case of feedforward artificial neural network, the information is moving in one direction from input to output without loops. The general working principle of the feedforward ANN is the following. The random weights are generated for input and hidden layers. The input parameters temperature and final time are multiplied with random weights, next is added bias and applied the transfer function of the hidden layer. The outputs of the hidden layer are multiplied with weights and the bias is added. Finally, the transfer function of the output layer is applied and output value is obtained. The weights and bias are updated by utilizing to Levenberg-Marquardt training algorithm. The iterations are repeated until the required accuracy is achieved or maximum number of iterations is reached.

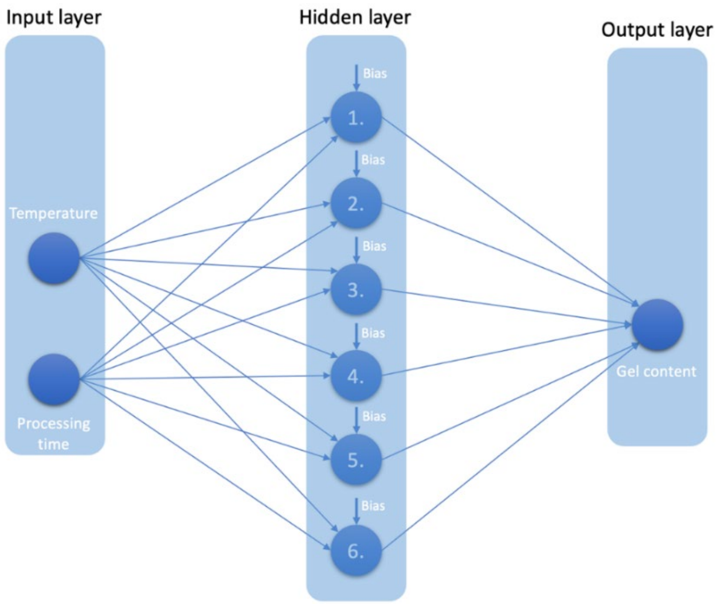


Figure 8. Scheme of employed artificial neural network.

The mean square error (MSE) was utilized for evaluation of the ANN model developed. As common for stochastic processes the ANN need certain tuning. More precisely, the development of final ANN architecture is stochastic process, after the training is completed, the ANN can be utilized as deterministic method. The architecture of the considered simple backpropagation ANN includes specifying the number of layers, number of neurons in each layer and transfer functions in each layer.

Based on literature and above remarks, the ANN with one hidden layer, two neurons in input layer (determined by number of input variables) and one neuron in output layer (determined by number of outputs) was developed. The initial value of the neurons in hidden layer is computed as (Gnana Sheela et al., 2013)

$$N_h = \left(N_{in} + \sqrt{N_{tr}}\right)/L, \tag{2.1}$$

In (2.1) L denotes a number of hidden layers (in the current study $L = 1$), N_{tr} is a training data capacity, N_h and N_{in} stand for a number of neurons in hidden and input layers, respectively. The transfer functions used in hidden and output layers are sigmoid and linear functions, respectively. In one layer is used the same function for all neurons. During tuning process of ANN, the number of neurons in hidden layers is increased by one until the mean square error decrease.

The dataset available for modelling the quality of encapsulant is limited at current time. The ANN model includes uncertainty and its results may vary, if the dataset available is too small. Thus, an alternate approach, based on the Haar wavelet expansion, is developed for modelling the quality of encapsulant.

2.5.2 Haar wavelet-based model

The Haar wavlet based approach for function approximation is new, may said in development (Lepik et al., 2014; Majak et al., 2021; Tšukrejev et al., 2021). The Haar wavelet expansion-based approach can be introduced for 2D function as (Haavajõe, 2019; Tšukrejev et al., 2021)

$$f(x,y) = \sum_{i=1}^{2M} \sum_{j=1}^{2M} a_{ij} h_i(x) h_j(y) \tag{2.2}$$

In (2.2) the function $f(x,y)$ is a function needed approximate (herein the gel content), x and y stand for the temperature and processing time, respectively. The Haar functions are given as

$$h_i(x) = \begin{cases} 1 & for \quad x \in [\xi_1(i), \xi_2(i)) \\ -1 & for \quad x \in [\xi_2(i), \xi_3(i)) \\ 0 & elsewhere \end{cases} \tag{2.3}$$

where

$$\xi_1(i) = A + 2k\mu\Delta x,\ \xi_2(i) = A + (2k+1)\mu\Delta x,\ \xi_3(i) = A + 2(k+1)\mu\Delta x,$$
$$\mu = M/m,\ \Delta x = (B-A)/(2M),\ M = 2^J \tag{2.4}$$

In (2.3)–(2.4) $m = 2^j$ is describes the resolution ($M = 2^J$ corresponds to maximal resolution), the translation parameter k indicates the location of the particular square wave and $i = m + k + 1$. The unknown coefficients a_{ij} in (2.2) can be determined by satisfying the relation (2.2) in given collocation points. In the case of uniform mesh the collocation points can be calculated as

$$x_l = (l - 0.5)/(2M),\ y_r = \frac{(r-0.5)}{2M},\ l, r = 1,2, \dots, 2M. \tag{2.5}$$

In the case of experimental input data, the measuring points may have nonuniform distribution. However, the coefficients a_{ij} can still be determined from relation (2.2), but the widely used Haar matrices for uniform mesh cannot be implemented. In practical applications, the boundary area is often more critical for changes of the function.

The function approximation approach given by (2.2) is deterministic, but its accuracy is rather low in the case of small mesh. For this reason, the workgroup has introduced more general Haar wavelet based function approximation approach as

$$\frac{\partial^{n+m} f}{\partial x^n \partial y^m}(x,y) = \sum_{i=1}^{2M} \sum_{j=1}^{2M} a_{il} h_i(x) h_l(y). \tag{2.6}$$

This approach, is based on higher order Haar wavelet method introduced in 2018 in (Majak et al., 2018). According to latter approach instead of the function its $n+m$ -th order derivative is expanded into Haar wavelets. In (2.6) $n, m = 1,2,..$ are model parameters. The function $f(x,y)$ can be determined by integrating the relation (2.6) $n+m$ -times. Obviously, such integration produces $n+m$ integration constants/functions, which can be determined by satisfying function $f(x,y)$ in points where its value is known (experimental or numerical data provided). In engineering applications, it is often suitable to use boundary points for this aim, since in boundary the function value if often known (may not need extra experiments).

In order to get understanding about accuracy of the approach (2.6) in the case of different model parameters n and m values, the approximation of the simple 2D exponent function $f(x,y) = e^{x+y}$ is explored. This allow to select most suitable model parameters values in the case of practical applications where the number of experiments is limited. The obtained results are given in Table 3 ($n = m = 0$), Table 4 ($n = m = 1$) and Table 5 ($n = m = 2$), respectively.

Table 3. Function approximation results for test function $f(x,y) = e^{x+y}$ in the case of $n = m = 0$

Grid size	Fn value at point x = 0.25, y = 0.25	Abs. error	Converg. rate
4	2.11700	4.68e-01	
8	1.86824	2.20e-01	1.0930
16	1.75505	1.06e-01	1.0458
32	1.70105	5.23e-02	1.0227
64	1.67468	2.60e-02	1.0113

Table 4. Function approximation results for test function $f(x,y) = e^{x+y}$ in the case of $n = m = 1$

Grid size	Fn value at point x = 0.25, y = 0.25	Abs. error	Converg. rate
4	1.63896	9.76e-03	
8	1.64840	3.14e-04	4.9561
16	1.64864	7.87e-05	1.9972
32	1.64870	1.97e-05	1.9993
64	1.64871	4.92e-06	1.9998

Table 5. Function approximation results for test function $f(x,y) = e^{x+y}$ in the case of $n = m = 2$

Grid size	Fn value at point x = 0.25, y = 0.25	Abs. error	Converg. rate
4	1.648734254	1.30e-05	
8	1.648721966	6.96e-07	4.2222
16	1.648721315	4.45e-08	3.9660
32	1.648721273	2.78e-09	3.9987
64	1.648721270	1.74e-010	9.9999

In the first column of the Tables 3-5 is given grid size, here the value 4 correspond to the 4 units in directions of the both coordinates i.e. actual mesh is 4x4. Thus, in each next row the mesh is doubled and the function value (given in column 2) is computed in the same selected point ($x = 0.25, y = 0.25$) in order to compare the accuracy achieved for different grid density. In the third and fourth columns of the Tables 3–5 are given the absolute error and the convergence rate, respectively. The values of the absolute error and the convergence rate are computed as

$$Abserror(N) = |Function(N) - Function\_Exact| \tag{2.7}$$

$$ConvergenceRate = log\ (Abserror(N)/Abserror(2*N))/log(2) \tag{2.8}$$

In (2.7)–(2.8) $Function\_Exact$ is the exact value of the function at given point ($x = 0.25, y = 0.25$). The formula (2.8) for computing the rate of convergence is valid in the cases, where the mesh is doubled. The computed numerical rate of convergence tends to one in Table 3, to two in Table 4 and to four in Table 5. The rate of convergence characterizes how fast the absolute error decrease in the case of increasing mesh. Obviously, the accuracy of the simplified model where $n = m = 0$ is low (see absolute error in Table 2), it achieves reasonable value when *N = 64*, but in 2D case it means 64 x 64 = 4096 mesh points and is unrealistic for experimental study. It can be seen from Table 4, that in the case of model where $n = m = 1$, improved accuracy is achieved already with meshes $N = 4$ and $N = 8$ (due to measuring errors extra high accuracy of the model is not required). It follows from Table 5, and Table 3, that in the case of the model where $n = m = 2$, the accuracy achieved with minimal mesh $N = 4$ is significantly higher than that of the model where $n = m = 0$ with maximum mesh ($N = 64$).

Latter approaches with ($n = m = 1$) and ($n = m = 2$) are based on higher order Haar wavelet method introduced recently by workgroup and provide higher accuracy/convergence rate (Majak et al., 2018), but require extra test points for determining complementary integration terms. With further increasing the orders of derivatives n and m in model (2.6), the accuracy and the rates of convergence can be improved, but the implementation of the solution will be more complex. The results of numerical analysis of the accuracy are in good agreement with theoretical convergence results (Babolian, 2009; Majak et al., 2015).

The ANN and Haar wavelet expansion-based models are found suitable for response modelling. Furthermore, the response surface developed can be utilized for further design optimization of the gel content value. For preliminary limited dataset the wavelet-based approximation can be preferred. In the case of small dataset, the results obtained in repetitive runs by using ANN may vary since the output value of the ANN is a statistical random variable that exhibits uncertainty. With increasing dataset, the results obtained in repetitive runs converge as rule. In the Haar wavelet approximations most commonly the uniform or uniformly changing mesh is used. However, in the case of experimental results, the measuring points are often uneven, depending on different limitations. In latter case, the Haar matrices and its integrals derived for uniform mesh are not applicable, but the formulas (2.2)–(2.4) are valid and applicable. Detailed implementation of the both models introduced (ANN and Haar wavelet based), is described in next chapter.

3 Development of Photovoltaic Module Production Monitoring System

The real-life production monitoring stands for continuous checking of parameters from the manufacturing object and its manufacturing processes (Eiskop et al., 2018; Shiva Prasad et al., 2016). It is an important tool for measuring needed parameters of the product and understanding how efficiently different manufacturing processes are working. Generally, are analyzed different Key Performance Indicators (KPI) depending on the: a) product parameters like surface roughness, accuracy, surface strength etc. and b) manufacturing process dependent KPI's like Overall Equipment Efficiency (OEE) in %, manufacturing speed in pcs per min or pcs per hour, Total Effective Equipment Performance (TEEP) in %, Cycle time in s, etc. Each KPI depend on the actual product and manufacturing process, because of that it is important to analyze the main KPI before the actual real-time monitoring and analyze process. There is need to identify the important parameters to be monitored during production in the other words there is need to define the KPI, using Enterprise Analyses Model (EAM) (Sell et al., 2008; Kumar et al., 2021; Zhou et al., 2007).

The KPIs should be related to the two main fields: jobs (labor) and resources (materials) and cover different areas like equipment, materials, processes, employees, workplace, facility, products, production order, etc.

3.1 Concept Development for Production Monitoring System of PV Module Manufacturing

There are number of approaches and requirements to the production monitoring systems, but it is important that the system should be integrated with the existing systems and be able to measure and visualize the most important parameters of the product and its particular manufacturing process, because of that let's proceed with the further development of the basic concept of production monitoring system developed by workgroup in TalTech (Tšukrejev et al., 2008) and shown in Figure 9.

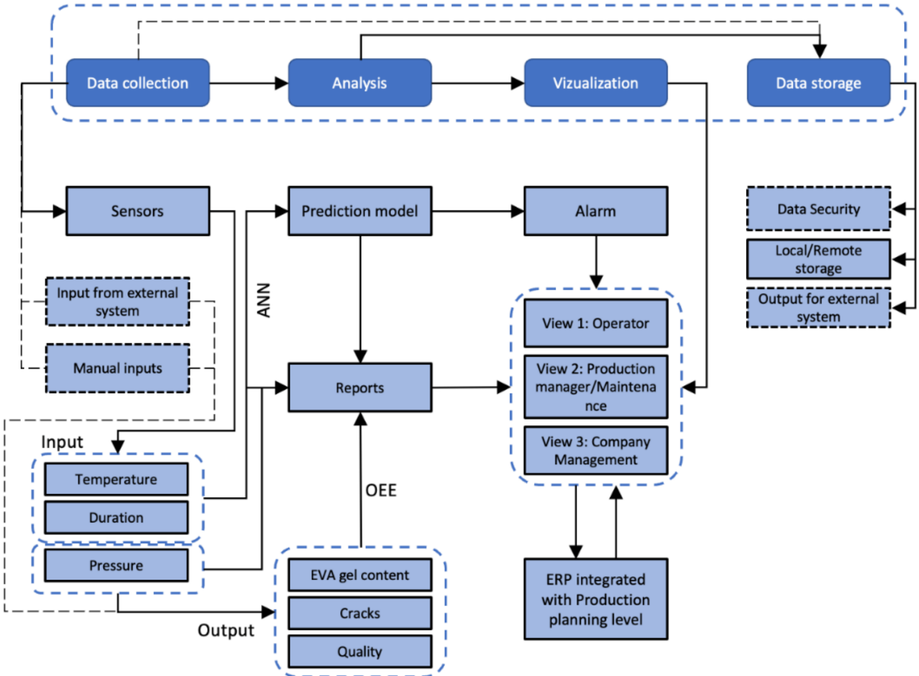


Figure 9. Developed concept of the production monitoring system.

This concept is developed on the basis of the concept proposed in previous papers of the workgroup. The concept on Figure 9. Is proposed for particular case study with additional measurable parameters like: pressure, temperature, duration and this system can be adapted with some minor changes to the manufacturing process of photovoltaic modules. The concept proposed for production monitoring system integrates the following main modules like Data Collection (process and product data); Analysis of collected data; Visualization dependent of the process and product; Data Storage; Data Security and Confidentiality. The sensor system is collecting different data from workstations (pressure, duration, displacements, electroluminescence). There is possibility to use different types of sensors, which could be embedded inside the photovoltaic module, such as RFID sensors (Majak et al., 2010).

The storing, computations and analysis is made on the server or cloud side and integration between the monitoring system and Enterprise Resource Planning System (ERP) is developed.

The real time monitoring system is detecting, measuring, and monitoring the variables, events and situations, which affect the performance and reliability of manufacturing and quality control systems in production line (see Figure 9 and 10). Efficient, real-time feed of information for production control and monitoring includes data acquisition about state of equipment, process, production orders, flow of materials, quality of products, process data and other necessary data which are used for making the proper and optimized decisions, regarding manufacturing planning, improved use of available resources and planning of equipment maintenance.

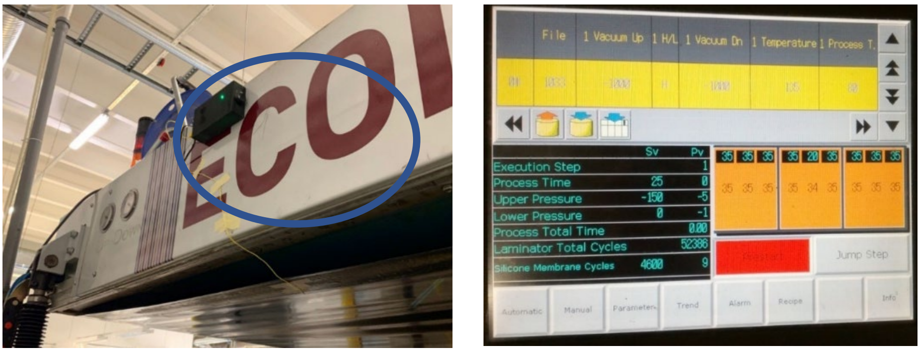
The web based Graphical User Interface (GUI) is developed with the support of JSON (JavaScript Object Notation) and AJAX (Asynchronous JavaScript and XML) technology to reduce the load on the server and the clients, as it allows specific objects to be updated in the GUI based on the specified interval and exchange data with a server asynchronously.

The Web-based approach allows the use of a wide range of devices with graphical interface support. Proposed GUI may be presented as a three-level structure:

View 1 – Operator mode;
View 2 – Production manager mode;
View 3 – Management mode.

Operator mode shows workplace KPIs, produced items, quality inputs, system condition monitoring and machinery or production line utilization. Production manager mode – combined department/workshop view, extended reports (performance comparison), reporting and statistics module, system administration. Management mode – production statistics, overall workshop performance, forecasts.

The collected information is sent to the ERP system where it is integrated with the production data and warehouse data including product Bill of Material (BOM).



(a) *(b)*

Figure 10. Production Monitoring System installed into workplace and integrated into the company system (a) and operator's control panel of lamination machine (b).

3.2 Real-time Measurement of PV module and lamination process

The PV module and lamination process, as one of the bottleneck processes in the manufacturing line requires to measure product and process sensitive parameters like temperature in °C (impacting the quality of encapsulant), pressure in Pa (impact on the quality of encapsulant and appearing of air bubbles), duration in s (influence EVA gel content and appearing of bubbles inside laminate).

The lamination machine used in the manufacturing facility is the Ecoprogetti Ecolam 05. The Ecolam 05 is automatic laminator, which is capable to laminate different sizes of PV modules and types of glasses. Laminator uses vacuum pump and a booster pump for creating an under pressure.

3.2.1 Tests for Temperature Measurement

Lamination temperature is important component of right lamination process as it influences the quality of encapsulation. In order to validate the concept of measuring parameters from inside the laminating chamber the temperature measurement was performed. The thermometer TES 1312A with two wired temperature sensors were employed. Sensors were installed on the back of solar module attached to the back sheet. Schematic placing of thermic sensors is brought out in Figure 11.

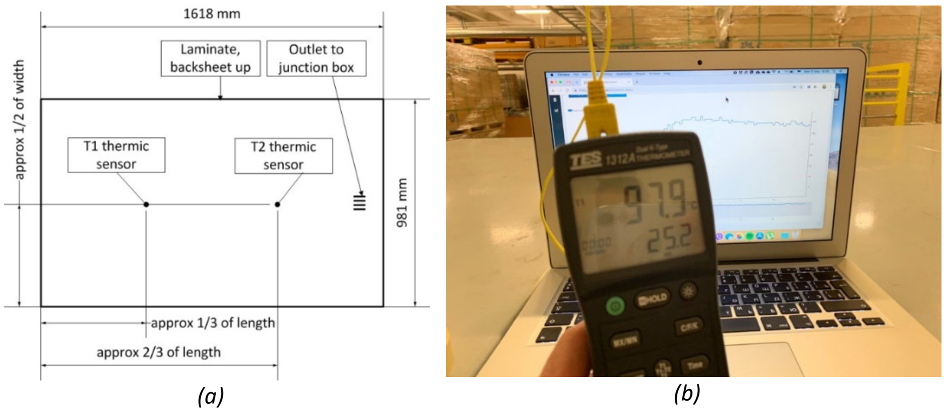


Figure 11. Schematic representation of experimental setup (a) and measurement parameters control (b).

There were three tests performed: the usual lamination program with temperature of 144 °C, with increased temperature of 150 °C and program with reduced temperature of 130 °C. The results of tests and gathered temperature data are represented in Table 6 and on Figure 12. The two measured values of temperature (Temp. 1 and Temp. 2 on Figure 12) can be considered as an output from particular temperature test. The temperature was checked and registered with time stamp and values of measured temperature. The set value of the temperature is known from laminator recipe and is given in the Table 6 as well. "Machine values" are the values that are either set by recipe or measured by machine, not by experimental setup.

The gathered results show that there is a difference in set and real temperatures present. The reason is in fact that the machine heating element with temperature sensor is located underneath the heating plate. The module is located on the heating plate and the thermic sensor used in the test was set on the top of module, so there is whole module structure in between two sensors. The fact that by the end of the program run the temperature on the top of the module did not reach the recipe set value in all tests. One important remark is that in used experimental set up were employed wired sensors and wires have left traces on the surface of back sheet. This means that actually particular module was defined as nonconformance and was scrapped. In order not to damage a module and further scrap it employment of wireless tracking solution should be considered.

Table 6. Results of the tests.

Measurement #	Time from start, (*minutes, seconds*)	Machine values				Measured	
		Set Temp. (℃)	Measured Temp. Value, (℃)	Set pressure, (*mbar*)	Measured pressure, (*mbar*)	Temp. 1, (℃)	Temp. 2, (℃)
1.1	2 min 47 s	144	143	-1000	-1024	60.3	68.7
1.2	6 min 42 s	143	142	-300	-303	95.6	99.3
1.3	10 min 4 s	143	143	-300	-293	117.8	119.1
1.4	14 min 22 s	143	143	-300	-289	130.3	130.7
1.5	14 min 54 s	144	143	0	-2	131.1	130.9
2.1	2 min 44 s	150	149	-1000	-1006	51.7	57.5
2.2	6 min 16 s	150	148	-300	-310	80.9	87.2
2.3	10 min 1 s	150	150	-300	-300	117.4	118.1
2.4	14 min 31 s	150	150	-300	-307	134.5	134.4
2.5	15 min 00 s	150	150	0	7	134.4	135.8
3.1	2 min 34 s	130	130	-1000	-1013	36.0	32.9
3.2	6 min 01 s	130	129	-300	-361	71.4	74.7
3.3	10 min 5 s	130	130	-300	-320	100.2	103.3
3.4	14 min 35 s	130	130	-300	-300	118.7	120.5
3.5	15 min 00 s	150	150	0	7	134.4	135.8

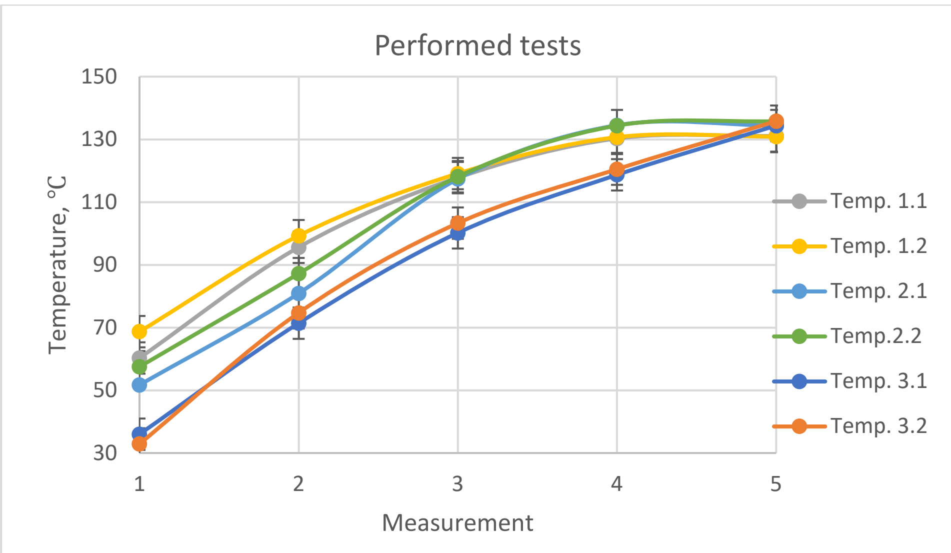


Figure 12. Temperature test results in different positions and input data.

On Figure 12 temperature measurement results from Table 6 are represented according to performed test number (the first number) and sensor position (second number). Measurements were performed five times. With measurements taken at the same time in process for all the samples. As time recording was done manually during the process, it was hard to ensure exact time of recording, this is why there are deviations in time stamps shown in Table 6. Manufacturer ensured that out of their practice those deviations are not critical. Error bars are representing maximum allowed deviation of +/- 5 degrees *C* (as stated by manufacturer). After laminator machine reaches desired under pressure the first-time parameters are recorded then recording had happened with a step of 4 minutes in accordance with a technological process. Last recording refers to the end of the process:

- 2 min 40 sec – vacuum reached. 6 min 40 sec – pressure change, new pressure reached. 10 min – according to the previous pressure change step. 14 min – finishing process. 15 min – pressures down, end process

3.2.2 Test for pressure measurement

Lamination machine is using two chambers which can be underpressurized depending on the recipe of the particular process

- The first chamber is the one where photovoltaic module is placed. In Figure 10 (b) it is referred as "Lower Pressure" with pressures gap in between 0 (atmospheric pressure) up to -1000 (vacuum). The main reason for that is pumping out the air and fumes from the PV module in order to ensure that air bubbles will not be trapped inside liquidous EVA;
- The second chamber is separated from the actual module with elastic membrane. In Figure 10 (b) it is referred as „Upper Pressure "with pressure gap in between 0 (atmospheric pressure) up to -1000 (vacuum) By under-pressuring the first chamber the membrane can apply pressure to the PV module in order to have proper adhesion between layers of the module.

Measurement of pressure is executed by the sensors inside the machine and presented on the operators control screen. Sensors are reset and calibrated according to the atmospheric pressure once a day prior to startup the machine.

It is complicated to measure pressure in real time with external equipment since chambers are closed and sealed during cycle run. At the same time there is no reason to doubt the accuracy of machine pressure data.

Table 6 represents the Vacuum time and Pressure time durations. Vacuum time refers to the duration of how long module is being in under pressured condition. Pressure time refers to how long module is being under applied pressure by membrane.

3.2.3 Test for duration measurement

The duration is considered as a processing time. It is being set according to the recipe. Time is being measured by machine's own equipment. Sampling by stopwatch showed that there is no major difference in time measurement neither by machine nor by stopwatch. Time sampling had been performed during gel content experiment's (see Table 6) first five cycles, results are represented in Table 7.

Table 7. Duration measurement test results.

#	Sample nr.	Time (sec), total	Time measured (sec)	Difference %
1	1	870	871	0,11
2	2	420	420	0,00
3	3	870	870	0,00
4	5	420	418	-0,48
5	6	870	870	0,00

3.3 Experimental evaluation of the quality of encapsulant

External equipment was employed in order to measure the temperature in real time with the possibility to trace everything via online cloud-based graphical user interface. During the experimental phase of measuring temperature by external equipment research group had faced the fact that there is a difference in real measured temperature from module and the temperature shown by lamination machine which is represented in Figure 13, error bars are representing deviation of +/- 5 degrees *C*. Also, there is dependence of temperature difference from the time lamination occurred: first laminations after startup, continuous numerous laminations or lamination after long pause. This is the point of interest to the PV manufacturer as the need for tune the recipes used in production appeared. The first three samples were laminated after machine startup. Finding shows that even though the laminator reports that heating up is finished and set temperatures are achieved it can be easily seen from Figure 13 samples 1–3, that actual measured temperature is highly different from the one that machine reports. Investigation showed that machine measures temperature directly from the heating element which is placed under the massive metal plate under the lamination chamber. During the first runs lamination chamber was still not achieving the desired temperature levels due to the heat was not yet transferred through metal to the chamber and the module's actual curing temperature is up to 65% lower than preset level by recipe (refer to Figure 13, sample 3). In addition, modules fed into the laminator are not preheated due to technological reasons. Module reaching the lamination chamber and being sealed absorbs some of the heat therefore actual temperature is dropping in the very beginning of the cycle.

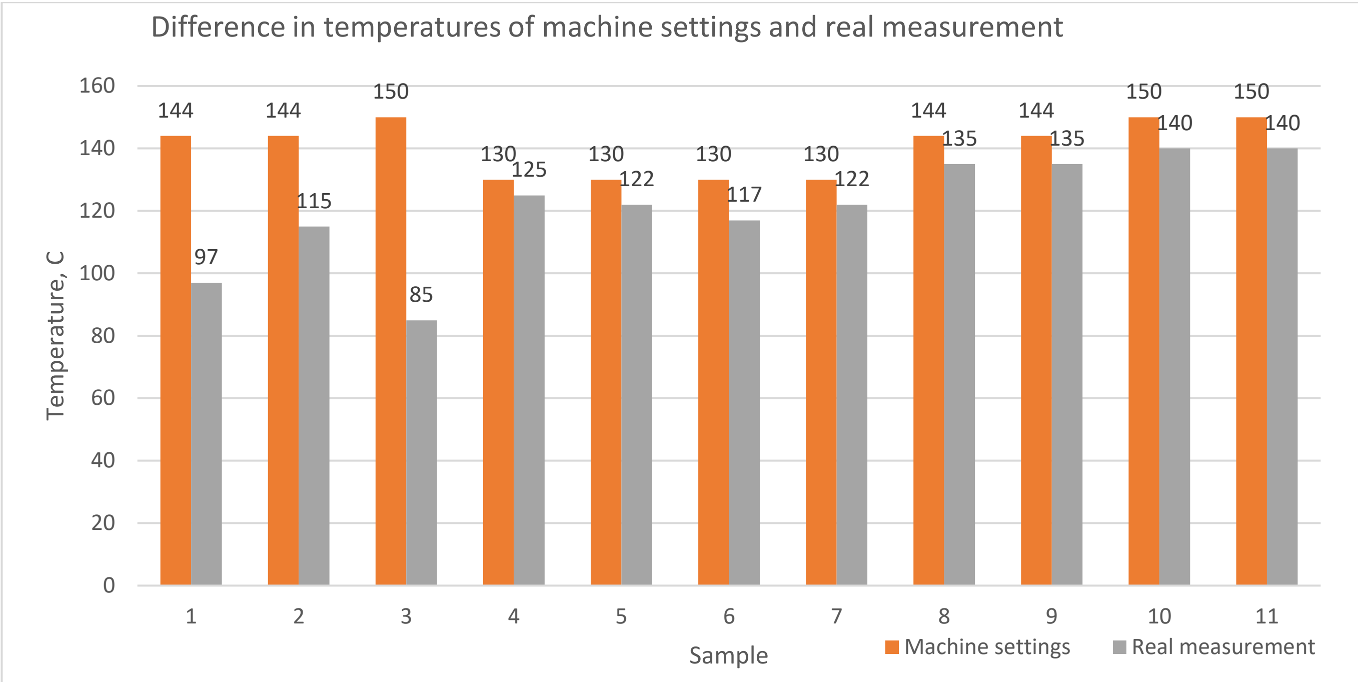


Figure 13. Difference between machine measured temperature against real measurement from module edge.

The temperature by external sensor and the processing time are considered as main factors having impact on Gel content. The results of the test are given in Table 8.

Table 8. Gel content and experimental data.

Temperature by external sensor (°C)	Processing time, (sec)	Gel content (%)
130	870	57.6
130	1025	58.4
130	1172	59.2
130	1320	59.9
137	870	56.4
137	1025	61.6
137	1172	62.7
137	1320	63.9
144	870	55.2
144	1025	64.8
144	1172	66.3
144	1320	67.9
150	870	70.7
150	1025	81.1
150	1172	81.8
150	1320	82.5

It can be noted that the experiments resulting the gel content percentage less than 50% were not considered. In order to gather data for prediction model of EVA gel content samples were made for defining it. The tests were prepared and performed in cooperation with PV manufacturer. It was decided to follow lamination programs as it is stated in Table 9. The samples were prepared in accordance with the EVA supplier requirements/procedures: EVA samples were cut out from real size laminated module, sample consists of two laminated together cured EVA sheets, size is 10 by 10 *cm*.

Temperature. The main lamination temperature for the process is 144 °C. It was decided to use also 150 °C, which is considered by manufacturer as upper limit and 130 °C, considered by manufacturer as lower limit.

Vacuum and Pressure Times. It was decided to use critical values such as no extra pressure at all or all the time vacuum. Additionally, some middle values were used in order to ensure that most of the wide variety of possibilities are covered.

Gel Content (degree of cross-linking). After preparing samples those were studied and measured in the laboratory, the result given in Table 8 are computed as average values of is repetitive measurements. In is worth to note that in the case of first 7 samples the measured percentage of gel content was lower than 50% and those results are not acceptable in manufacturing. Here, the testing process for measuring the gel content % need further evaluation and possible refinement. However, the results obtained are still useful in regard to get more detailed and realistic picture on behavior of the temperature measured by machine and real time external sensor (discussed below).

Table 9. Settings for parameters and gel content results of the experiment.

Sample	Temperature (°C) (machine)	Temperature (°C) (external sensor)	Total time (sec)	Vacuum time (sec)	Pressure time (sec)	Gel content (%)
1	144	97	870	870	0	<50
2	144	115	420	420	0	<50
3	150	85	870	870	0	<50
4	130	125	420	420	0	<50
5	130	122	870	310	560	<50
6	130	117	870	870	0	<50
7	130	122	1320	310	1010	<50
8	144	135	1320	310	1010	67.90
9	**144**	**135**	**870**	**310**	**560**	**74.90**
10	150	140	870	310	560	62.20
11	150	140	1320	310	1010	82.50

The main working recipe is marked in bold and is referring to sample number 9, other recipes were developed on the basis of original one. Such parameter’s values as duration (time) and vacuum are taken from the machine measured values as there is no reason not to trust those values.

The temperature’s value is measured by both machine sensors and by additional equipment installed on to the machine. This piece of equipment allows to measure temperature by thermocouple sensor inside the lamination chamber directly from the edge of surface of module only from one spot (due to the specification of equipment used) and send gathered data with a time tag to the cloud. The graphical user interface is developed. The graphs are drawn in real time and also saved for further analysis. Figure 14 represents how web-based temperature graph is looking like.

It can be observed that according to measurements real temperature inside the lamination chamber is always less than temperature measured by machine’s sensors. This aspect could lead to the situation when PV producer is getting quality results which differ from predicted ones (theoretical).

It is stated that EVA is considered to be well cured if cross-linking level is reaching 65% (Eiskop et al., 2017). Supplier of encapsulant material proposed the target value for gel content of EVA in PV modules to fit 70 – 80 % in order to ensure quality of encapsulation and further structural health of the module. If this interval is reached, the lamination can be considered succeeded and the module quality is assumed to be sufficient. While all other values of the gel content cannot ensure the quality of cured encapsulant and overall module.

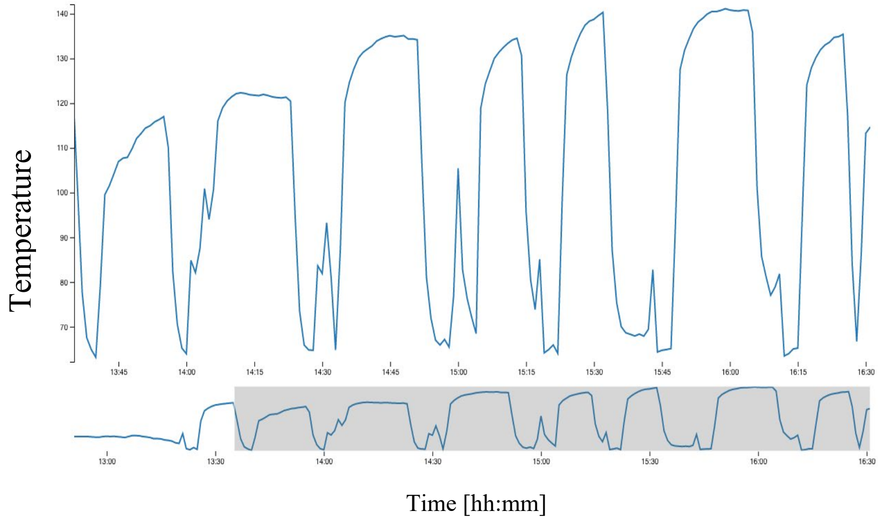


Figure 14. The partial view of graphical user interface of tool for real-time temperature measuring and recording.

Analyzing the result of laboratory tested gel content it can be concluded that conditions of last four tests (samples 8–11) are good enough to deliver sufficient quality of module. Especially tests number 9 and 11 are showing very good results. Figure 15 represents the gel content of encapsulant depending on temperature considering that other parameters were also changed.

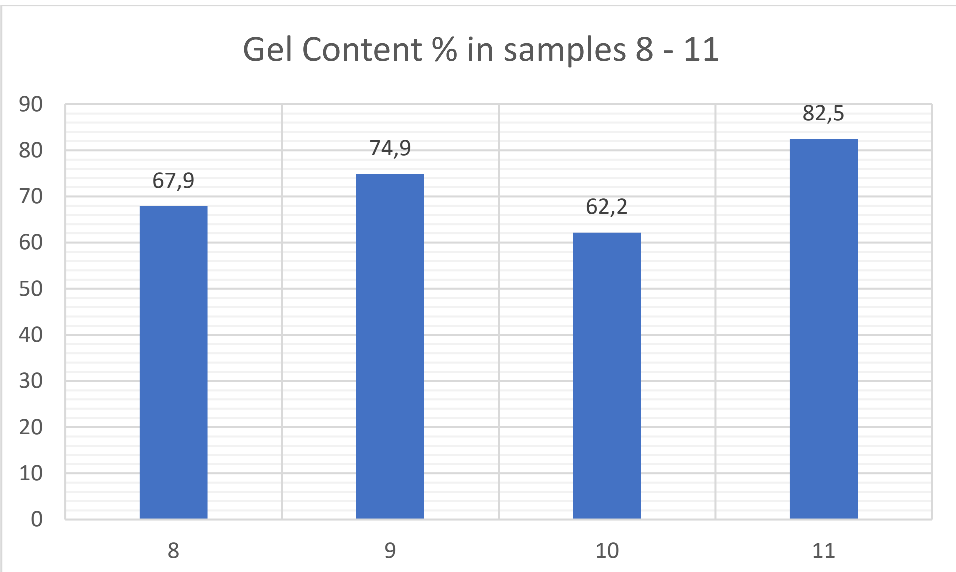


Figure 15. Gel content percentage of samples 8–11.

As noted above, the test results of samples 1–7 are insufficient for securing quality of the module. The testing process need evaluation and possible refinement, utilizing at least five repetitive tests. Further experimental study is required in order to develop an accurate mathematical model and perform design optimization (the testing process for measuring gel content need evaluation and improvement). Based on workgroup long time experience in area of mathematical modelling and design optimization [48–51] (Majak et al., 2003; Kaganski et al., 2017; Snatkin et al., 2015; Paavel et al., 2017), the development of back-propagation artificial neural network model and evolutionary algorithms for determining optimal configuration of the design parameters for providing maximum quality has been foreseen.

3.4 Mathematical modelling

The two mathematical models, introduced in section 2.4 are utilized for describing relation between the gel content and its impact factors – the processing time and the temperature measured by external sensor.

3.4.1 Artificial neural network based model

Development of artificial intelligence (AI) based solutions in engineering is exponentially growing in wide range of areas. Herein the main focus is paid on function approximation and the feedforward artificial neural network (ANN) model is utilized. As already pointed out in section 2.5.1 the feedforward ANN with one hidden layer is satisfactory for modelling any continuous function on a closed interval (Gnana Sheela et al., 2013). Proceeding from data given in Table 8 (Gel content) the tuning of the ANN has been performed by applying Levenberg-Marquardt training algorithm. In hidden layer the nonlinear tansig transfer function is applied. In outer layer the linear purelin transfer functions is employed. The initial number of neurons in hidden layer N_h was calculated based on formula (2.1) as

$$N_h = \frac{2+\sqrt{16}}{1} = 6. \tag{3.1}$$

The further increase of the number of neurons in hidden layer does not improve the accuracy of the model. Thus, the optimal number of neurons was fixed as six. The response surface of the Gel content, obtained by employing the ANN model developed, is depicted on Fig. 16.

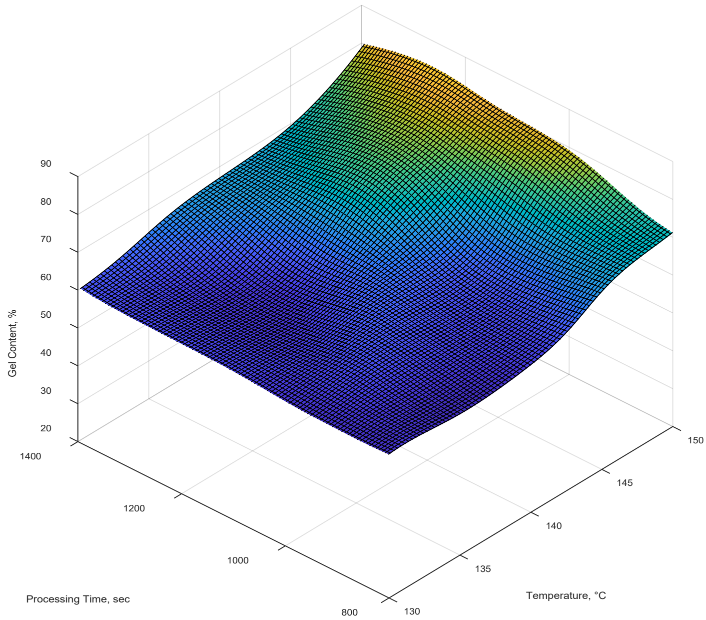


Figure 16. The response surface for Gel content built on ANN based model.

The ANN model given in Fig. 16 is obtained by using 101x101 model points, providing smooth surface. In Fig. 17 is presented the mean squared error of the ANN model proposed.

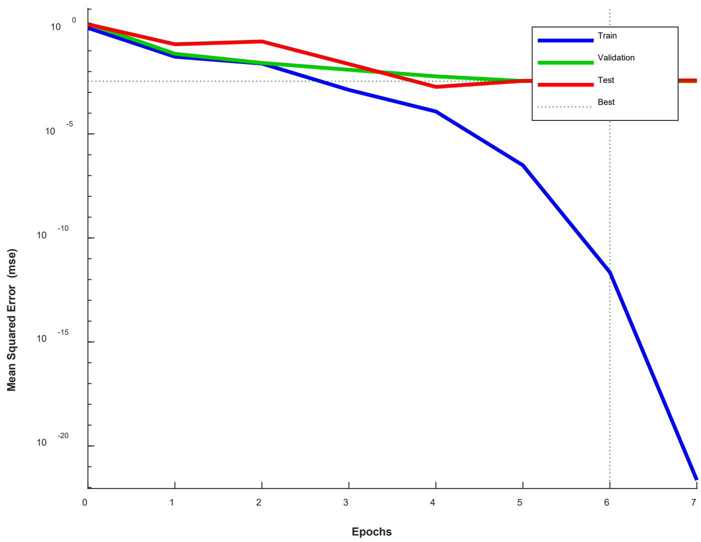


Figure 17. The mean squared error of the ANN model.

The accuracy achieved is satisfactory, since the test data include measuring error. Here still exists problem – different runs of ANN model generate little different results. Latter issue is caused due to fact that in ANN model the initial weights are generated by random and in the case where the dataset is not big enough, the final models, also their accuracy may differ. Thus, preliminary results are obtained, but ANN model need improved dataset.

3.4.2 Haar wavelet based model

Based on analysis of the two wavelet models performed in chapter 2.4, in the following the Haar wavelet- based model (2.6) with $n = m = 2$ is employed i.e. the fourth order derivative of the function (second order derivative with respect to both variables) is expanded into Haar functions

$$\frac{\partial^4 f}{\partial x^2 \partial y^2}(x,y) = \sum_{i=1}^{2M} \sum_{j=1}^{2M} a_{il} h_i(x) h_l(y). \tag{3.2}$$

By integrating equation (3.2) two times with respect x and two times with respect to y one obtains the formula for computing the values of the gel content function $f(x,y)$ (omitted herein for conciseness sake).

It can be observed that the surface corresponding to the Haar wavelet (HW) model is smoother than that ANN based model, since in HW based model in each element is used simple second order polynomial with respect to both variables (Fig. 16 and 18). In ANN model is used hierarchical structure with nonlinear tansig function in hidden layer and linear in outer layer. The accuracy of the ANN based model is higher in general. However, as mentioned above, in the case of limited dataset, the ANN model has some drawbacks (repetitive runs may give too different results). Thus, in the case of preliminary, limited dataset the deterministic HW based model is preferred in the current study. The ANN remains for future use with completed dataset. In Fig. 18, using model (3.2) the function value is computed in 101 x 101 grid points (correspond to 100x100 elements).

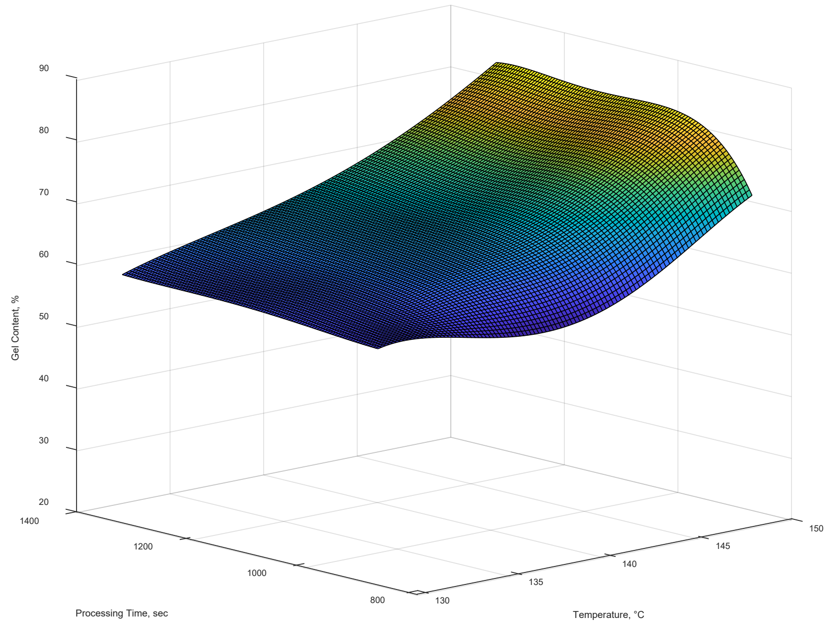


Figure 18. The response surface for Gel content built on Haar wavelet based model (2.6) $n = m = 2$.

Note, that the test dataset introduced in Table 8 (Gel content) correspond to non-uniform grid. In the case of non-uniform grid, the widely used Haar matrices, derived for uniform grid, are not applicable. In latter case the Haar functions can be evaluated using formula (2.3).

Based on practical considerations from production process, here is not available one fixed target value for gel content. However, the desired value of the Gel content is in the range 70–80%. One possible approach for further optimization is to use midpoint value of the interval [70–80%] as the target value for the gel content. Both, traditional gradient based and global optimization methods are applicable for solving such an optimal design problem.

4 Conclusions

Current thesis focuses on identifying the common faults of PV module which can occur during production cycle and leading to the further issues with module structural health and efficiency, developing the algorithms for processing the gathered information. The key parameters are identified and utilized for improvement of the quality of module.

The research proved the possibility to use external equipment to measure the parameters from inside the lamination chamber of laminator machine without damaging or destroying the photovoltaic module. As well as it proved the possibility to use the same set up embedded into the production line and reading the parameters from every single module without disrupting the manufacturing process or operator's work.

The research questions formulated are covered by the results obtained:

Q1. Basic concept of production monitoring system featured for manufacturing of photovoltaic module's is developed. The real time monitoring system is detecting, measuring, and monitoring the variables, events and situations, which affect the performance and reliability of manufacturing and quality control systems in production line. The Data Collection (process and product data), Analysis, Visualization, Storage functionalities are developed.

Q2. Based on methodology proposed for development of monitoring system, the Gel content was considered as key performance characteristic for the quality assessment of the module, the temperature and processing time are identified as design variables.

Q3. Mathematical models provide fast evaluation of the key performance characteristic using simple analytical formulas. The recent techniques based prediction tool(s) are developed for modelling Gel content. The deterministic Haar wavelet based model can be utilized in the case of existing limited dataset. The stochastic feedforward artificial neural network based model can be utilized in the case of improved/larger dataset.

Q4. Some findings of the thesis are applied directly in practice. For example, based on study performed it was found that the temperature set to machine and measured by sensors, installed on the back of solar module attached to the back sheet are different. Thus, the value of temperature can be evaluated more accurately using proposed measurement setup. The real time monitoring system developed is implemented in practice can be used.

As a conclusion it is possible to state that particular research has found the way for manufacturer to conduct a non-destructive way of assessing the quality of the photovoltaic module while the production cycle is running without disrupting the production operations and gives a tool for predicting the structural health and future performance of the product.

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Abstract

Photovoltaic Modules, Design and Manufacturing

Photovoltaic modules are considered one of the main factors in reducing environmental impact and turning from fossil fuel power production to a clean and green power generation. Rapid growth of number of installations during last decade is driven by cost reduction of PV module manufacturing process as well as improved efficiency of raw materials used in modules manufacturing.

A PV module consists of different materials with different properties. The production process of the modules changes both physical and chemical structure of materials used. During the manufacturing process different parameters are considered: such as duration of the process, pressure, temperature. It is essential to adjust the production process in a way that all those parameters will work together and will be delivering a long lasting and efficient product. Some of quality assessment can be conducted with destructive testing in laboratory, taking time. In the current study the predictive model is developed in order to provide manufacturer the possibility of deciding on the quality of module during the process of manufacturing without destructing the product and waiting for laboratory answer.

Current study is focused on improvement of the quality of PV module. The monitoring system was developed for PV module manufacturing process. This system allows to gather and process real time data. Based on data analysis performed main characteristics and the key parameters are determined. The Gel content was found as main characteristic influencing the quality, the temperature and total processing time are detected as key parameters.

For response modelling of the Gel content two advanced mathematical models are developed. First model is based on feedforward artificial neural network and is more suitable for use with completed bigger dataset. Second model is based on Haar wavelet expansion and is applicable also in the case of preliminary limited dataset. Novelty of the study is that herein is employed higher order Haar wavelet expansion, introduced by workgroup in 2018 is applied for function approximation first in 2021. This new approach provides principal improvement of the accuracy and convergence rate in comparison with widely used Haar wavelet approximation. Furthermore, the proposed approach includes model parameters, which can be evaluated according to accuracy needs of the particular problem considered. With taking use higher order approach the increase of computational and implementation complexities is not significant. As result, the models developed allow to predict the values of the Gel content for required input data affecting the quality of the PV module.

Main findings/novelty of the study can be outlined as

Theoretical:

1. The real time monitoring system based on improved concept model is developed.
2. Two advanced mathematical models are developed (Haar wavelet and artificial neural network based).

Practical:

1. The real time monitoring system developed is implemented in practice i.e. tested.
2. Improved setup and procedure are proposed for accurate measuring of temperature.

The work done form base for further design optimization of Gel Content. Here unique optimal value is not defined, practical interest is rather that the value of the Gel content remains in given limits. Thus, there are several problem formulations available: to select middle point of the interval of acceptable values as a target, to consider interval as a target, etc.

Lühikokkuvõte

Fotoelektrilised moodulid, disain ja tootmine

Fotoelektrilisi mooduleid peetakse üheks peamiseks teguriks keskkonnamõjude vähendamisel ja fossiilkütuste tootmiselt puhta ja keskkonnasäästliku energia tootmisele üleminekul. Paigalduste arvu kiire kasv viimasel kümnendil on tingitud PV-mooduli tootmisprotsessi kulude vähendamisest ning moodulite valmistamisel kasutatavate toorainete kvaliteedi ja omaduste paranemisest.

Kuna PV-moodul koosneb erinevatest erinevate omadustega materjalidest ning tootmisprotsess muudab osa materjalidest nii materjalide füüsikalist kui ka keemilist struktuuri, arvestatakse tootmisprotsessis erinevaid parameetreid nagu protsessi kestus, rõhk, temperatuur. Oluline on kohandada tootmisprotsessi nii, et kõik need parameetrid töötaksid koos ning tagaksid kauakestva ja tõhusa toote. Osa kvaliteedi hindamisest saab läbi viia destruktiivse testimisega laboris, mis võtab aega. Antud töö keskendub ennustava mudeli väljatöötamisele, et anda tootjale võimalus otsustada mooduli kvaliteedi üle tootmisprotsessi käigus ilma toodet rikkumata ja laboratoorset vastust ootamata.

Käesolev uurimistöö on fokuseeritud fotoelektrilise mooduli kvaliteedi parandamisele/tagamisele. PV mooduli tootmisprotsessi jaoks on antud töös arendatud jälgimissüsteem, mis võimaldab koguda ja töödelda andmeid reaalajas. Kogutud andmete põhjal teostatud analüüs võimaldas selgitada välja peamise karakteristiku/kriteeriumi ja võtmeparameetrid. Gel-i sisaldus identifitseeriti kui peamine karakteristik, mis mõjutab PV paneeni kvaliteeti, temperatuur ja protsessi kestus kui võtmeparameetrid.

Gel-sisalduse jaoks vastavuse pinna loomiseks arendati kaks matemaatilist mudelit. Esimene mudel põhineb pärilevi (tsükliteta) tehisnärvivõrkude kasutamisel ja sobib paremini suurema/täiendatud andmehulga korral. Teine mudel põhineb Haari lainikute kasutamisel ja on sobiv ka väiksema olemasoleva andmehulga korral. Antud juhul on tegemist uudse lähenemisega kuna rakendatakse 2018a. töögrupi poolt väljatöötatud kõrgemat järku Haari lainikute arendust, mida on rakendatud funktsioonide lähendamiseks esmakordselt 2021. Kasutatud lähenemise tagab olulise täpsuse ja koonduvuskiiruse kasvu võrreldes siiani kasutusel oleva Haari lainikute meetodiga. Uus meetod sisaldab mudeli parameetreid, mille väärtused saab valida vastavalt konkreetse ülesande jaoks, tagades vajaliku täpsuse. Kõrgemat järku meetodi rakendamisel algoritmi ajaline ja implementastiooni keerukus kasvavad, kuid see kasv jääb mõõdukaks. Lõpptulemusena võimaldavad arendatud mudelid võimaldavad arendatud mudelid hinnata Gel-i sisaldust etteantud sisendparameetrite korral.

Antud töö uudsuse võib välja tuua järgmiselt

Teoreetiline arendus:

1. Arendatud on täiendatud kontseptsioonil põhinev reaalajas PV mooduli jälgimissüsteem.
2. Koostatud on kaks kaasaegset matemaatilist mudelit (Haari lainikutel ja pärilevi tehisnärvivõrkudel. põhinev).

Praktiline:

1. Arendatud PV mooduli jälgimissüsteem on rakendatud/testitud tootmisprotsessis.

2. Arendatud on täiustatud seadistus ja protseduur temperatuuri täpsemaks mõõtmiseks.

Teostatud uurimistöö on baasiks edasiseks GeI-i sisalduse optimeerimiseks. Siinkohal pole olemas ühest sihifunktsiooni optimaalset väärtust, praktikas on pigem huvi et GeI sisalduse väärtus jääks etteantud piiridesse. Seetõttu on võimalikud mitmed erinevad optimeerimisülesande formulatsioonid: valida lubatud väärtustega määratud lõigu keskpunkt soovitud väärtuseks, defineerida lõik kui soovitud väärtus, jne.

Appendix

Publication I

Tšukrejev, P.; Karjust, K.; Majak, J. (2021). Experimental evaluation and numerical modelling of the quality of photovoltaic modules. Proceedings of the Estonian Academy of Sciences, 70 (4), 477–483.

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MANUFACTURING
ENGINEERING

Experimental evaluation and numerical modelling of the quality of photovoltaic modules

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Abstract. All over the world a rapid increase in demand for photovoltaic system installations has generated an outstanding growth in production numbers in the manufacturing facilities of photovoltaic (PV) systems. Production companies are facing challenges in providing the best quality along with rising manufacturing quantities. Due to the underlying technology not all the quality decisions can be made in real time. This research is focused on the development of experimental study and mathematical modelling of the quality control parameters for PV modules, which could only be tested during chemical processes and not be monitored constantly by operators at the production line.

Key words: production monitoring, photovoltaic modules, Haar wavelets, artificial neural network.

INTRODUCTION

Smart manufacturing shows the direction for production companies to stay competitive on the market and to deliver the maximum return on assets. The companies have to continuously search for innovative ways to improve their production and quality control processes, to optimize manufacturing processes using new I4.0 based technologies and perform work in a faster and better way [1,2]. Production processes should be effectively monitored and controlled to avoid malfunction and unplanned downtime.

Product quality is becoming an increasingly important function for the company due to the increased customer demands and product quality requirements. The manufacturing company has to deal with the increasing number of data and alternatives to be decided during on-time or off-time process, as well as with product quality control. As regards the latter, usually the fully dedicated data experts and expensive information technology solutions are not readily available, making it very hard to track the important and process related information which should be gathered and used for optimization. Manufacturing companies apply modern quality control techniques to improve the production line and the quality of its processes, and through that also the final end product quality [3]. A range of techniques are available to control product or process quality. These include seven statistical process control (SPC) tools, acceptance sampling, quality function deployment (QFD), failure mode and effects analysis (FMEA), six sigma, and design of experiments (DoE). Quality control (QC) and quality assurance (QA) can be defined as meeting the specification or customer requirements without any defect. A product is said to be high in quality if it is functioning as

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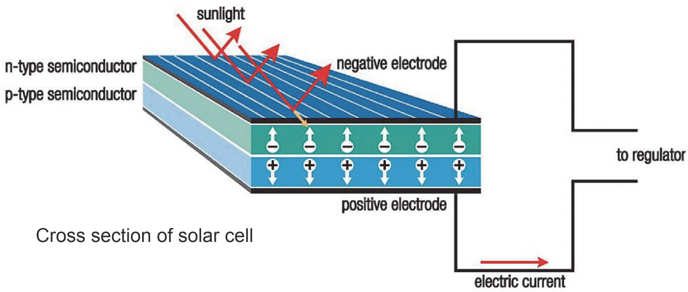

Fig. 1. Schematic cross section of c-Si solar cell [5].

expected and is reliable. Quality control refers to activities ensuring that produced items meet the highest possible quality level.

The volumes of installations of photovoltaic (PV) modules are rapidly growing annually. The global compound annual growth rate of cumulative photovoltaic installations during the period from 2010 to 2019 was as high as 35% [4]. Photovoltaic modules utilize the photovoltaic effect that generates flow of electrons inside the materials which are exposed to light. Different materials can be used for achieving the photoelectric effect. Currently the most popular way of manufacturing (due to efficiency, price and manufacturability) PV modules is by using the silicon-based solar cells. According to [4], 95% of manufactured modules are built on silicon-based solar cells. The simplified cross section of a solar cell and the PV principle are presented in Fig. 1.

Different materials are employed to build a PV module, in order to ensure maximization of light gathering, structural health as well as electric and climate insulation. The structure of a PV module includes several components [6]:

- Front sheet – glass or some other transparent material for light transparency as well as for climate and mechanical protection;
- Photovoltaic cells – for current generation;
- Ribbon connections – for electrical circuit;
- Back sheet – for electrical and climate insulation;
- Encapsulant – for laminating everything together, protection from moisture and air as well as being transparent for light.

The current work collects the experimental data in real time, and based on these data builds mathematical model(s) for prediction of the quality of encapsulant gel content. The obtained results will allow manufacturers to predict the crosslinking level instantly on site on the basis of real measured parameters and increase the feedback of the final end product quality.

EXPERIMENTAL EVALUATION OF THE QUALITY OF ENCAPSULANT

Quality of lamination is a general focus of a series of papers and an emerging problem for solar companies. The encapsulant under study is ethylene/vinyl acetate (EVA), as it is mainly used by the partner PV manufacturer of this study.

For particular research assessment, lamination success could be divided into two main categories, as presented in Fig. 2:

1. Visual component – all possible visual faults that lead to bigger issues in the future.
2. Quality of encapsulant (crosslinking level) – gel content of the EVA material, should be defined during the time-consuming process [7].

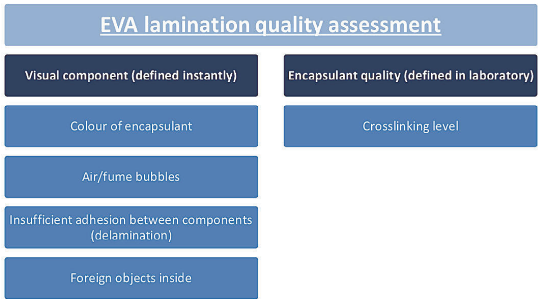

Fig. 2. Quality assessment of cured ethylene/vinyl acetate.

Ensuring the quality of encapsulant is challenging due to the lack of possibilities to assess and evaluate the quality of lamination on the chemical composition level right after the lamination cycle is completed. In order to define the crosslinking level, laboratory tests are needed. A good cross-linking level is considered to be 65% [8]. The supplier of EVA suggests the target value for PV modules to be between 70% and 80%. Sample gathering is a process that makes a PV module non-usable later.

There are a number of inputs that impact the quality of the lamination process [9]: temperature, duration, pressure/vacuum time. As according to us, temperature and duration of the process have the greatest impact on the quality of encapsulation, we decided to measure the temperature from the edge of the module during the real manufacturing lamination cycle. Previous experience has shown that measuring from the surface of the module is damaging to the back sheet and the module becomes visually defected and non-usable.

External equipment was employed in order to measure the temperature in real time with the possibility to trace everything via online cloud-based graphical user interface. During the experimental phase of measuring temperature by external equipment, the research group faced the fact that there was a difference between the real measured temperature from the module and the temperature shown by the lamination machine, which is demonstrated in Fig. 3. Also, there was dependence on temperature difference related to the time the lamination occurred: first laminations after the startup, numerous continuous laminations or lamination after a long pause. This is a point of interest to the PV manufacturer as the need has arisen to tune the receipts used in production.

The dataset used includes 16 different values, 2–3 repetitive tests were performed for each value (see Table 1). It should be mentioned that the mesh-points have non-uniform distribution.

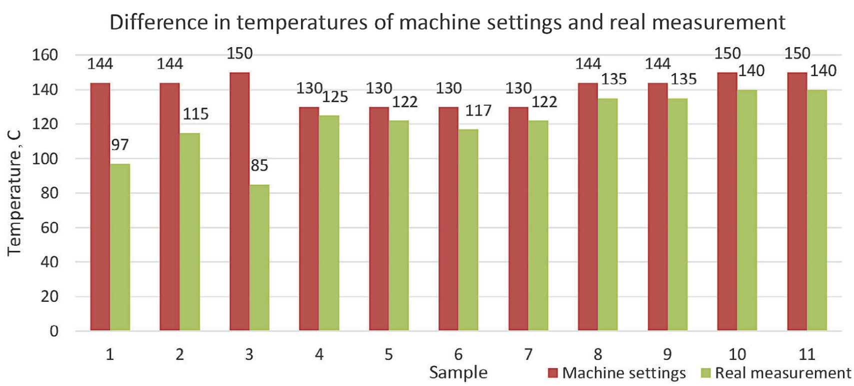

Fig. 3. Difference between machine measured temperature against real measurement from the module edge.

Table 1. Gel content dependence on temperature and processing time

No.	Temperature, C	Total processing time (s)	Gel content, %
1	130	870	57.6
2	130	1025	58.4
3	130	1172	59.2
4	130	1320	59.9
5	137	870	56.4
6	137	1025	61.6
7	137	1172	62.7
8	137	1320	63.9
9	144	870	55.2
10	144	1025	64.8
11	144	1172	66.3
12	144	1320	67.9
13	150	870	70.7
14	150	1025	81.1
15	150	1172	81.8
16	150	1320	82.5

Only test data with the gel content value over 50% are considered.

NUMERICAL MODELS

The following two numerical models are presented for describing the dependence of the gel content on the processing time and the temperature measured by external sensor.

Artificial neural network-based model

In engineering design, the emerging growth in the use of artificial intelligence (AI) tools and methods can be observed [10,11]. In the current study, the artificial neural network (ANN) model was utilized. It is well known that in the case of a limited dataset available (see Table 1), the feedforward ANN with one hidden layer is satisfactory. The tuning of the ANN was performed on the dataset provided in Table 1. The Levenberg–Marquardt training algorithm was applied. The nonlinear tansig and linear purelin transfer functions were utilized in hidden and output layers, respectively. The optimal configuration of the ANN was found with only four neurons in the hidden layer. The mean squared error of the developed ANN model is given in Fig. 4.

The accuracy achieved is satisfactory, since the test data still include the measuring error. Nevertheless, a problem exists that different runs of the ANN model generate slightly different results. This issue is caused by the fact that in the ANN model the initial weights were generated at random and if the dataset is not sufficiently big, the final models and their accuracy may differ. Thus, the preliminary results were obtained, but the ANN model needs an improved dataset.

Haar wavelet-based model

The following provides an alternative approach using the existing dataset. More generally, the n-th order derivative of the function can be expanded into Haar wavelets as

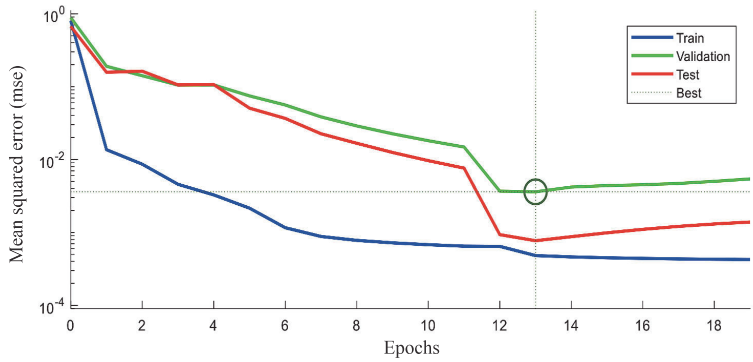

Fig. 4. The mean squared error of the ANN model.

$$f^{(n)}(x,y)=\sum_{i=1}^{2M}\sum_{j=1}^{2M}a_{ij}h_i(x)h_j(y). \tag{1}$$

Herein the gel content function $f(x, y)$ is expanded directly into Haar wavelets as

$$f(x,y)=\sum_{i=1}^{2M}\sum_{j=1}^{2M}a_{ij}h_i(x)h_j(y), \tag{2}$$

i.e. the simplest case, where $n = 0$ is used. In the case of $n \geq 1$, the accuracy of the Haar wavelet model will increase with the increasing n value, but extra test data is required for determining the integrating constants (functions).

In (1)–(2) a_{ij} are unknown coefficients, x and y are design variables. The Haar functions are defined as

$$h_i(x)=\begin{cases}1 & for \quad x\in[\xi_1(i),\xi_2(i)) \\ -1 & for \quad x\in[\xi_2(i),\xi_3(i)) \\ 0 & elsewhere\end{cases}, \tag{3}$$

where $i = m + k + 1$, $m = 2^j$ is the maximum number of square waves deployed in interval $[A,B]$ and the parameter k indicates the location of the particular square wave,

$$\xi_1(i)=A+2k\mu\Delta x,\ \xi_2(i)=A+(2k+1)\mu\Delta x,\ \xi_3(i)=A+2(k+1)\mu\Delta x,\ \mu=M/m,\ \Delta x=(B-A)/(2M),\ M=2^J, \tag{4}$$

where $j = 0.1, \ldots, J$ and $k = 0.1, \ldots, m-1$ stand for dilatation and translations parameters, respectively. Note that equations (1) and (2) correspond to the higher order method and the widely used Haar wavelet method, respectively [12].

As pointed out above, in the case of limited dataset, the ANN model has some drawbacks and the Haar wavelet-based deterministic model can be preferred. In most applications the Haar wavelet method is used with a uniform mesh. However, the test data given in Table 1 correspond to a non-uniform mesh. In the latter case the Haar matrices derived for a uniform mesh are not applicable. Instead, the Haar functions can be evaluated by using formula (3). The accuracy achieved utilizing a Haar wavelet-based model relies on the same range as that of the ANN. Here, the gel content does not have one fixed target value but its desired value is in the range of 70–80%. Further optimization of the gel content can be performed by taking the target value of 75% and employing the traditional gradient based and global optimization methods [13–18].

CONCLUSIONS

The external measurement equipment has been elaborated for measuring temperature in real time. Furthermore, it has been observed that the real measured temperature from the module and the temperature shown by the lamination machine differ. The temperature and process duration are considered for the modelling quality of the gel content. The two mathematical models, feedforward ANN and Haar wavelet models, have been developed. For the given dataset the accuracy of both models lies in the same range. However, the deterministic Haar wavelet method can be preferred since the ANN model varies in different runs. Implementation of the higher order Haar wavelet method requires extra design experiment with the required test points within the boundary of the design domain.

In further study it is planned to measure the pressure/vacuum conditions directly from the lamination chamber without relying on machine data, embedding a wireless sensor inside the PV module.

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Päikesepaneeli moodulite kvaliteedi eksperimentaalne hindamine ja numbriline modelleerimine

Pavel Tšukrejev, Kristo Karjust ja Jüri Majak

Päikesepaneeli mooduli temperatuuri täpsemaks mõõtmiseks reaalajas on välja töötatud riistvara- ja tarkvaralahendus. Mõõtmistulemuste analüüs näitas, et väljatöötatud seadme abil mõõdetud temperatuur moodulis erineb mõnevõrra lamineerimismasina mõõdetud temperatuurist. Töös uuriti etüleen-vinüülatsetaadi kihi geelisisaldust mõjutavaid parameetreid ja valiti välja kaks olulisemat mõjutegurit: temperatuur ja lamineerimisprotsessi aeg. Geeli sisalduse kirjeldamiseks koostati kaks matemaatilist mudelit: tehisnärvivõrkude ja Haari lainikute kasutamisel põhinevad mudelid. Mõlemaid mudeleid on lihtne kasutada, kuid tehisnärvivõrkude mudel sõltub juhuslikkusest ja andmehulga väiksuse tõttu olid eri käivitustel saadud tulemused erinevad. Seega antud andmehulga korral võib eelistada Haari lainikute kasutusel põhinevat mudelit. Kõrgemat järku lainikute meetodi rakendamine eeldab selleks kohandatud katsete planeerimist. Edasistes uuringutes on kavas integreerida juhtmeta andur päikesepaneeli moodulisse ja mõõta rõhu/vaakumi tingimusi otse lamineerimiskambrist.

Publication II

Tšukrejev, P.; Karjust, K.; Majak, J. (2021). Quality of Photovoltaic Modules, Experimental Evaluation and Mathematical Modelling. IOP Conference Series Materials Science and Engineering, 1140 (1), 012044. DOI: 10.1088/1757-899X/1140/1/012044.

Quality of Photovoltaic Modules, Experimental Evaluation and Mathematical Modelling

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Abstract. Over the world rapid growth of demand for photovoltaic systems installations brings forward magnificent increase in production numbers in manufacturing facilities of PV systems. Production companies are facing challenges in providing the best quality simultaneously with rising manufacturing quantities. Due to technology behind not all the quality decisions can be done in real time. This study is focused on the development of experimental study and mathematical modelling of the PV modules quality control parameters, which could only be tested during chemical processes and could not be monitored constantly by operators at the production line.

1. Introduction

Current trends in smart manufacturing show the direction to stay competitive on the market and to deliver the maximum return on assets for production related companies. To achieve this, companies have to continuously search for innovative ways to improve their production and quality control processes, to optimize manufacturing processes using new I4.0 based technologies and perform work in a faster and better way [1-2]. Production processes should be effectively monitored and controlled to avoid malfunction and unplanned downtime.

Quality is becoming an increasingly important function for the company due to the increased customer demands and product quality requirements. Manufacturing companies apply modern quality control techniques to improve the production line and its processes quality. A range of techniques are available to control product or process quality [3]. These include seven statistical process control (SPC) tools, acceptance sampling, quality function deployment (QFD), failure mode and effects analysis (FMEA), six sigma, and design of experiments (DoE). Quality Control (QC) and Quality Assurance (QA) can be defined as fulfilling specification or customer requirements, without any defect. A product is said to be high in quality if it is functioning as expected and is reliable. Quality control refers to activities to ensure that produced items are fulfilling the highest possible quality.

Photovoltaic (PV) modules installations are growing annually, global Compound Annual Growth Rate of cumulative photovoltaic installations between years 2010 and 2019 was as much as 35% [4]. Photovoltaic modules are utilizing the effect that generates flow of electrons inside the materials under the light. There are different possibilities for the materials to be used. According to [4] 95% of production based on silicon-based solar cells which is presented in Figure 1.

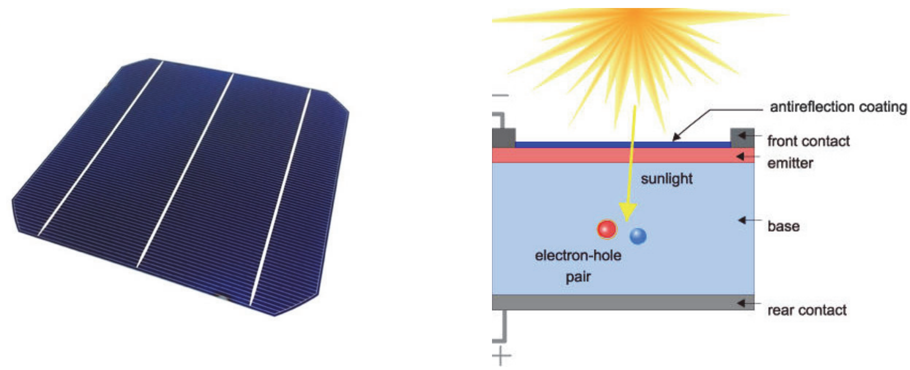

Figure 1. c-Si silicon solar cell and its schematic cross-section [5].

To build a PV module there are also other materials used in order to ensure maximization of light gathering, structural health as well as electric and climate insulation. The structure of PV module considered includes [6]:

- Frontsheet – usually glass or some other transparent material for light transparency and climate and mechanical protection;
- Photovoltaic cells – for current generation;
- Ribbon connections – for electrical circuit;
- Backsheet – for electrical and climate insulation;
- Encapsulant – for laminating everything all together, protection from moisture and air as well as being transparent for light.

Current study aims to gather experimental data and based on these data to build mathematical model(s) for prediction the quality of the encapsulant gel content. The obtained results will allow manufacturers to predict the crosslinking level instantly at place on the basis of real-measured parameters.

2. Experimental evaluation of the quality of encapsulant

Quality of lamination is a general focus of the series of papers and emerging problem for solar companies. Encapsulant under study is Ethylene/Vinyl-Acetate (EVA), as it is mainly used by the partner PV manufacturer of this study.

In terms of particular research assessment of lamination success could be divided into two main branches, represented in Figure 2:

1. Visual component – all possible visual fault that leading to bigger issues in the future;
2. Quality of encapsulant (crosslinking level) – Gel content of the EVA material, should be defined during time consuming process [7].

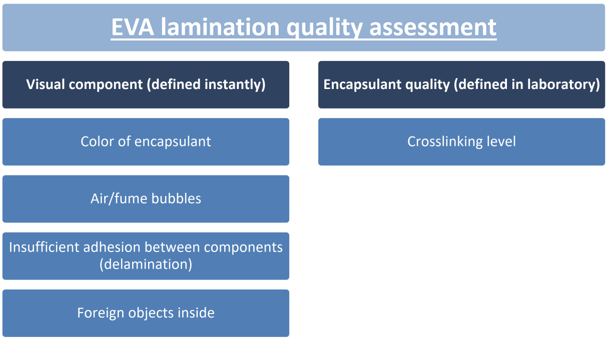

Figure 2. Quality assessment of cured Ethylene/Vinyl-Acetate.

Ensuring quality of encapsulant is a challenging due to lack of possibilities to assess and evaluate quality of lamination on chemical composition level just after the lamination cycle is done. In order to define the crosslinking level laboratory tests are needed. Good cross-linking level is considered to be 65% [8]. Supplier of EVA suggesting target value for PV modules to be between 70% and 80%. Sample gathering is something that is making a PV module not usable anymore.

There are number of inputs that are impacting the quality of the lamination process [9]: temperature, duration, pressure/vacuum time. As temperature and duration of the process are considered by the authors to make the biggest impact on the quality of encapsulation it was decided to measure the temperature from the edge of the module during the real manufacturing lamination cycle. Previous experience showed that measuring from the surface of the module is damaging backsheet and module is becoming visually defected and not usable.

External equipment was employed in order to measure the temperature in real time with the possibility to trace everything via online cloud-based graphical user interface. During the experimental phase of measuring temperature by external equipment research group had faced the fact that there is a difference in real measured temperature from module and the temperature shown by lamination machine which is represented in Figure 3. Also, there is dependence of temperature difference from the time lamination occurred: first laminations after startup, continuous numerous laminations or lamination after long pause. This is the point of interest to the PV manufacturer as the need for tune the receipts used in production appeared.

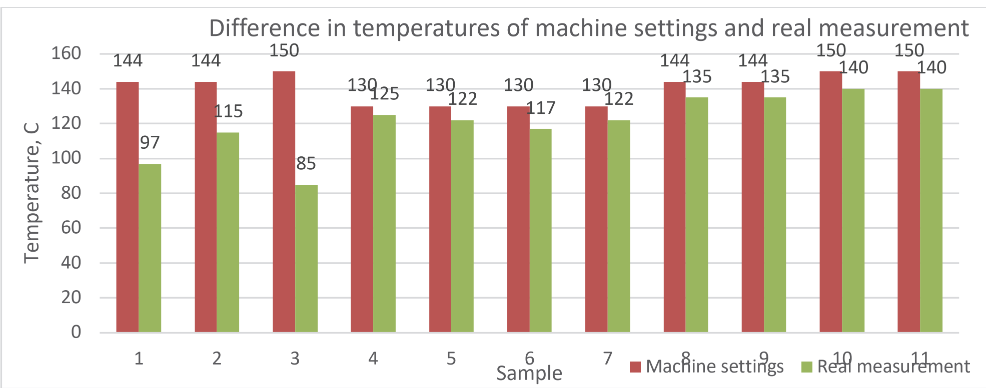

Figure 3. Difference between machine measured temperature against real measurement from module edge.

Total of 11 samples were sent to the laboratory testing. Unfortunately, only four of those are having trustworthy results (see Table 1).

Table 1. Gel content. Experimental data

Temperature by external sensor (°C)	135	135	140	140
Processing time, (sec)	1320	870	870	1320
Gel content (%)	67,9	74,9	62,2	82,5

Other experiments cannot be considered due to the fact that gel content percentage was too low (less than 50%). Obviously, additional gel content tests are needed.

3. Mathematical modelling of the quality of encapsulant

The workgroup has long time experience on adaption of AI tools for wide class of engineering problems [10-11]. Herein, the feedforward artificial neural network (ANN) model with one hidden layer was adapted for modelling gel content. Such an approach provides required accuracy if dataset is trustable and big enough. However, due to limited trustable dataset available from experiments at current time, the final tuning of the ANN is not yet performed (determining optimal number of neurons in hidden layer, adjusting weights). ANN has hierarchical structures and is powerful tool for modelling various problems. However, due to fact that it is based on random generation of initial weights, its application is complicated in the case of limited dataset available. The full factorial design of experiment is performed using at least four levels for both variables. Corresponding test are planned, but trustworthy results not guaranteed, due to complex measurements required.

For this reason, the authors introduce also one new and interesting alternate mathematical model – Haar wavelet based approximation [12]. This model is deterministic, does not include uncertainty and can be utilized in the case of limited dataset. The Haar wavelet expansion based 2D mathematical model is introduced as

$$f(x,y) = \sum_{i=1}^{2M} \sum_{j=1}^{2M} a_{ij} h_i(x) h_j(y) \tag{1}$$

where the function $f(x,y)$ stand for the gel content, x and y for the temperature and processing time, respectively. The a_{ij} are unknown coefficients, h_i (also h_j) are the Haar functions defined as

$$h_i(x) = \begin{cases} 1 & for \quad x \in [\xi_1(i), \xi_2(i)) \\ -1 & for \quad x \in [\xi_2(i), \xi_3(i)) \\ 0 & elsewhere \end{cases} \tag{2}$$

where $i = m + k + 1$, $m = 2^j$ is the maximum number of square waves deployed in interval $[A, B]$ and the parameter k indicates the location of the particular square wave,

$$\xi_1(i) = A + 2k\mu\Delta x,\ \xi_2(i) = A + (2k+1)\mu\Delta x,\ \xi_3(i) = A + 2(k+1)\mu\Delta x,\ \mu = M/m,\ \Delta x = (B - A)/(2M),\ M = 2^J \tag{3}$$

In (3) j=0,1,...,J and k= 0,1,...,m−1 stand for dilatation and translations parameters, respectively. According to higher order Haar wavelet method in (1), the function $f(x,y)$ is replaced with its n-th order derivative, where n=1,2… Latter approach is based on higher order Haar wavelet method introduced recently by workgroup and provide higher accuracy/convergence rate [12], but require extra n test points for determining complementary integration constants.

Both mathematical models, described above, can be utilized for prediction as well as further optimization of the gel content value utilizing traditional gradient based and global optimization methods [13-18]. In the case of limited dataset the wavelet based approximation can be preferred since ANN approach uses random and may lead to different results in different runs is dataset is not satisfactory. The Haar wavelet approximations are commonly treated for uniform mesh. In the case of experimental study not all results may be available for applying uniform mesh. This means that widely used Haar matrices and its integrals derived for uniform mesh cannot by utilized. However, the Haar functions can be evaluated in any points based on simple formula (2). Thus, the increase of complexity is not significant.

4. Summary

The external measurement equipment has been elaborated for measuring temperature in real time. Furthermore, it has been observed that real measured temperature from module and the temperature shown by lamination machine differs. The temperature and process duration are considered for modelling quality of the gel content. The two mathematical models, feedforward ANN and higher order Haar wavelet model, are developed. In order to refine and validate these models, an additional test data should be acquired.

In further study it is planned to measure the pressure/vacuum conditions directly from the lamination chamber with no relying on machine data, to embed a wireless sensor inside the PV module [16].

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Publication III

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Real-Time Monitoring of Solar Modules Manufacturing

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Keywords: photovoltaic module; solar module; real-time monitoring.

Abstract. One of the most important steps during manufacturing of solar modules is lamination. This paper focuses on monitoring of behavior of used encapsulant Ethylene/Vinyl-Acetate (EVA) and impact on overall quality of module during lamination. Monitoring is performed by employing external thermocouple sensor inside the lamination chamber as well as by. Real-time analysis of the results helps to predict the quality of final product in terms of ensuring lamination quality in real time and provides possibility to tune the process during manufacturing cycle to achieve the best result of encapsulant cross-linking.

Introduction

Photovoltaic module is composed of different materials such as glass, encapsulat, photovoltaic cells, backsheet laminated together. In this study encapsulant used is Ethylene/Vinyl-Acetate as this is the material mainly used by the PV manufacturer who helped with the research. Other encapsulant possibilities are not in the focus of the study.

This paper is considered to be further development of study started by authors in [1]. Initial study focused on examining the possibility and need in measuring temperatures of lamination process by external sensors, need for further research with employing laboratory cross-linking test was defined. There are several factors that are both, impacting the final quality of the photovoltaic module and could be tuned during manufacturing process. According to [1] these factors are considered as input/design parameters:

- lamination temperature of the module;
- pressure and vacuum time during process;
- duration of the process (time).

All factors considered separately and as well as their combination plays role. The considered parameters have impact on the cross-linking (gel content) of Ethylene/Vinyl-Acetate. This is something that is complicated to track in real time as there is need to define it during laboratory tests. There are several of different procedures for defining gel content, but those do not vary a lot. Determining of gel content is a time consuming process [2]. This study uses cross-linking measurement by dissolving encapsulant samples in toluene solution for 24 hours. The gel content percentage is important to the further performance of the module during operation. The good cross-linking of encapsulant material is one of the points to ensure structural health of the module. It is found that encapsulant and backsheet failures are responsible for nearly 22 % of PV modules returns [3]. This paper to be focused on application of real time measurement of temperature during lamination, representing it in a graphical view with possibility to analyze lamination conditions in accordance with further cross-linking results of EVA for developing a module lamination quality prediction algorithm in future studies.

Results of Cross-Linking Measurement

In order to gather data for prediction model of EVA gel content samples were made for defining it. The tests were prepared and performed in cooperation with PV manufacturer. It was decided to follow lamination programs as it is stated in Table 1. The samples were prepared in accordance with the EVA supplier requirements/procedures: EVA samples were cut out from real size laminated module, sample consists of two laminated together cured EVA sheets, size is 10 by 10 [cm].

Temperature. The main working temperature in the production facility is 144 °C. It was decided to use also 150 °C, which is considered by manufacturer as upper limit and 130 °C, considered by manufacturer as lower limit.

Vacuum and Pressure Times. It was decided to use critical values such as no pressure at all or all the time vacuum. Additionally, some middle values were used in order to ensure that most of the wide variety of possibilities are covered.

Gel Content. After preparing samples those were studied and measured in the laboratory, the result given in Table 1 are computed as average values of is repetitive measurements. In is worth to note that in the case of first 7 samples the measured percentage of gel content was lower than 50 % and those results are not acceptable in manufacturing. Here, the testing process for measuring the gel content % need further evaluation and possible refinement. However, the results obtained are still useful in regard to get more detailed and realistic picture on behavior of the temperature measured by machine and real time external sensor (discussed below).

Table 1. Settings for parameters and gel content results of the experiment

Sample	Temperature [°C] (machine)	Temperature [°C] (external sensor)	Total time [s]	Vacuum time [s]	Pressure time [s]	Gel content [%]
1	144	97	870	870	0	<50
2	144	115	420	420	0	<50
3	150	85	870	870	0	<50
4	130	125	420	420	0	<50
5	130	122	870	310	560	<50
6	130	117	870	870	0	<50
7	130	122	1320	310	1010	<50
8	144	135	1320	310	1010	67.90
9	**144**	**135**	**870**	**310**	**560**	**74.90**
10	150	140	870	310	560	62.20
11	150	140	1320	310	1010	82.50

The main working receipt is marked in bold and is referring to sample number 9, other receipts were developed on the basis of original one.

Such parameter's values as duration (time) and vacuum are taken from the machine measured values as there is no reason not to trust those values.

The temperature's value is measured by both machine sensors and by additional equipment installed on to the machine. This piece of equipment allows to measure temperature by thermocouple sensor inside the lamination chamber directly from the edge of surface of module only from one spot (due to the specification of equipment used) and send gathered data with a time tag to the cloud. The graphical user interface is developed. The graphs are drawn in real time and also saved for further analysis. Fig. 1 represents how web-based temperature graph is looking like.

It can be observed that according to measurements real temperature inside the lamination chamber is always less than temperature measured by machine's sensors. This aspect could lead to the situation when PV producer is getting quality results which differ from predicted ones (theoretical).

It is stated that EVA is considered to be well cured if cross-linking level is reaching 65 % [4]. Supplier of encapsulant material proposed the target value for gel content of EVA in PV modules to fit 70 – 80 % in order to ensure quality of encapsulation and further structural health of the module. If this interval is reached, the lamination can be considered succeeded and the module quality is assumed to be sufficient. While all other values of the gel content cannot ensure the quality of cured encapsulant and overall module.

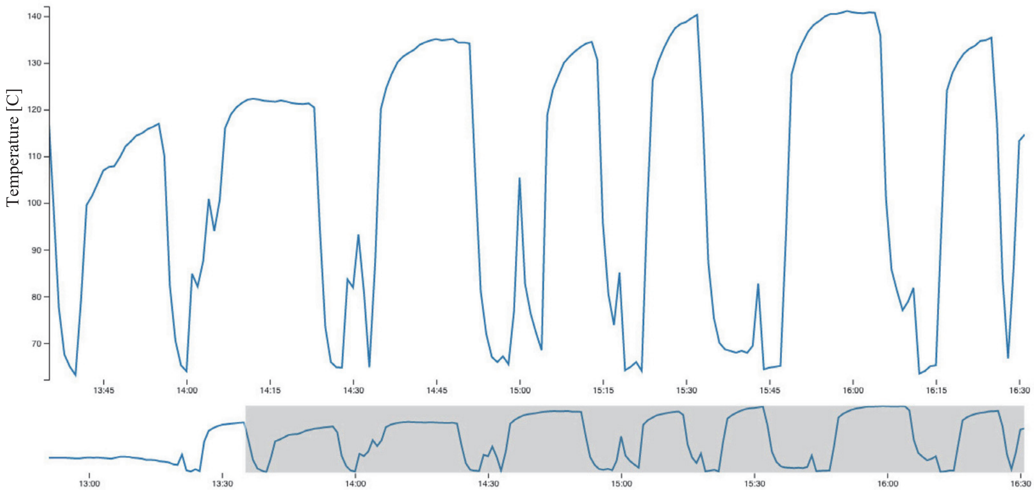

Fig. 1. The partial view of graphical user interface of tool for real-time temperature measuring and recording

Analysing the result of laboratory tested gel content it can be concluded that conditions of last four tests (samples 8 – 11) are good enough to deliver sufficient quality of module. Especially tests number 9 and 11 are showing very good results. Fig. 2 represents the gel content of encapsulant depending on temperature considering that other parameters were also changed.

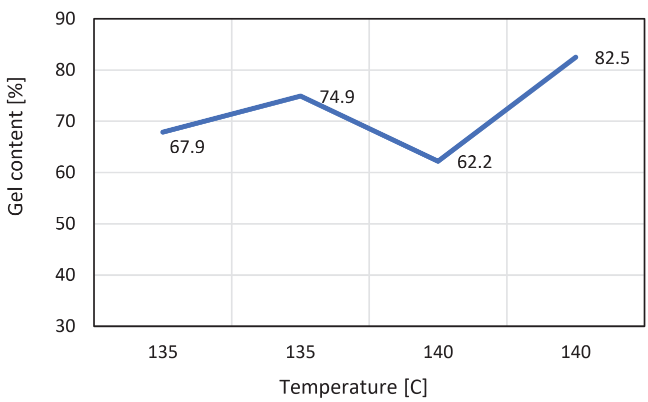

Fig. 2. Gel content percentage of samples 8 – 11

As noted above, the test results of samples 1 – 7 are insufficient for securing quality of the module. The testing process need evaluation and possible refinement, utilizing at least five repetitive tests. Further experimental study is required in order to develop an accurate mathematical model and perform design optimization (the testing process for measuring gel content need evaluation and improvement). Based on workgroup long time experience in area of mathematical modelling and design optimization [5-8], the development of back-propagation artificial neural network model and evolutionary algorithms for determining optimal configuration of the design parameters for providing maximum quality has been foreseen.

Summary

The real-time temperature measurement system with graphical user interface has been developed. The experimental study performed show, that the real temperature inside the lamination chamber is always less than temperature measured by machine's sensors. Thus, it can be concluded that using the external equipment in order to get temperature result from inside the lamination process makes sense in manufacturing process, but there is a need to measure temperature from more points in order to get more trustworthy results. The main profit is that measurement goes in real time from the particular module being laminated, not from heating element as machine measures it.

Investigation for EVA cross-linking of photovoltaic (PV) modules has been performed. The input/design parameters considered were temperature, vacuum time and pressure time. An analysis of the results has been performed and the effect the temperature on gel content percentage appears most significant.

The obtained results confirm that the values of the design parameters used currently in manufacturing process are satisfactory but can be improved further by applying design optimization. Based on this research further study will be focused on developing the algorithm for defining cross-linking based on measured values.

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Publication IV

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MANUFACTURING
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Production monitoring system development for manufacturing processes of photovoltaic modules

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Abstract. The main goal of the study is to develop the concept of the real time monitoring system for manufacturing processes of photovoltaic modules. Driven by reduced costs the solar power generation is growing rapidly and increases the number of photovoltaic modules being delivered to the customers. Automatic and early detection of defects/shortcomings reduces production costs and increases productivity. This paper is focused on detecting main issues, influencing performance of the manufacturing process of photovoltaic modules. Parameters that need to be monitored will be proposed in order to eliminate the faults. The main impact factors are analysed.

Key words: solar modules, photovoltaic process, real time monitoring process, smart sensors.

1. INTRODUCTION

The current study focuses on finding possibilities of monitoring the processes inside the photovoltaic modules during manufacturing process to see how changing some parameters can influence the quality of modules and how to use this information to make further predictions. The biggest challenges were real-time measurements of different parameters inside the module without destroying it.

2. GENERAL STRUCTURE AND MANUFACTURING PROCESS OF PHOTOVOLTAIC MODULES

The burning of fossil fuels has caused big part of atmospheric pollution and the greenhouse effect in general [1]. According to [2], the growth of photovoltaic (PV) capacity of the European countries (including Turkey) in 2017 was 28% higher compared to the year 2016. The main technology for manufacturing solar modules, with market share over 90%, is the silicon-based photovoltaic cells [3,4]. Fraunhofer ISE report notes that the efficiency of the silicon cells influences the laboratory efficiency depending on the used technology. Efficiency increases in case of monocrystalline or polycrystalline silicone 26.7% and 22.3%, respectively. The market efficiency is about 21.5%. Additionally, there are also other different perspective materials that can be used. One option is to use perovskite instead of crystalline silicon inside the solar cells, as it is considered to be cheaper material reaching the efficiency of 22.1% [5]. Another example of the future material that can be used as a solar cell is the black silicon, which has significant quantum efficiency (QE) over 90% [6]. The solar modules with silicon cells are consisting of different layers, composing a sandwich structure [7] shown in Fig. 1.

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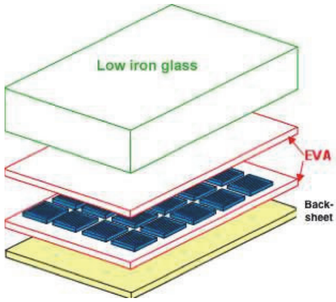

Fig. 1. Layers of solar module [8].

This paper addresses the manufacturing process of photovoltaic modules with silicon-based cells and focuses on the lamination part of it. The lamination step is essential for the manufacturing process. After lamination nothing can be changed as the whole module is already encapsulated.

3. MAIN ISSUES IN PHOTOVOLTAIC MODULES MANUFACTURING PROCESSES

As noted in [9,10], the major faults in solar modules are caused by wrong design or troubles during production. Main faults are as follows: air bubbles inside the modules; broken cells; micro cracks; hot spots; potential induced degradation (PID); snail trails. The photovoltaic modules production issues are analysed and the results are brought out in Table 1. It is explained how those types of issues and faults appear inside the module and what are the reasons. Certain suggestions, how it is possible to overcome these issues, are proposed in the last column of Table 1.

Understanding the nature of those faults helps to follow the set of selected parameters in order to prevent the issues listed above. Most of the issues in photovoltaic modules appear during lamination process. This process is very important for successful production of modules but very complicated to be tuned. Setting depends on used materials. Laminator has to perform

Table 1. Different issues in photovoltaic modules

Issue	How does it look like in the product	Why is it bad?	What is causing it?	How to avoid it?
Air bubbles	Bubbles are laminated inside the module – in different spots.	Bubbles can cause delamination. Impossible to repair.	1. Trapped air. 2. Fumes of EVA (ethylene-vinyl acetate). 3. Cooling process [9].	Fine tuning of lamination cycle is the only possibility to avoid bubbles.
Broken cells	Cells are broken inside the laminated module. Either there is a crack or a whole piece of cell is apart.	Can impact power performance. Cannot be repaired.	1. Micro cracks in cells. 2. Transportation issues. 3. Production handling. 4. Issues in production process itself.	Ensuring that handling during manufacturing and processing would not damage cells.
Micro cracks	Not visible to the eye. The crack does not penetrate the whole cell (ca 200 micrometers).	Can impact performance of cell. Risk of a real crack. Growing due to the weather influence.	1. Transportation issues. 2. Supplier ships faulty cells. 3. Wrong handling during production.	Making electroluminescent picture of every single cell that is going to be used in production.
Hot spots	The burnt spot under the glass on the surface of cell.	Spots that become warmer inside the module, leading to short circuit.	Issues in soldering the ribbon to cell. Structural defects of cell.	Ensuring the quality of soldering interconnectors.
PID	Cannot be visually determined.	Accelerated aging of modules. Solar modules could lose performance.	Potential difference between solar module and the earthing.	Improving design of the module and the choice of materials used.
Snail trails	“Browning” of contact fingers of cell in a form of trails. Appears after some years.	Appearance of module. Can cause loss in power output.	Moisture penetrating the module causing oxidation of the components of cells on the trails of micro cracks.	Avoiding different types of cracks in cells.

the whole cycle (up to 25 minutes) in order to produce a module. During lamination the chamber is closed and it is not possible to see if something is going wrong there. After every change in the program it is important to wait the whole cycle. In case of wrong settings modules will be scrapped.

There are different steps in lamination process with different temperatures and pressures. The encapsulant material EVA becomes liquid during lamination. This may influence cells to float inside and cause undesirable displacements. During the lamination EVA transforms and forms a polymeric connection inside itself.

3.1. Measurable parameters

The study of lamination process allows selecting the parameters that need to be tracked:

- *pressure (input)* – essential during lamination process (impact on the quality of encapsulant and appearing of air bubbles);
- *temperature (input)* – main parameter for photovoltaic module lamination. Impacting the quality of encapsulant;
- *duration (input)* – lamination time. Influences the content of EVA gel and bubbles inside the laminate;
- *displacements (output)* – is essential to understand if module's structure is right. Finding displacements which are not visible to the eye and understanding why they occurred helps to improve modules in general;
- *content of EVA gel (output)* – important parameter to be followed but hard to be tracked by sensors in real time, as it is determined during chemical processes;
- *cracks (output)* – finding different types of cracks before laminating process allows to replace the cell;
- *measured temperature (temporary output)* – installation of additional sensors to collect data about the temperature should be considered as it could help making decisions how to measure temperature in a right way. Figure 3 shows the experimental setup of photovoltaic module with thermal sensors installed on the top of the module.

In order to track those parameters, the main idea is to embed a sensor inside the photovoltaic module body in the stage of production. Embedded sensors inside the composite materials was studied by Herranen et al., in [12] and the optimal shape for sensor's protective housing was proposed. The optimization procedure based on combining hybrid genetic algorithm (HGA), artificial neural networks (ANN) and reduced-order models (ROMs) [13–17], was adapted for optimal design of housing of the electronic component.

4. DEVELOPING THE CONCEPT OF MONITORING METHOD FOR PRODUCTION OF PHOTOVOLTAIC MODULES

The real-life production monitoring stands for continuous checking of parameters from the manufacturing object [18, 19]. This could be a powerful tool for measuring necessary parameters and understanding what is happening inside the product during the manufacturing process. There is possibility to use different types of sensors, which could be embedded inside the photovoltaic module, e.g., RFID (radio-frequency identification) sensors [11].

Before monitoring the manufacturing process of photovoltaic modules, it is necessary to identify important parameters that need to be monitored during production process. In other words, key performance indicators (KPIs) will have to be defined for using enterprise analyses model (EAM) [20–24].

The KPIs should be related to two main fields: jobs and courses and cover different areas like machinery, materials, processes, employees, facility, products, production order, etc.

4.1. Basic concept of monitoring system for photovoltaic modules

There is a number of approaches and requirements for the production monitoring systems. Let us proceed with the basic concept of production monitoring system developed by the workgroup in [18] and shown in Fig. 2.

This concept is proposed for particular case study with additional measurable parameters like pressure, temperature, and duration. This system can be adapted to the manufacturing process of photovoltaic modules with some changes. The concept proposed for production monitoring system integrates the following five main modules: data collection, analysis, visualization, storage, and security. The sensor system is collecting different data (ambient temperature, pressure, duration, displacements, and electroluminescence) from workstations. The storing, computations and analyses are made in the server or cloud side; and integration between the monitoring system and enterprise resource planning (ERP) system is developed. The collected information is sent to the ERP system where it is visualized.

4.2. Tests of temperature measurement

As noted above the lamination temperature has impact on quality of encapsulant and can be considered as key factor in lamination process. In order to validate the

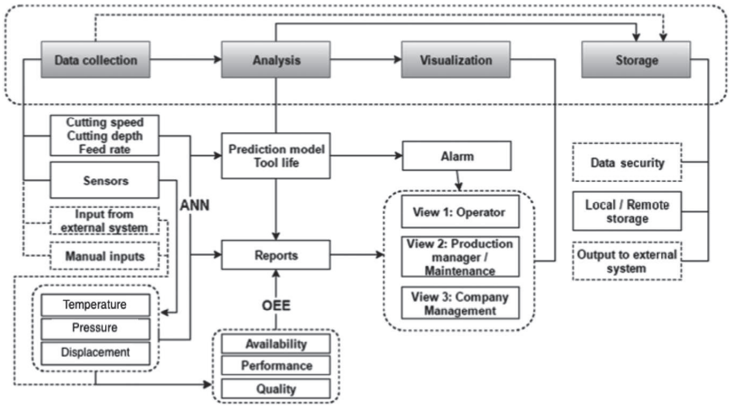

Fig. 2. Concept of the production monitoring system [18].

concept of measuring parameters inside the laminating chamber the temperature measurement was performed. The thermometer TES 1312A with two wired temperature sensors was employed. Sensors were installed on the back of solar module attached to the backsheet. Placing of thermal sensors can be seen in Fig. 3.

There were three tests performed: (1) usual lamination program with temperature of 144 °C; (2) program with increased temperature of 150 °C; (3) program with reduced temperature of 130 °C. The results of tests and gathered temperature data are represented in Table 2 and Fig. 4. Two measured values of temperature (Temp. 1 and Temp. 2 in Table 2) can be considered as an output from particular temperature test. The temperature was checked and registered with time stamp and values of

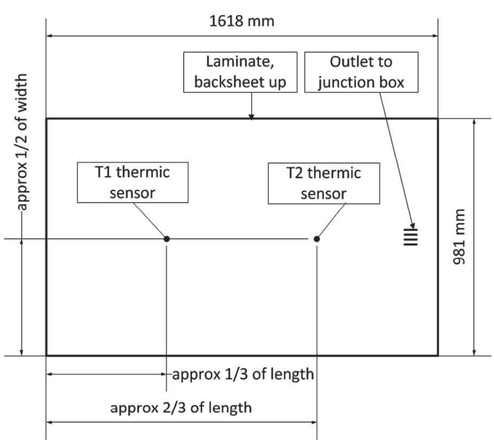

Fig. 3. Schematic representation of experimental setup.

measured temperatures. The set value of the temperature is known from laminator receipt and is given also in Table 2. "Machine values" are the values that are either set by receipt or measured by machine, not by experimental setup.

Gathered results show that there is a difference in set and real temperatures. The reason is the fact that heating element of the machine with temperature sensor is located underneath the heating plate. The module is located on the heating plate and the thermal sensor used in the test was set on the top of the module, so the whole structure of the module is between two sensors. Surface temperature of the module never reached program receipt value by the end of lamination cycle in any of tests. One important remark is that wired sensors were used in experimental set-up and wires had left traces on the surface of the backsheet. This means that particular module was defined faulty and was scrapped. Wireless solution or other type of wires should be used.

In Fig. 4, temperature measurement results from Table 2 are presented according to performed test number (the first number) and sensor position (decimal number). Measurements were performed five times.

5. CONCLUSIONS

It is essential to understand, what is happening inside the modules during production as well as to react fast to aoid faults in products. This kind of data gathering and reacting to the results of analysis will help to improve overall quality of products as well as understand what is happening inside the modules during different stages of production.

Table 2. Results of the tests

Measure-ment	Time from start	Machine values				Measured	
		Set temp., °C	Measured temp. value, °C	Set pressure, mbar	Meaured pressure, mbar	Temp. 1, °C	Temp. 2, °C
1.1	2 min 47 s	144	143	–1000	–1024	60.3	68.7
1.2	6 min 42 s	143	142	–300	–303	95.6	99.3
1.3	10 min 4 s	143	143	–300	–293	117.8	119.1
1.4	14 min 22 s	143	143	–300	–289	130.3	130.7
1.5	14 min 54 s	144	143	0	–2	131.1	130.9
2.1	2 min 44 s	150	149	–1000	–1006	51.7	57.5
2.2	6 min 16 s	150	148	–300	–310	80.9	87.2
2.3	10 min 1 s	150	150	–300	–300	117.4	118.1
2.4	14 min 31 s	150	150	–300	–307	134.5	134.4
2.5	15 min 00 s	150	150	0	7	134.4	135.8
3.1	2 min 34 s	130	130	–1000	–1013	36.0	32.9
3.2	6 min 01 s	130	129	–300	–361	71.4	74.7
3.3	10 min 5 s	130	130	–300	–320	100.2	103.3
3.4	14 min 35 s	130	130	–300	–300	118.7	120.5
3.5	15 min 00 s	150	150	0	7	134.4	135.8

Fig. 4. Temperature test results in different positions and input data.

In the current paper, the main issues and their sources have been pointed out. The concept for production monitoring system is proposed. The real time tests for measuring set temperature and temperatures in two additional nodes are performed and the results are analysed. Further studies will be performed regarding embedding sensors into solar modules.

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Tootmise seiresüsteemi arendamine fotoelektriliste moodulite tootmisprotsesside jaoks

Pavel Tšukrejev, Kaarel Kruuser ja Kristo Karjust

Fotoelektriliste moodulite tootmise seiresüsteemi väljaarendamiseks on läbi viidud uuring põhilistest kvaliteediprobleemidest, mis võivad tekkida moodulite valmistamise käigus. Uuringust selgus, et enamik probleeme tekib lamineerimise etapi jooksul. Tehti kindlaks põhjused, mis viivad kvaliteediprobleemide tekkimiseni. Põhjuste alusel on koostatud loend parameetritest ja mõjufaktoritest, mida on vaja lamineerimisel jälgida. Üldine tööpõhimõte seiresüsteemi arendamisel on integreerida moodulisse andurid, teha mõõtmised ja edastada tulemused serverisse. Saadud andmete põhjal saab teostada analüüsi, prognoosi ja visualiseerimist.

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