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.
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 backsheat 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

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

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

\[ h_i(x) = \begin{cases} 1 & \text{for } x \in [\xi_i(i), \xi_i(i)] \\ -1 & \text{for } x \in [\xi_i(i), \xi_i(i)] \\ 0 & \text{elsewhere} \end{cases} \]  

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,

\[ \xi_i(i) = A + 2k\mu \Delta x, \quad \xi_i(i) = A + (2k + 1)\mu \Delta x, \quad M = m, \quad \Delta x = (B - A)/(2M), \quad M = 2^j \]

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 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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References

[1] Sell R, Otto T 2008. Remotely controlled multi robot environment. *Proc. of 19th EAEIE Annual Conf.: 19th EAEIE Annual Conference, Tallinn, Estonia, June 29 - July 2, 2008. Tallinn*, pp 20–25. DOI: 10.1109/EAEIE.2008.4610152.

[2] Kuts V, Otto T, Tähemaa T, Bukhari K, Pataraya T 2018. Adaptive industrial robots using machine vision. ASME 2018 International Mechanical Engineering Congress and Exposition, 2: IMECE2018, November 9-15, Pittsburgh, PA, USA. ASME. DOI: 10.1115/IMECE2018-86720.

[3] Judi HM, Jenal R, Genasan D 2011 Applications and Experiences of Quality Control. *Quality Control Implementation in Manufacturing Companies: Motivating Factors and Challenges* (InTech) chapter 25 pp 495-508. DOI: 10.5772/15997.

[4] Fraunhofer Institute for Solar Energy Systems, ISE, Photovoltaics report (Sept. 16, 2020).

[5] Honsberg C, Bowden S 2014 " Solar Cell Structure" [Online]. Available: https://www.pveducation.org/pvcdrom/solar-cell-operation/solar-cell-structure. [Accessed 03.12.2020].

[6] Satpathy R, Pamuru V 2021 *Solar PV Power* ed R Satpathy and V Pauru (Academic Press) chapter 5 pp 135–241.

[7] Jaunich M, Böhning M, Braun U, Teteris G, Stark W 2016 Investigation of the curing state of ethylene/vinyl acetate copolymer (EVA) for photovoltaic applications by gel content determination, rheology, DSC and FTIR. *Polymer Testing, 52* pp 133-40.

[8] Chinnadurai T, Nalajam P, Vendan AS 2018 Analysis of mechanical and thermal behaviors for cross linked ethylene vinyl acetate (EVA) protective film employed for PV cells. *Materials Today: Proceedings, 5*, 11, Part 2 pp 23369-74.

[9] Karjust K, Kruuser K, Tšukrejev P 2019 Production monitoring system development for manufacturing processes of photovoltaic modules. *Proc. of the Estonian Academy of Sciences, 68* (4), pp 401–6. DOI: 10.3176/proc.2019.4.09.

[10] Kaganski S, Majak J, Karjust K 2018 Fuzzy AHP as a tool for prioritization of key performance indicators. In: *Procedia CIRP* pp 1227–32. 1st CIRP Conference on
Manufacturing Systems (CIRP CMS 2018). Stockholm, Sweden.
DOI: 10.1016/j.procir.2018.03.097.

[11] Paavel M, Karjust K, Majak J 2017 PLM Maturity model development and implementation in SME. Procedia CIRP, 63, The 50th CIRP Conference on Manufacturing Systems, Taiwan, 3-5 May. Ed. Tseng, M. Elsevier, 651–657. DOI: 10.1016/j.procir.2017.03.144.

[12] Majak J, Shvartsman B, Ratas M, Bassir D, Pohlak M, Karjust K, Eerme M 2020 Higher-order Haar wavelet method for vibration analysis of nanobeams. Materials Today Communications, 25, #101290. DOI: 10.1016/j.mtcomm.2020.101290.

[13] Zhu J, Zhang W, Xia L, Zhang Q, Bassir D 2012 Optimal packing configuration design with finite-circle method. Journal of Intelligent and Robotic Systems: Theory and Applications 67, 3-4 pp 185-199.

[14] Zhang WH, Domaszewski M, Bassir H 1999, Developments of sizing sensitivity analysis with the ABAQUS code. Structural Optimization 17, 2 pp 219-225.

[15] Guessasma S, Bassir D, Hedjazi L 2015 Influence of interphase properties on the effective behaviour of a starch-hemp composite. Materials and Design 65, pp 1053-1063.

[16] Nahas M, Alzahrani M 2020 Optimal Stochastic Distribution of CNTS in a Cantilever Polymer Microbeam Using Artificial Neural Networks. Mechanics of Composite Materials 56, pp 665–672.

[17] Cui D, Li DK 2019 Optimization of Extension-Shear Coupled Laminates Based on the Differential Evolution Algorithm. Mechanics of Composite Materials 54, pp 799–814.

[18] Plotnikova SV, Kulikov GM, Shape Control of Composite Plates with Distributed Piezoelectric Actuators in a Three-Dimensional Formulation. Mechanics of Composite Materials 56 pp 557–572.