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Connecting Artificial Intelligence and Structural Glass Engineering – Overview, Potentials and Case Studies

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This paper introduces the Artificial Intelligence (AI) technology to structural glass engineering and glass industry audience. The first part of the paper is concerned with lying nomenclature and theory foundation of AI and its subclasses of Machine and Deep Learning (ML/DL), elaborating the specific needs and requirements for the application in a structural glass context. A subsequent section explores applications of AI for different subjects within the production and quality assessment of glass products as well as the design, verification and monitoring of facades and glass structures. This paper presents successfully conducted industry projects by the authors, which are: supervised ML for material parameter identification of polymeric interlayers used in laminated glass, the prediction of sound insulation properties of insulation glass units and glass laminates and the application of computer vision DL methods to image classification of the Pummel test. A visionary outlook highlights how to use AI for future generative design and verification of glass structures for rapid collaborative prototyping. The summary and conclusion section wraps up the main findings for the applicability and impact of AI for the presented structural glass research and industry problems. This paper shows, that already by today in many cases AI, data, software and computing resources are already in place to successfully implement and conduct AI projects in the glass industry and structural glass engineering practice.

Keywords: digital fabrication, Artificial Intelligence, Means and Methods, structural glass engineering

1 Introduction

Artificial Intelligence (AI) nowadays drives the most animated discussions today in companies of the tech sector, universities and startups, but also in other low-tech companies with a small degree of digitization. A progressing digitization of all sectors of industry [1–3] together with steadily decreasing costs of data processing and storage [4,5] pave the way for AI from a subject of academic considerations into both private and professional everyday life in a wide variety of forms. People not concerned with AI have a vague belief of the technology mainly inspired by popular science fiction movies such as "Terminator", "Blade Runner", "Matrix" or "A.I. Artificial Intelligence". However, today AI is present and a substantial part in every day's life in way less spectacular and humanoid forms such as spam filters, recommender systems or digital language assistants such as "Alexa" (Amazon) or "Siri" (Apple). However, this paper is concerned with the implications of AI in a glass industry and engineering context and elaborate on new potentials,

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certain advantages over existing methods and already successfully conducted developments for the glass industry and engineering practice.

2 Background on Artificial Intelligence, Machine and Deep Learning

This subsection provides a non-comprehensive introduction to AI, ML and DL, whereas theoretically more substantial introductions to AI and its sub-classes can be found in [5].

2.1 Artificial Intelligence, Algorithms, Models and Data

Figure 2-1 (left) shows, that AI is used as an umbrella term for all developments of computer science, which is mainly concerned with the automation of intelligent and emergent behavior [6] such as visual perception, speech recognition, language translation and decision making. Over the course of history, a number of AI sub-fields have emerged, such as amongst others especially ML [7], which initially focused on pattern recognition [8], and later DL, using exclusively artificial neuronal networks [9]. Models and algorithms form essential building blocks for the application of AI to practical problems.

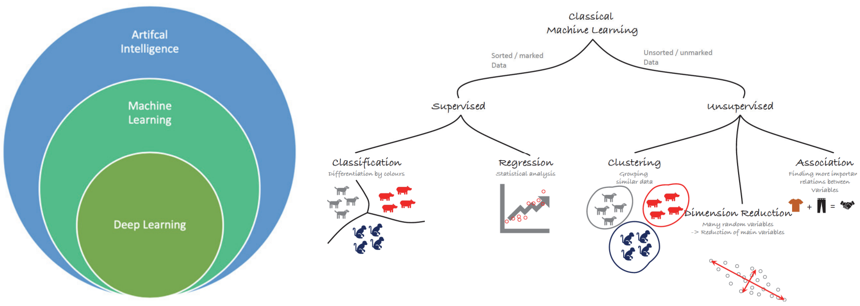

Figure 2-1 Schematic hierarchy of AI, ML and DL (left) and Overview on ML techniques (right).

An algorithm is defined as a set of unambiguous rules given to an AI program to help it learn on its own from experience E (here: data) for a specific task T (here: the problem under investigation) under a performance measure P (here: the error between AI prediction and a known ground truth within the data set) [10, 11]. The experience E is an entire data set, consisting of N data points (also called examples). A single data point consists at least of features x (individual measurable property [12]; explanatory variable). For specific tasks also targets / labels $\boldsymbol{y}$ (dependent variables) may be associated to features $\boldsymbol{x}$. The simplest example here is a regression task, where the tasks T for an AI algorithm is to find optimal model parameters given experience E (the data as a set of N $\{\boldsymbol{x},\boldsymbol{y}\}$ pairs) under e.g. the least-squares performance measure P. The data can be further distinguished into structured data (e.g. tables; the location of each part of the data as well as the content is exactly know) and unstructured data (e.g. pictures; either does not have a predefined data model or does not fit into relational tables) [13].

For the glass industry and engineering context, data may be encountered in either of the mentioned types, depending on the specific glass-related problem under investigation. In Section 3 examples for unstructured data in the form of photographic data is used for quality inspection and production control, whereas structured data in form of simulation data from numerical mechanical investigations or experiments is used to infer about patterns or model parameters by an AI algorithm. For practice, it is key to select an appropriate AI models and algorithms with special consideration of the given data set and structure to guarantee meaningful results and a successful conduction of the project [11, 14]. For reasons of brevity of this paper, the reader is referred to the already mentioned literature for further details on training and evaluation of AI/ML/DL models, over- and underfitting of models to data, data splitting therefore as well as on performance measures besides the least-squares loss.

2.2 Machine Learning

Machine Learning (ML) is a sub-branch of AI concerned with algorithms for automating the solution of complex learning problems that are hard to program explicitly using conventional methods. ML algorithms construct a mathematical model M for inference between features and targets based on data in order to make predictions or decisions without being explicitly programmed [6, 15, 16]. For ML, two different main algorithm types can be distinguished: supervised and unsupervised learning [10, 11, 14], cf. Figure 2-1 (right). In supervised ML, two separate tasks of classification (discrete target variables) and regression (continuous target variables) are distinguished. In supervised learning a predictive model M based on both influence and response variables is to be developed while in unsupervised learning a model is inferred solely on the basis of the features (clustering; dimension reduction). The goal of regression is to predict the value of one or more target variables given the value of a vector of input variables, whereas the goal in classification is to take an input vector and to assign it to one of K discrete classes C_k where $k = 1, ...,K$ [14]. The goal of unsupervised learning algorithms is to either discover structure, patterns and groups of similar examples within the data (clustering), or to determine the distribution of data within the input space (density estimation), or to project the data from a high-dimensional space down to lower dimensions [10, 11, 14, 17–19]. For reasons of brevity of this paper, the reader is referred to the already mentioned literature for further details on ML, the specific models as well as the training and validation of these ML models via ML algorithms.

2.3 Deep Learning

Historically, Deep Learning (DL) evolved as a sub-field of ML [11] using solely so-called artificial neural networks as models M to recognize patterns and highly non-linear relationships in data. An artificial neural network (NN) is formed from a collection of connected nodes (the neuron), which resemble the human brain (cf. Figure 2-2). Today many of architectures of neural nets are known [20], however in the context of this paper only the specific sub-classes of feedforward neural nets (FNN) and convolutional neural nets (CNN) are of interest, cf. Figure 2-2. Details on the specifics of the various other types of NN can be found for example in [11,21]. Due to their ability to reproduce and model non-linear processes, artificial neural networks have found applications in many areas.

A FNN is constructed by connecting layers consisting of several neurons (schematic sketch is shown in Figure 2-2), where the first layer of the FNN is the input layer, the last layer is the output layer, and the layers in between are called hidden layers. If a FNN possesses more than three hidden layers it is said to be a deep neural net (DNN).

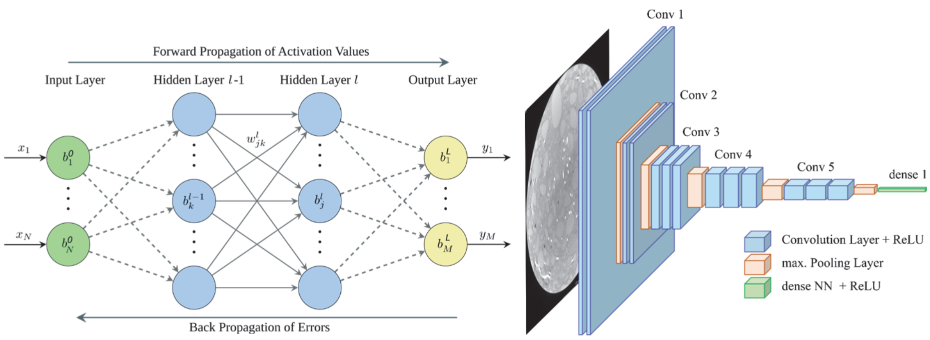

Figure 2-2 Schematic sketches of principle ANN architectures: Feedforward Neural Network (FNN) (left) and Convolutional Neural Network (CNN) (right).

Developing an appropriate architecture for a (deep) NN is problem dependent and only few rules of thumb exist for that setup [14, 22, 23]. Convolutional (neural) networks [11, 21] (CNN) mark a specialized kind of NN for processing data with grid-like topology, such as time-series data (1-D grid) and image data (2-D grid of pixels). This paper will not further elaborate on details of CNN along with training approaches for the different kinds of NN, instead the reader is referred to [11, 14].

3 Artificial Intelligence and Structural Glass Engineering

Having established the definitions and basics of relevant AI, ML and DL concepts, this section covers already investigated examples and future potential use cases for different areas of interest for the application of AI in the glass industry and structural glass engineering context. In the remaining section, the examples will always be elaborated according to the scheme of describing the problem, explaining the traditional engineering solutions, elaborating new possibilities and added value due to using AI and judging challenges and difficulties related to this approach.

3.1 AI for Quality Assurance and Inspection of Glass Products

Currently, building products and pre-fabricated building components are required to meet certain national and international standards to ensure a global minimum level of reliability and uniformity of these products [24]. State-of-the-art production techniques (e.g. additive manufacturing) together with new strategies for achieving requirements of building regulations demand an automation of the material quality inspection process. Especially material testing with as little human intervention as possible is favorable to ensure repeatability and objectivity of the testing process. Today, the quality control of glass and glass products relying on visual inspections is in the great majority carried out by humans to evaluate for example the cleanness of the glass, the quality of cut edges [25], anisotropy effects caused by thermal tempering of glass [26] or to determine the degree of adhesion between interlayer and glass [27]. The assessment and judgment of a human tester is significantly utilized to quantify the degree of fulfilling building regulation requirements. This fact of human quality quantification results leads to decisions prone to non-negligible statistical uncertainty through the human tester decisions [28]. Given that status-quo, the application of AI in the field of production control of glass and glass products hence seems promising for reaching above-human level accuracy in quality inspection results based on objectification, systematization and automation. That AI is able to outperform humans especially in non-structured data case was shown especially for with DL for computer vision (i.e. how computers can gain high-level understanding from digital images or videos) in related scientific fields [29, 30].

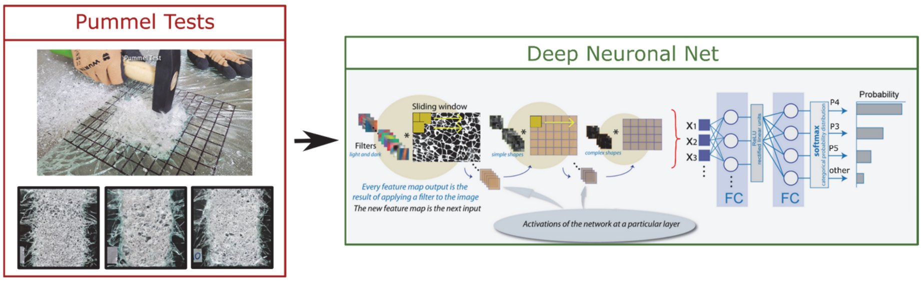

Figure 3-1 Schematic workflow for the AI supported evaluation of the Pummel test.

Quality management processes with visual inspections components are often organized to probe the whole production process through several human-based controls of product specific quality measures. In most cases the testing and inspection is prescribed or determined by national or international building regulations. This process induces uncertainty in objectification and repeatability of the quality measures since humans in principle are unable to provide an objective result of a quality control due to their own bias [31].

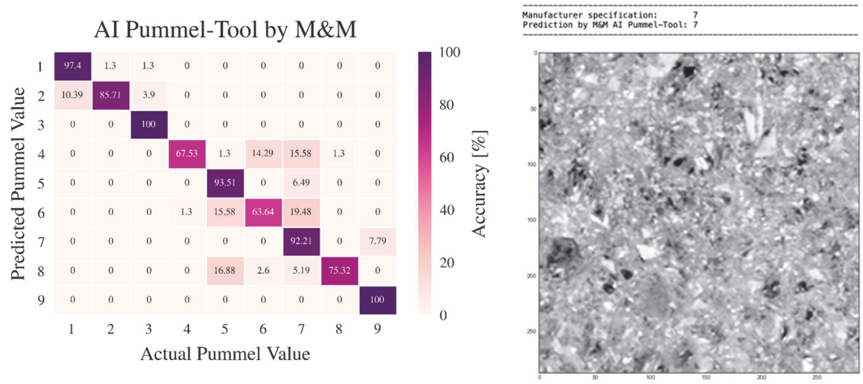

Figure 3-2 M&M AI Pummel Tool: Confusion matrix for the AI-based pummel value prediction (left); Example Results of the AI Pummel tool for an input image of class 7 (right).

Given this situation, it is thus preferable to supply a technological solution in the form of combining AI and computer vision to automate the quality inspection while minimizing human intervention. This paper presents an example for the objectification, systematization and automation of a visual product inspection for laminated glasses by the so-called Pummel test. The Pummel test specifically characterizes the degree of adhesion between the polymeric interlayer and the glass pane of a glass laminate, where an optical scale ranging from 0 to 10 characterizes the level of adhesion. The resulting Pummel value thus delivers an indicator for the quality and safety properties of laminated glass, where a value of 0 quantifies no adhesion and 10 very high adhesion [32, 33]. The laminated glass specimen for the Pummel test consist of two float glass panes with a maximum thickness of 2 x 4 mm. The specimens are exposed to a climate conditioning at -18 °C for about 8 h and subsequently are positioned on an inclined metal block and processed with a hammer (pummel). The Pummel value is then estimated by a human inspector based on the surface area of polymer interlayer exposed after pummeling (Figure 3-1, left). Further details on the Pummel test and its evaluation can be found in [24, 32, 33].

To address these challenges, an AI based classification tool (AI-Pummel Tool, cf. Figure 3-1 and Figure 3-2 (right)) using a deep convolutional neural network on grey-value images of pummeled glass laminates is proposed in order to completely automate pummel evaluation while excluding human bias or complex image pre-processing. A schematic illustration of the AI pummel tool is given in Figure 3-1, where the workflow for an AI-based automated pummel classification via a data-driven approach is illustrated. The AI model relies on the input of grey-value images after pummeling the laminated glass. These pictures then are processed by a pre-trained deep CNN for classification into one of the 11 Pummel value categories. Details on the principal architecture of CNNs were already given in Sec. 2.3, further details on CNNs especially within the field of computer vision are not described here in detail with reference to [29, 34]. Since only a few labeled Pummel image data were available for training the CNN, the authors used image data augmentation to expand the training data set.

Training results of the AI-Pummel-Tool are shown in Figure 3-2, where the accuracy is no less than 67 % under this AI-based training approach. It is expected, that an additional significant performance gain is obtained if more actual labeled Pummel image data (e.g. from manufacturers) could be provided to the training in a future step of this project. Accuracy of classification within the context of this example is measured via the confusion matrix (error matrix), cf. Figure 3-2 (left), where each row represents the AI-predicted Pummel values while each column represents the ground-truth Pummel value defined by the manufacturer. Inspection of Figure 3-2 (left) shows, that the CNN for the pummel value classes 1, 3, 5, 7, 9 reaches prediction accuracies over 92 %, whereas for class 6 only an accuracy value of 63 % is found. At this point it could be interpreted, that the AI confusion matrix suggests a lumping of the 11 classes into 5 or 6 Pummel classes. Figure 3-2 (right) shows one example of a Pummel image to be classified together with the CNN-based prediction of the Pummel value as well as the Pummel value determined by manufacturer (ground-truth Pummel value). Figure 3-2 (left) together with Figure 3-2 (right) proves, that the AI Pummel tool is very well able to generalize (i.e. to correctly classify) Pummel images which were not used during the training of the CNN.

This example showed that an AI-approach can successfully be trained to standardize, automate and objectify human-based classification of pummel images into the Pummel categories during production control along with a statistically sound quantification of uncertainties of this process (further details can also be found in [5]). Since the training of the CNN within this example was based on a small amount of publicly available data, more theoretical justification for a potential Pummel class lumping along with a quantification of the improvement of the performance and robustness of the CNN and further investigations on alternative architectures or even alternative approaches such as clustering [35] has to build upon future studies with an increasing amount of ground-truth Pummel images. We cordially invite relevant partners from academy and industry for cooperation along these lines.

3.2 AI for Acoustic Glass Design

Modern facades are designed to fulfill a multitude of objectives such as superior aesthetic appearance, a higher degree of weathering reliability, quick installation, high transparency as well as economic and ecologic efficiency. The assessment of acoustic properties and especially sound insulation abilities in early design stages is cumbersome today and relies largely on the designer's prior experience, some existing data from manufacturer's or laboratory's databases and in only a few number of cases on numerically investigations.

Specific sound insulation values can currently only be determined by complex and expensive experimental investigations or numerical simulations for certain glass set-ups. The conduction of experiments or lengthy computations to assess the acoustical properties of the framing systems and glass unit compositions in the concourse of a project quickly becomes time-consuming and demanding, hence a reliable and fairly accurate estimation of sound insulation properties of such systems is required. At the moment, there is no efficient tool available for convenient and reliable estimation of the sound insulation performance of glazing systems. The authors of this paper provided in [36] a ML based estimation tool of acoustic properties (weighted sound insulation value R_W, *STC* and *OITC*) of different glazing set-ups.

A sufficiently rich database of the Kuraray company was formed by conducting extensive studies on various glazing systems consisting of different glasses and aluminum frames and subsequentially used to train a decision tree-based ML algorithm. The weighted sound insulation value R_W, *STC* and *OITC* is determined by comparing the third-octave or octave band spectrum of the sound reduction index with a reference curve (typical curve for solid construction elements) specified in the standard DIN EN ISO 717-1.

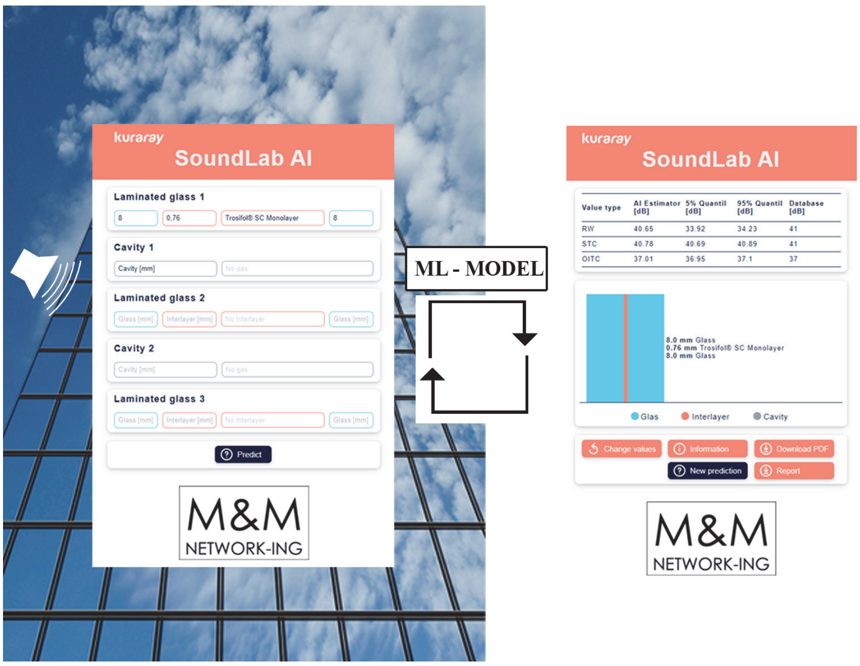

Figure 3-3 Sketch of the SOUNDLAB AI Tool software: input and output masks. (Copyright: MM Network-Ing & Kuraray Europe GmbH)

The investigation and evaluation of different glass setups for a facade design can be conducted using a handy web-based prediction program, the so-called SOUNDLAB AI Tool (cf. Figure 3-3). The software-tool will be available online and provided by Kuraray Europe GmbH on the homepage for a broad audience. This program can provide a quick analysis (around 1 second) and accurate prediction of arbitrary glazing set-ups, interlayers and glazing infills. A series of laboratory tests were conducted to validate the predictions by the SOUNDLAB AI Tool. The goal of this program is to provide designers, engineers, and architects an effective and economically efficient tool to facilitate the design w.r.t. acoustical properties, further details on this AI application can be found in [36].

3.3 AI for Structural Glass Engineering Design

The glass and facade sector is very innovative when it comes to using new materials, new design approaches and even new design philosophies. Especially polymeric materials such as structural silicones or interlayers of laminated glasses are amongst those materials, which require complicated mechanical, numerical and experimental treatments in order to establish safe and reliable structures. These polymers typically need to be described by constitutive models, which are able to capture the nonlinear stress-strain relationship adequately. In [36], [37] a novel functional form for the free Helmholtz energy for modeling hyperelasticity was introduced and calibrated for various polymeric materials, especially for structural silicones such as DOWSIL™ TSSA or DOWSIL™ 993 as well as glass laminate interlayers Poly-Vinyl-Butyral (PVB) and Ethylen-Vinyl-Acetate (EVA) by traditional optimization techniques. This section uses Bayesian supervised ML for calibrating this specific hyperelastic material model (Helmholtz potential) to experimental data of TSSA silicone. Within this paper, the isochoric Helmholtz free energy functional in the context of hyperelasticity is of interest and may be written in form of the Nelder function as:

$$\Psi_{iso}(I_1, I_2|\boldsymbol{\theta}) = \frac{I_1-3}{x_1+x_2(I_1-3)} + \frac{I_2-3}{x_3+x_4(I_2-3)} \tag{3.1}$$

using the two invariants I_1, I_2 of the left Cauchy-Green tensor $\boldsymbol{b}$ and four parameters $\boldsymbol{\theta} = \{x_1, x_2, x_3, x_4\}$.

For this study experimental data of the transparent silicone TSSA are taken from [37, 38], where the material was tested in uniaxial tension and compression, shear and biaxial deformation. Within this example, the material parameters $\boldsymbol{\theta}$ have been determined using Bayesian supervised ML algorithms upon the DREAM MCMC algorithm [39], cf. Figure 3-4.

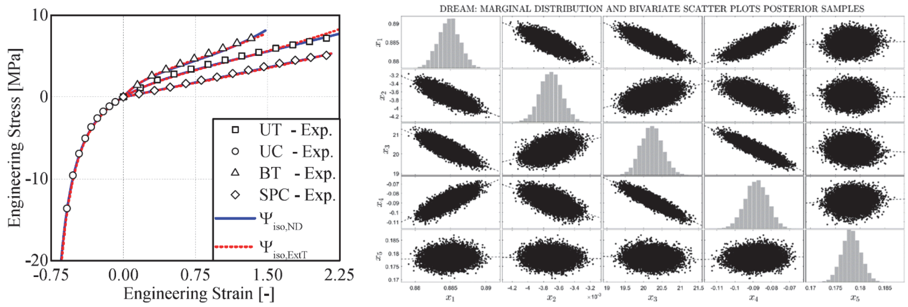

Figure 3-4 Fitting results for TSSA silicone by different approaches (Extended Tube and Nelder) and experiments under arbitrary deformations: DOWSIL^{TM} TSSA by parameter mean values of the Bayesian optimization supervised learning (left); uni- and bivariate distributions of the parameters θ of the proposed Helmholtz potential for DOWSIL^{TM} TSSA (right); with UT = uniaxial tension, UC = uniaxial compression, BT = biaxial tension, SPC = shear pancake and SPC = shear pancake tests, from [5].

Figure 3-4 shows that the Bayesian ML MCMC calibration leads to a well suited calibration of Ψ_{iso}. Interestingly, the MCMC simulation on a standard laptop lasted about 20 minutes and led to results (mean values of the parameters) that were very close to the smallest squares determined with the software MATHEMATICA, although MCMC means a significantly higher numerical effort compared to the smallest squares. This additional computational effort pays off for the structural engineering context, as the Bayesian framework further allows for a deduction of partial material safety factors as the uncertainties in the associated model parameters are naturally captured, cf. Figure 3-4 (right).

As a conclusion, the application of Bayesian ML in the context of this example was successful. In addition, it delivers even more insight on the model parameter certainties as well as model assessment quantities for further use in a reliability analysis at no extra cost compared to traditional optimization-based material calibration strategies. Further examples of AI applications for the structural engineering context in glass related applications can be found in [5].

4 Future Potentials for AI within Structural Glass Applications and Engineering

This last subsection highlights three main future potentials for the application of AI in design, verification and monitoring of glass structures in short, further details, discussions and examples in this context can be found in [5].

4.1 Potential 1: Design Supported by AI

Currently first research ideas combine AI with architectural design tasks [40–42], where it is commonly found, that the examples of an AI-generated built environment existing today still need further years of research and cooperation between the different fields to achieve the announced quality. [42] uses Generative Adversarial Networks (GAN) to design floor plan designs for various boundary conditions and interactively with a human designer. Note, that GAN is a special form of NN from the family of NN as presented in Section 2.3. During the training of the GAN floor plan designer, the organization learned by each model revealed the existence of a deeper bias (i.e. architectural style). For new floor plans, this trained GAN can now be used to assist a designing architect in generating a coherent room layout and furnishing and to finally reassemble all apartment units into a tentative floor plan. Further details can be found in [5].

4.2 Potential 2: Structural Verification Supported by AI

For the case of AI for structural verification of glass structures, an example was already given in Section 3.3 for TSSA silicone. Recent developments in the field of AI at the interface with the natural and engineering sciences have led to the formation of the terms "physics-informed" or "theory-guided" AI [5]. These special formulations of AI models are intended to achieve two goals:

- Compensation of the possibly small amount of data for training the AI model (data sparsity).
- Use of existing theoretical knowledge of the respective subject domain in a formal way.

While the general definition of physics-informed DL using physics-informed neural networks (PINN) uses the partial differential equations beyond physical problems, the paper of the authors of this publication are among the first to really apply these concepts for civil engineering situations [43, 44]. Physics-consistency is achieved through proper formulation of the loss function for training of an AI model, were especially PINNS may remedy limitation to small amounts of data in the learning process, since already existing and theoretical knowledge (from science as well as from experts), e.g. in the form of the loss function or special regularization expressions are formally taken into account. Furthermore, PINNs allow the interpretation as digital twin of a structure and hence provide one single data and computational model for structural verification and monitoring. Further details and explanations can be found in [5].

4.3 Potential 3: “Intelligent Home/ Office” – User-centered Buildings by AI

In the future, facades are not only considered as barrier against environmental influences with additional demands on functionality and appealing design but will have to account for user comfort and interaction with the facade. Hence, innovative adaptive control systems for facades using AI in order to cope with the arising multi-objective optimization problem are needed. For this approach models of AI are combined with a digital twin of the facade to form a cyber-physical control loop with user feedback on its well-being and comfort while AI accounts also for energetic and sustainability aspects. Today a first research approach by the authors exist to reach the “intelligent home/office” by modelling such adaptive facades as a multi-criteria optimization problem with highly nonlinear and imprecise (in the fuzzy sense; for user/occupant modeling) correlations, which a priori may not be known to a certain extend (especially the user well-being part of the equation) or have to be "learned" from data of experiments (e.g. multi-occupant requirements; features from multi-sensor measurements). This system uses adaptive elements within the facade (windows, shading elements, air conditioning) and sensors (humidity, wind speed, temperature, user feedback via smart watches) together with an AI controlling unit to process all data and learn over time the individual preferences of the occupants. Further details and explanations can be found in [5].

5 Summary and Conclusions

This paper introduced the reader to the main concepts and brief backgrounds on Artificial Intelligence (AI) and its sub-groups Machine Learning (ML) and Deep Learning (DL). The nomenclature and practical meaning of core AI vocabulary was explained and illustrated. Selected nomenclature and glass-context relevant models from ML and DL were presented to the reader. The main part of this paper presented a total of three examples and future potentials for the glass industry and structural glass engineering. It was found, that AI methods enabled training a model at all or were superior compare to traditional approaches. The two example applications of AI covered deep learning based quality control of glass laminates under the Pummel test, the prediction of sound insulation quantities for different glazing set-ups and the calibration of a Helmholtz potential for TSSA structural silicon. Within the examples especially information on the amount of necessary data together with the challenges and final solution strategy was reported in order to enable the reader to judge temporal and monetary effort for AI methods in comparison to existing engineering models and approaches (in case these are existing). A visionary outlook on the role of AI within supporting engineers for an early stage design of structures finished the paper.

This paper shows that the introduction of AI technologies in the glass and its neighboring industries as well as structural glass engineering is possible to a great extend already immediately. This is due to the fact, that essential requirements of an AI application such as the existence of data and an understanding of the task formulation is already fulfilled in many cases. The main concern for research and especially industry is now to digitalize and structure (existing) data in such a way that AI algorithms can apply, train and validate diverse models on it in order to lead to successful projects in combination with engineering expertise. Digital workflows and databases have to be established within companies and research institutes for that purpose. The theoretical framework and the respective software are already available by today, yet they have to be augmented by domain expert knowledge of structural/glass engineers, who are familiar with the statistical and methodical concepts of AI. For this reason, in the eyes of the authors of this paper, it is essential to introduce these methodological knowledge and practicing with AI in the study curricula of students of civil engineering and architecture in the near future as well.

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