Transfer Learning for Optimization of Carbon Fiber Reinforced Polymer Production

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Abstract. The main problem that keeps many areas of research from using Deep Learning methods is the lack of sufficient amounts of data. We propose transfer learning from simulated data as a solution to that issue. In this work, we present the industrial use case for which we plan to apply our transfer learning approach to: the production of economic Carbon Fiber Reinforced Polymer components. It is currently common practice to draw samples of produced components statistically and perform destructive tests on them, which is very costly. Our goal is to predict the quality of components during the production process. This has the advantage of enabling not only on-line monitoring but also adaptively optimizing the manufacturing procedure. The data comes from sensors embedded in a tooling in a Resin Transfer Molding press.

Keywords: Transfer Learning, Simulation-based Machine Learning, Organic Computing, Carbon Fiber Reinforced Polymer

1 Motivation

Machine Learning (ML) and especially Deep Learning (DL) algorithms have been successfully applied to certain fields of research recently: Computer Vision [11] or Speech Recognition [2]. Moreover, Reinforcement Learning (RL) in combination with DL was used to solve games (e.g., Go [21] and Atari games [15]). Other areas, for instance, industrial production or medical sciences, try to benefit from these algorithm families as well. The problem that keeps those and many other areas from adapting DL to the respective problems is the immense need for data when using deep neural networks. The gathering of enough data and the subsequent labeling phase is costly or can be almost impossible for certain kinds of data.

The use case we present is the automation, optimization, and adaptation of industrial production of Carbon Fiber Reinforced Polymer (CFRP) that should be improved by transfer learning from simulated data. Components made of Carbon fiber make vehicles lighter by 50-70 % compared to conventional steel and therefore more energy-efficient: A 1 % weight reduction reduces the energy consumption by approximately 0.6-0.7 % [6]. Currently, the production of CFRP is too expensive for automotive volume scale, because it is by far more complicated to produce CFRP than press steel or aluminum [22]. The factors that drive the cost the most are difficult automation, high cycle times, personnel, industrial manufacturing equipment, and material cost. In low-scale production industries such as avionics and aerospace, even more cost-inefficient factors such as increased manual labor and intermediate products, called "carbon pre-pregs"[1] increase costs even further. Our solution addresses several of these problems: we use an automated Resin Transfer Molding (RTM) process (see Fig. 1) with more cost-efficient materials: non-wovens made of recycled carbon fibers and a small share of natural fibers and caprolactam as resin. This combination of an RTM process with non-wovens and online in-situ monitoring during the production process is unique to our knowledge and makes the whole endeavor very complex. The manufacturing of components for mere training purposes is non-economical, since they are disposed of thereafter. The press and its components are shown in Fig. 1. A and B are containers for the two-component resin. The mixing unit is marked with C. D illustrates the press. The carbon mat E is about to be injected with resin. F represents the tooling that holds the negative of the future component and is equipped with acoustic, electric, temperature and pressure sensors.

The process steps are:

1. The non-woven carbon mat is brought into the press, which has around 100 degrees Celsius.
2. Resin is injected into the mold.
3. The Press is pressed and resin spreads in the mat.
4. Sensors measure the spread distribution and the hardening of the resin.
    4.1. If necessary, the press keeps shut for a longer period or additional pressure is applied.
5. The press is opened and the finished component is extracted.

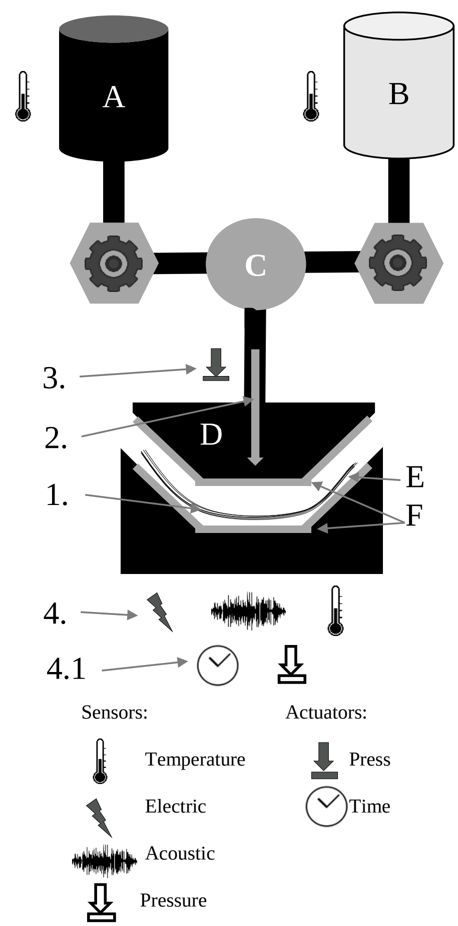

Fig. 1. Schematic RTM press with symbolic sensors and actuators.

[1] Pre-preg stands for "pre-impregnated" composite fibers. Within these, a polymer matrix material, e.g., epoxy, is already present in the fiber.

In this position paper, we present the initial goals of the project and suggested paths towards them. We propose learning on simulated data (as in robotics [20] or gaming [15, 21]) and refining that knowledge with few real-world samples as a solution. While the dataset of real-world samples within our project is too small for DL by a magnitude, as many simulated runs as necessary can be produced. Additionally, the time-consuming data labeling step is no longer necessary since the data is already labeled when it comes from the simulation: all stages of resin distribution and curing are available for every spot of the component.

Researching *transfer learning* from simulated to real data is a major focus of our work. We want to identify and tackle the Machine Learning (ML) challenges at the gap between simulation and the real world.

The smart CFRP press that is constructed during my dissertation is self-learning and self-adaptive. These self-X capabilities are a key concept of organic computing systems [4]. The restore invariant approach [16], another key notion of organic computing that describes the corridor of correct behavior can be applied to this machine. Initially, the press has to be parametrized to get into this corridor of correct behavior: it produces CFRP components with a high quality. Whenever the quality is declining—moving out of the corridor—the process is adapted by the machine itself.

In Section 2 we present the expected challenges and the goals of the project. Section 3 entails recent works on transfer learning on the one hand and works on non-destructive testing of CFRP components via acoustic and electric sensors on the other hand. Methods, algorithms, and ideas on how to tackle the challenges of this project are shown in Section 4. The last part, Section 5 gives an overview of future research activities. Additionally, our work is put into context with respect to our project partners' contributions.

2 Objectives

Bridging the gap between simulated *flow fronts*[2] and real sensor data will be a major challenge. Grössing et al. [3] compared the simulation software we are going to use, PAM RTM[3], a subset of PAM Composites by ESI, and an open source alternative with regards to how realistic they model flow fronts. During the work on the project, we will test how suitable PAM RTM is for our setup. One key question is how to merge the two types of data. Are we going to be able to learn on raw sensor data, time series of ultrasonic and electric sensors, or do we use abstracted flow fronts from real data for training? Both types of training data have to be aligned to make it possible to coherently train on them.

[2] The flow front is the edge between the part of the mat that has been impregnated with resin and the rest that has to be impregnated yet. The flow front simulation software is able to simulate the distribution process of the resin.

[3] `https://https://www.esi-group.com/de/software-loesungen/virtual-manufacturing/composites/pam-composites/pam-rtm`, Accessed on August 29, 2018

The research on transfer learning from simulated and real data is an important aspect of my dissertation.

Partners in the project have been working on similar questions in the past. Kalafat and Sause [7] sensed damages in carbon components with acoustic sensors. In our project, similar sensors, as well as piezo-electric sensors, will be used to sense the distribution of the resin in the carbon fiber mat and the polymerization.

Another challenge is to handle varying environmental factors such as air temperature and humidity. These can interfere with the production progress: especially the caprolactam is sensitive to humidity. In a controlled production environment, such environmental factors should become tamable.

Carbon long fibers, the raw material, have a variance in weight per meter of 10 %[4]. That makes the material's behavior less predictable than that of steel or aluminum. Variations in the production material will be a central issue. In addition to the variance in weight of the raw material, a mix of recycled carbon and natural fibers will be used to produce the non-woven mats for our project. Different distributions of these materials in the non-wovens will cause different permeabilities. Permeability is a very important property when predicting the distribution of the resin in the mat. We want to tackle this challenge by varying the input parameters of the simulation to cover problematic non-woven mats.

The goals for our part in this project, that build on top of each other, are:

1. Classifying the quality[5] of one component from mere sensor input
2. Optimizing the quality over the production process of multiple components
3. Get a real-time prediction of one component as it is still in the press and adjust certain parameters if the outcome is expected to be sub-optimal, see Fig. 1, step 4.1.

Furthermore, the optimization of the algorithm is part of our work, as soon as the goals regarding functionality are met. The main priority is to ensure that the inference step meets the requirements for online adaption of parameters at production speed. The hard time limit needs to be determined first, once the timing of the process is clear. As soon as the timing of the process is defined, we can set the specifications for our algorithm and start optimizing.

3 State of the art - Related work

There have been preliminary works on optimizing the production of CFRP products. Sorg [22] compared several data mining algorithms on data coming from

[4] Source: Voith Composites, `http://voith.com/composites-de/index.html`, Accessed on November 15, 2018

[5] The quality of a CFRP component is determined by several factors. The resin has to be distributed equally and has to reach all parts of the fiber mat. Additionally, no air or other materials shall be enclosed in the component. Then the stability is optimal.

the production of a carbon car roof. The sources of the data were already established process logs which held data about several time spans, thicknesses of the product at certain points, temperatures, and pressures. Within our project these sorts of data will be available as well as data that is specifically gathered for our needs: sensor data that shows the flow front and curing progress.

These acoustic and electric sensors have already been used to detect damages in CFRP components in-situ on one hand. Kostka et al. [10] and Larrosa et al. [12] both have been working on monitoring the health status of an already finished CFRP component with sensors (acoustic and electric), that were embedded in the component during production. Kostka et al. used decision trees and Larrosa et al. implemented Gaussian discriminative analysis to reach their goals. Kalafat and Sause have shown that the localization of defects in CFRP via neural networks is feasible and outperforms other techniques [7] .

Opposed to these authors that used sensor data to determine the health status of a CFRP component, we will use acoustic and electric sensors to determine the flow front and the curing process within in the press. Their works are important with regard to using sensors to determine the state of a component already in use.

A research company named Synthesites, on the other hand, has published several works on online monitoring of the production of CFRP. Pantelelis et al. [18] have shown that it is possible to monitor not only the distribution of the resin but also the curing of the product with electrical and temperature sensors. In another work which was carried out in a EU project[6], they have shown that they can use neural networks for the optimization of the curing process [26]. In their work, the heating profile for a CFRP component was optimized so that production could be accelerated by 36 % with 5 % less heating energy involved compared to no curing monitoring and control. They used very shallow neural networks with only one hidden layer and used bootstrap aggregating to combine the output of 30 networks. Besides the data from online monitoring and the neural networks involved, there is a third similarity of their work to our project: they used simulated data for initial training.

We delimit our work from theirs by several points. First, the online monitoring in our project concerns not only the distribution of resin and curing of the component at several points of interest, but the exact flow front process, damage detection during deforming, and monitoring of temperature, pressure, and acoustics in the tooling. We operate on a much larger scale regarding data compared to the other project: a sensor network made of many more sensors will be used in our project. They used only five single sensors. We will use more sophisticated flow front simulations that are specially made for CFRP production refined with data coming from the aforementioned sensor network. Fr the other works, a simpler, one-dimensional simulation method by Pantelelis et al. [17] was used. Another difference lays within the utilized materials: we use caprolactam as resin and non-woven carbon mats whilst they were using epoxy and wovens. As

[6] IREMO (intelligent REactive polymer composites MOulding) `https://cordis.europa.eu/project/rcn/94018_en.html`, Accessed on August 22, 2018

mentioned in Section 2, Grössing et al. compared PAM RTM, and OpenFOAM[7] regarding their ability to model flow fronts. To test how realistic the simulations are, they installed a transparent upper half on an RTM press to make the flow front advancement visible. In contrast to our work, they used a resin with high viscosity and carbon pre-pregs. Their experiments showed that PAM RTM is computationally more efficient because of the different underlying mathematical model. It is easier to operate, but has the disadvantage that it cannot model the transition between porous and non-porous/solid material. Once we start using PAM RTM, we will see if this issue is relevant to our work and, if so, we need to check if that issue is solved in a recent version of the software since the paper appeared in 2016.

After covering the related work concerning CFRP, the following part will present research on learning methods that have been utilized for other use-cases. We expect for at least some of these approaches to work well in the context of CFRP production.

Weiss et al. [23] give a comprehensive and in-depth overview of the methods of transfer learning. They present different domains where algorithms of this sort have been implemented successfully, i.e. for image classification, human-activity classification, and software defect classification. They do not explicitly treat simulation-to-real data transfer learning but give a good overview of common techniques to adapt the knowledge of an algorithm from one domain to the other.

The main method to do so is to fine-tune a neural network, a method that is described more thoroughly in Section 4. Progressive Neural Networks [19] are another interesting idea to handle the transfer of knowledge from one domain to another. They have been used for transferring knowledge from simulation to real data in a robot use case [20], which makes them well suited for our problem. Section 4 gives an introduction to the operating principle behind this type of network.

Other sources focus on different applications of DL algorithms to specific use cases with the help of simulations. These include traffic flow prediction [14] and the understanding of dynamical scenes from video data [24]. Both works have shown that it is possible to learn from simulated data and to adapt that knowledge to real-world applications. They lack the link to CFRP or industrial production in general, a gap we plan to fill.

4 Methodology

Initially, we will train our model to predict the quality (our definition of quality is described in Footnote 5) of a small and simple carbon component. In a second step, a *chicane component* that exhibits a complex geometry, for instance ascents or round edges, will be produced. These three steps are necessary due to the fact that the production equipment will be installed in parallel to the first steps in the project and the final system will be available late in the project. This stepwise

[7] `https://www.openfoam.com/`, Accessed on August 29, 2018

approach makes it inevitable to devise an algorithm that is capable off keeping some of its knowledge from previous steps and adapt it for the next level. That makes it unnecessary to learn from scratch for each new component and lowers development and production costs.

The idea of transfer learning was already described in Section 3: adapting a pre-trained algorithm to a new domain to save time and training effort, especially when there is not enough data available in the new domain. The common and straightforward approach to do so for neural networks is called *fine-tuning*. The following four steps sketch the approach in a simplified manner.

1. Load network topology and initialize it with pre-trained weights
2. Cut off last layer - the output layer
3. Add new output layer that fits the new problem
4. Train the last network again and keep all old layers in their original state, do not update their weights

This approach, originally described by Hinton et al. [5] has the advantage that the training converges and it takes much less time to train compared to training from scratch. In our case, we use simulated data for pre-training and the real data of one type of component for fine-tuning. For the more sophisticated parts, the network can be adapted again. An approach that could be an even better fit to

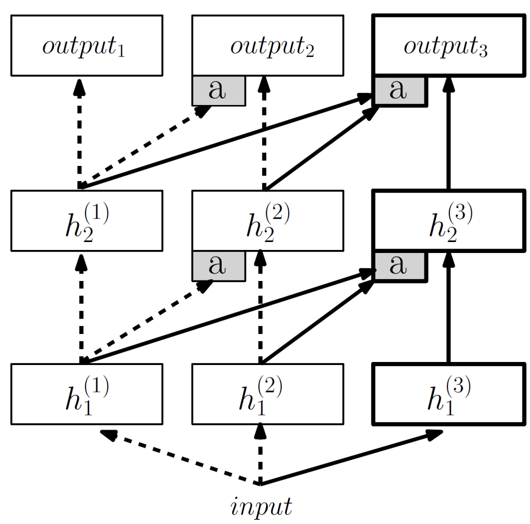

Fig. 2. Progressive neural network with three columns. From [19]

our multi-component/task problem are progressive neural networks [19] because their topology is especially made for transfer learning from one to multiple tasks. The principle works as follows and is shown in Fig. 2:

1. Train a neural network with an arbitrary topology (CNN, RNN, ...); this is the first *column*.
2. Add a second network/column that is trained for another task alongside the first column.
3. Add adapter connections from the layers of the first to the second column (denoted (a) in Fig. 2).
4. Column one is disabled for training.
5. Column two uses features from column one to solve the new task.

This approach has some great advantages: it circumvents *catastrophic forgetting* [1], an unwanted behavior that happens to fine-tuned networks very often: once a new task is learned, the algorithm performs poorly in the original task.

Another interesting feature for our purpose is that new tasks can be added easily: one new column per task. Helpfully, new tasks do not have to contain as many parameters as the previous ones and thus need less data. For our project a good first start is to train the first column for simulated data for the simple component. The second column could be the real data for the simple component. This learning from previous stages continues when switching to the chicane component: it is very desirable to keep the training effort low when transferring knowledge.

The disadvantage of these networks is the massive amount of parameters they utilize. For every new task, a new column is added, which lets the number of weights grow enormously when training many tasks. In our project, we do not have to meet hard storage constraints but keeping an eye on the dimensions of a network is always reasonable.

In the explanation above, one detail was skipped: the adapter connections between the layers of different columns. These connections are single layer Multi Layer Perceptrons (MLPs), which means they have weights and activation functions and thus can be disabled. As the number of columns grows, the number of adapters and their related parameters grows exponentially. Since the number of parameters in a progressive neural network is high anyway, disabling certain connections between layers helps to keep the size of the network in check.

For the different components, we obtain simulated data from flow front simulations. As described in Section 3, the preferred simulation software is PAM RTM by ESI.

Flow front simulations have certain similarities to videos: the single images are 2D if the component is not too complicated and they have a time series nature. Colors indicate different stages of wetting and/or polymerization. One obvious path to handle this type of data is to treat it similar to video data which opens the possibility to adapt approaches for video analysis that have proven successful: previous studies include e.g., video classification as shown by Karpathy et al. [8] and Ng et al. [25]. Another idea based on the *video path* is to use image segmentation methods [13] to pre-train a network in a first step to let it gain knowledge on segmenting flow fronts and the optimal distribution of resin and curing. In a second step, that network is retrained for regression, i.e. inferring one value for the quality of the component. Convolutional

Neural Networks (CNNs) are neural networks that work very well for image segmentation and overall analysis of single images. If we follow the image path, a mixture of CNNs is the network topology we choose, no matter if we fine-tune a network or use several networks together in a progressive neural network. For CNNs, the hyperparameters to tune are: the overall topology, which can be a residual network, or made of inception modules or simpler topologies or another architecture. The next parameter is the number of layers and neurons. For training, the learning rate and the optimizer are interesting parameters to tune. We will start with proposed values and start optimizing training as soon as progress is visible, that means the training is working.

The idea of using raw sensor data input would make it necessary to select of a different kind of topology that is well suited for that data because it is uncertain if raw data has the same properties as images: repeating patterns at certain areas, areas of higher interest than others and likewise. Since we do not know yet if we can use the raw data for learning, this path of raw data is not described further here.

Despite the fact that deep neural networks have proven to work for many different kinds of problems, we will consider other types of algorithms for our approach. Sorg [22] showed that a method for constructing decision trees, which was invented a long time ago, CHAID [9], was more suitable for his optimization problem of the process mining the production of a carbon car roof. When it comes to the acceptance of an algorithm within production and management, a very important aspect of an algorithm is its interpretability. Decision trees are easily understandable whilst neural networks are black boxes with next to no interpretability. If the performance figures of these algorithms are similar and even if the decision tree is a little weaker than the neural network, chances are that the overall decision rules in favor of the understandable decision trees. Decision trees carry another interesting feature: they do not need as much training data as deep neural networks. Opting for them, or any other data frugal algorithm would have the advantage of setting aside using simulated data, as well as transfer learning and just use the real data collected by the sensors. That would be a much simpler approach. For our goals (the detailed construction of a flow front, curing, etc.), these algorithms are likely not capable enough, but we will give them a try as well. One other simple approach are shallow neural networks as utilized by Pantelesis et al. [18]. But even for these networks carrying only one hidden layer with a handful of neurons, simulated data was used for training. This reduces the hope that only real data will help to successfully train any kind of learning algorithm.

The real data is coming from sensors within the press: ultrasonic, electric, pressure and temperature sensors, which are also shown in Fig. 1. Deriving the flow front and the curing and all other target values from this data is another challenge, which will be tackled with the help of experts in material science.

After this first step of predicting quality of a finished component from sensor input, optimizing the quality of components over the course of time is the next level of complexity. With the acquired quality inference method, a RL approach to increase the quality of the component will be developed and applied. The parameters to change, e.g., the actions for RL, are the pressure of resin, the pressure of the press and the temperature of the press. Ultimately, we will optimize our algorithm to recognize possible defects in the component in the press and to consequently take countermeasures such as increasing the pressure of the press or leaving the component in the press for a longer time.

To obtain a baseline to compare to, approximately 100 units of the simple sample components will be produced. Their quality will be tested and they will therefore be destroyed. This quality assessment of 100 simple components will work as our labels and we will split this set into training, test, and validation data sets. We will then compare the outcome our algorithm produces with this real data. For the more complex component, not as many units will be produced. Nonetheless, the real data will also be used for training and testing, but at a smaller scale.

5 Outlook

We suggested transfer learning from simulated data as a tool to make DL usable for domains with small datasets. The optimization of the production of CFRP is the use case our project is dedicated to. We showed the expected challenges and the proposed methodology for that project.

After a training for PAM Composites, enough data for initial neural network trainings have to be produced and the first trainings have to be carried out. These two steps, gathering data and training, including tweaking of parameters have to be repeated until the results satisfy our demands.

When the first batch of sample components and related quality data is completed, we can start our transfer learning effort. Depending on the success of these attempts on transferring knowledge, the following steps include, first, to incrementally optimize the quality of components with RL over time, and second, to interfere in the production process, if necessary. At last, adapting knowledge from the simple to the complicated component has to be accomplished.

Our part in this project is comprised of all data science and ML tasks. At the moment, especially the work on transfer learning and the combination of various learning methods are scientific challenges. Others will follow during the lifetime of the project. The research of these problems will be a major part of my thesis.

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