Concept for Finding Process Models for New Classes of Industrial Production Processes

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***Abstract*— The required knowledge about relations between quantities governing the control and quality estimation of production processes is represented in so-called process models. Such models may relate process parameters and process goals allowing to find appropriate parameter values for given goals. Other models allow the derivation of the process state from observable quantities. Controls based on Markov Decision Processes require a state transition model and a cost function model of subsequent states. The functional relationships between the quantities of a model are usually represented by a dedicated combination of some base functions with given, fixed parameter values. In many cases, this is a linear combination of Kernel functions, where the parameters are determined by fitting known experimental data, such as in Support Vector Regression methods. The process models always refer only to a dedicated process class with given conditions (e.g., parts materials and geometries or machine properties). There are model populations in most industrial process domains, such as laser metal sheet welding, representing several metal alloys in combination with sheet thicknesses and welding equipment. In this paper, we propose novel methods on how to make use of this already existing model knowledge, which is used for the derivation of models of new process classes in the same process domain. For this purpose, the formation of a common model representation is derived from the individual models of the domain. The parameters of the individual models in this common representation form a model space, in which a model of the models can be formed: the hyper-model. General ideas of hyper-model formation are presented and approaches are discussed how dedicated models for specific, new process classes (e.g., with different conditions) can be derived from it.**

Keywords: machine learning; data modeling; hyper-model; process model; welding.

I. INTRODUCTION

Mathematical models represent the mapping of adjustable quantities on resulting phenomena, such as process parameters on process results. Models of processes can represent many dependencies of process quantities, depending on the purpose of model exploitation. In the case of simple controlled processes, the model might describe the relation of process parameter values with quality measures to be achieved (goal values). In the case of a Markov Decision Process the model might represent the state transition probability depending on present state and control action [2].

In simple controlled processes the process parameters describe the variable control quantities, which can be represented by a vector $\boldsymbol{p}$ and which determine the actions. All fixed quantities otherwise governing the process are the process conditions, which are represented in a vector $\boldsymbol{c}$. They are fixed externally and independently from process execution. The desired end state of the process ("goal") is described by goal quantities forming the goal vector $\boldsymbol{g}$. For example, in car seat manufacturing metal sheets are joined by laser welding seams. The process parameters are laser power, laser focus and welding speed. The variable conditions are the material thicknesses of the two sheets. The goal is a certain seam width and seam depth, which have to be obtained. The welding task is then given by the combination of the goals and the conditions $\boldsymbol{t} = [\boldsymbol{g}, \boldsymbol{c}]$. At least one method (consisting of process parameters $\boldsymbol{p}$) has to be found, fulfilling a given task $\boldsymbol{t}$. In other words, a mapping from $\boldsymbol{t}$ to $\boldsymbol{p}$ has to be performed. We call this the task-to-method transform (T2MT) which is the inverse process model. The process model itself in the simple case is the functional relationship $\boldsymbol{g} = f(\boldsymbol{p}, \boldsymbol{c})$ of the goal quantities with the condition and control quantities $\boldsymbol{c}$ and $\boldsymbol{p}$. It is used to find the suitable control quantities or process parameters by solving the equation for $\boldsymbol{p}$ at given $\boldsymbol{c}$.

A process model can be built from experimental data where a variety of process conditions is explored. For each specific condition, a set of methods $\boldsymbol{p}$ is applied and the resulting goal values $\mathbf{g}$ are measured. Each single experiment gives a vector triple $[\boldsymbol{g}, \boldsymbol{p}, \boldsymbol{c}]$ and the available experimental series give a set of such triples. We build an abstraction of the experimental data by the formation of a goal function $g(\boldsymbol{p}, \boldsymbol{c})$ [1]. It represents the knowledge contained in the experimental data: the model. The model function $\boldsymbol{g}$ is representative in our example of a class of processes, where the thicknesses of the two metal sheets may vary within the bounds covered by the experimental sample.

In this formulation of the model formation, we have implicitly assumed that many other external conditions have been controlled and kept constant during all experiments for setting up the sample to learn the abstraction. In our example case above these are the material types of the metal sheets and the welding laser head type for instance. Laser welding manufacturers usually set up process models as described

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above for the common materials and welding heads as required by their customers by creating full, independent experimental samples in each case. The possible relationships between models are not exploited. On the other hand side, the "implicit" conditions can be represented by numerical quantities ς as well (such as orientation density function and grain size distribution in poly-crystalline metal sheets or optical parameters of the laser head), forming a vector $\boldsymbol{\varsigma}$.

Then, each model function is in correspondence to a point in the space of vectors $\boldsymbol{\varsigma}$. The relations between models could be exploited if it would be known how a model of some $\boldsymbol{\varsigma}^*$ transforms into the model of some other $\boldsymbol{\varsigma}'$, when moving from $\boldsymbol{\varsigma}^*$ to $\boldsymbol{\varsigma}'$. The knowledge of such a transformation

$$g(p, c|\varsigma') = h\left[g\left(p, c|\varsigma^*\right)\right] \quad (1)$$

is called a hyper-model. Once such a hyper-model is set up, it can be exploited to derive estimates of process models for new process classes.

The paper is organized as follows:

We first review some common modelling approaches in Section II to create the basis for hyper-models. Then in Section III we propose the novel hyper-model approach which consists of a method to derive a hyper-model from a set of existing process models and a method to derive a new process model from the hyper-model for a given $\boldsymbol{\varsigma}$. Finally, we show in Section IV how this approach might be applied to our laser welding example. The acknowledgement and conclusions close the article.

II. Modelling Processes and Model Exploitation

In process state tracking (following the state evolution during processing) and quality estimation (properties of the final state) and in control (determining the process-governing control quantities or process parameters) various models are required. These models map available or given quantities $\boldsymbol{x}$ (such as observable measurement values) to other quantities $\boldsymbol{z}$ bearing the information required to decide upon actions. This mapping is usually represented as mathematical transformation, which is specified as a dedicated transformation function $\boldsymbol{z} = f(\boldsymbol{x})$ between the corresponding vector spaces of vectors $\boldsymbol{x}$ and $\boldsymbol{z}$ where the vector components are assumed to be real-valued. This function has to be determined in order to represent the required knowledge. Due to the complexity of real-world production processes it is almost always impossible to determine the model form analytically from physical principles. The common way of arriving at models is a generalization of the relations encountered in experimental data, which are supposed to represent the process. This is performed by specifying a quite general function with a set of parameters, the values of which are determined to optimally fit the data. For this purpose many machine-learning methods, such as Support-Vector-Regression [3], Artificial Neural Networks [7], Symbolic Regression [8] or Levenberg-Marquart fitting of parameters of dedicated functions derived from physical considerations [9] are used.

In many cases, it is the inverse of the desired transformation, which is captured by the experiments. An example of this is the goal function, where experiments yield the process result, induced by the selected process parameters. The process is sampled by varying the process parameters and recording the respective results. Now the functional dependency of the result quantities on the process parameters (the goal function) can be fitted, while in the process control the parameter values required for a given process result are required. For this purpose the goal function must be used to find the set of solutions resulting in the desired goal value.

The process of model formation is depicted in Fig. 1.

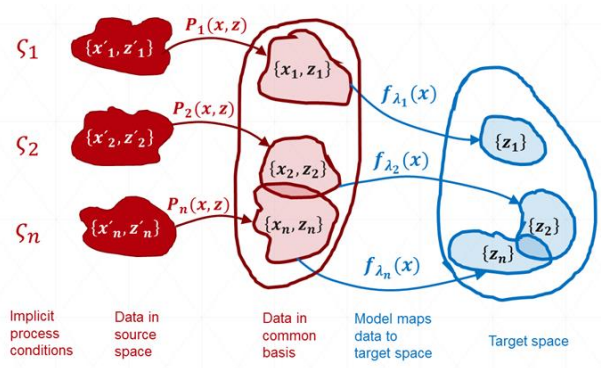

Figure 1. Data from experiments under different implicit conditions serve to form process models.

A model is a function (parametrized by a vector $\boldsymbol{\lambda}$) which describes the target value $\boldsymbol{z}$ depending on a variable $\boldsymbol{x}$. In general, the input variable $\boldsymbol{x}$ is a vector of quantities, which are controlled by the user to generate the target quantity. The generation of a model from given data corresponds to the determination of $\boldsymbol{\lambda}$. Available data always depends implicitly on other conditions not covered by $\boldsymbol{\varsigma}$. This implicit dependency is retained in $\boldsymbol{\lambda}$ and the corresponding model $f_{\boldsymbol{\lambda}}$ is only valid under these implicit conditions. The first step after the experimental acquisition of the sample data set $\{\boldsymbol{x'_n}, \boldsymbol{z'_n}\}$ under a certain condition $\boldsymbol{\varsigma}_n$ is to bring the data into a common representation basis via a "normalizing" transformation $\boldsymbol{P_n}(\boldsymbol{x}, \boldsymbol{z})$. This allows to operate on the data with the same functional representation of model functions. With these "normalized" data $\{\boldsymbol{x}, \boldsymbol{z}\}$ the parameters $\boldsymbol{\lambda}$ of a transformation function are estimated to optimally represent the mapping $\boldsymbol{z} = f_{\boldsymbol{\lambda}}(\boldsymbol{x})$ with methods as mentioned above. This results in dedicated models

$$\mathbf{z}_n = \mathrm{f}_{\boldsymbol{\lambda}_n}(\mathbf{x}) \quad (2)$$

for each of the implicit process conditions $\boldsymbol{\varsigma}_n$. The model functions can be linear combinations of some base functions

$$\mathrm{f}_{\boldsymbol{\lambda}_n}(\mathbf{x}) = \sum_{i=1}^{N} \lambda_i \boldsymbol{\phi}_i(\mathbf{x}). \quad (3)$$

If the model functions obtained this way represent the required mapping, they can be directly used to retrieve the desired quantity value of $\boldsymbol{z}$ by inserting the given value $\boldsymbol{x}$ and evaluating the formula.

If –on contrary- the data and the derived model function represent the inverse transformation, and $\boldsymbol{x}$ is the quantity to be retrieved for a given instance of $\tilde{\boldsymbol{z}}$, then the solution set $\tilde{\boldsymbol{x}}$ of values $\boldsymbol{x}$ has to be found which satisfies

$$\tilde{\mathbf{z}} = \mathrm{f}_{\boldsymbol{\lambda}}(\mathbf{x}). \tag{4}$$

The target function $\boldsymbol{z} = f_{\boldsymbol{\lambda}}(\boldsymbol{x})$ represents a surface embedded into a high-dimensional space spanned by the given quantities $\boldsymbol{x}$ (e.g., process parameters and process conditions). A specific, desired value $\tilde{\boldsymbol{z}}$ of the quantity $\boldsymbol{z}$ defines a parallel hyperplane over the space of vectors $\boldsymbol{x}$ at constant height $\tilde{\boldsymbol{z}}$, which intersects with the curved target function $\boldsymbol{z} = f_{\boldsymbol{\lambda}}(\boldsymbol{x})$. The intersection hyper-curve is then the sought-after solution set, which is called the level set:

$$\{\tilde{\boldsymbol{x}}\} = \{\boldsymbol{x} \mid \tilde{\mathbf{z}} = \mathrm{f}_{\boldsymbol{\lambda}}(\mathbf{x})\}. \tag{5}$$

The level set can be found by meshing the $\boldsymbol{x}$ space if the dimension is not too high. The mesh is refined by incrementally subdividing cells, which are intersected by $\tilde{\boldsymbol{z}} = f_{\boldsymbol{\lambda}}(\boldsymbol{x})$, until the desired accuracy is reached. The level set is afterwards given by a discrete set of solutions.

The final level set is then a list of $\tilde{\boldsymbol{x}}$ vectors. Each of them will produce the result $\tilde{\boldsymbol{z}}$ as requested by the task. Every solution in the found level set is associated with some cost such as energy, wear of tools, production cycle time and so on, which is used to select a best solution.

III. HYPER-MODEL APPROACH

If there exist several process models $\boldsymbol{z}_n = f_{\boldsymbol{\lambda}_n}(\boldsymbol{x})$, each representing a different process class under dedicated, different implicit process conditions $\boldsymbol{\varsigma}_n$, these models can be considered as a sample of models over the space of $\boldsymbol{\varsigma}$. The dependencies of the models on the implicit process conditions $\boldsymbol{\varsigma}_n$ are implicitly reflected by the values of the model parameters $\boldsymbol{\lambda}_n$. Finding a model corresponding to new conditions $\boldsymbol{\varsigma}^*$ means finding the corresponding parameter values $\boldsymbol{\lambda}^*$. The new model can then be applied for its usual purpose (task-to-method transform, quality estimation, state prediction, etc.) in the new situation. If a valid functional relation between $\boldsymbol{\lambda}$ and $\boldsymbol{\varsigma}$ can be established, based on existing models, it is possible to derive new models from the generalization represented by this functional relation. We call such a relation

$$\boldsymbol{\varsigma} = \mathrm{g}_{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \tag{6}$$

a hyper-model, e.g., a sum of weighted base functions Ψ_k,

$$\mathrm{g}_{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \sum_\mathrm{k} \beta_\mathrm{k} \boldsymbol{\Psi}_\mathrm{k}(\boldsymbol{\lambda}). \tag{7}$$

A hyper- model is a function (parametrized by a vector $\boldsymbol{\beta}$) which describes the connection between the implicit conditions $\boldsymbol{\varsigma}$ and the models represented by $\boldsymbol{\lambda}$. The hyper-model operates on model parameters and represents the differences between models.

Another point of view on a hyper model is that of a transformation between models. The transformation operator $T_{\boldsymbol{\varsigma}}$ depends on the implicit conditions $\boldsymbol{\varsigma}$ and maps a model $f_{\boldsymbol{\lambda}'}$ to $f_{\boldsymbol{\lambda}}$.

$$\mathrm{T}_{\boldsymbol{\varsigma}}\, \mathrm{f}_{\boldsymbol{\lambda}'}(\mathbf{x}) = \mathrm{f}_{\boldsymbol{\lambda}}(\mathbf{x}) \tag{8}$$

This is equivalent to another transformation operator $T'_{\boldsymbol{\varsigma}}$ which maps the model parameters $\boldsymbol{\lambda}'$ to $\boldsymbol{\lambda}$.

The operator $T'_{\boldsymbol{\varsigma}}$ can be represented by a function G' depending on model differences $\boldsymbol{\varsigma}$ and model parameters $\boldsymbol{\lambda}$.

$$\mathrm{G}'(\boldsymbol{\varsigma}, \boldsymbol{\lambda}') = \boldsymbol{\lambda} \tag{9}$$

If $\boldsymbol{\lambda}'$ represents a fixed standard reference model (derived under standard conditions), then $\boldsymbol{\lambda}'$ can be absorbed completely in the function leading to

$$\mathrm{G}(\boldsymbol{\varsigma}) = \boldsymbol{\lambda} \tag{10}$$

This formulation of a hyper model brings us back to the previous definition of a hyper-model. The two points of view are equivalent if the hyper-model $g_{\boldsymbol{\beta}}$ is invertible:

$$\boldsymbol{\varsigma} = \mathrm{g}_{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \Rightarrow \mathrm{G} = \mathrm{g}_{\boldsymbol{\beta}}{}^{-1} \tag{11}$$

This way, the hyper-model can be considered either as a transformation between models or as a generating function, which relates model parameters to situations $\boldsymbol{\varsigma}$.

The hyper-model $\boldsymbol{\varsigma} = g_{\boldsymbol{\beta}}(\boldsymbol{\lambda})$ can be determined as a generalizing function from sample models, since each model, belonging to a condition $\boldsymbol{\varsigma}$ is then represented by a point in the space of vectors $\boldsymbol{\lambda}$. A set of models corresponds to a set of points in $\boldsymbol{\lambda}$ –space with associated condition values. This can be considered as a set of sample points of a (eventually vector-valued) condition ($\boldsymbol{\varsigma}$-)surface over the space of $\boldsymbol{\lambda}$. This surface can be represented by the function $g_{\boldsymbol{\beta}}(\boldsymbol{\lambda})$, which is a generalization of the sample points (models). A hyper-model must not necessarily represent conditions which are associated with the models but can represent any quantifiable semantic information.

IV. LASER WELDING EXAMPLE

An application of the T2MT to laser welding is described in [4]. In order to weld metal sheets by laser, the sheets are held in fixed positions. The laser head is delivering the radiation power of the laser to a focal area, where the metal sheets are molten by the absorbed energy. When the focus is moving on, the energy delivery to the previous area ceases and the metal solidifies again after cooling off. A robot moves the laser head along the intended seam, while the head adjusts angle and distance of the laser focus relative to

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the sheet surface. Three parameters determine the process: "focal distance" z_f (in the range of ±10 mm), "laser power" P (up to 6 kW) and translational speed of the focus ("speed") v (up to 200 mm/s). The resulting welding seam can be described by weld width w and penetration depth d (Fig. 2), which are usually specified by the customer as w_0 and d_0. The required parameter values of z_f, P and v are derived by inversion of the process model $w_0 = w(z_f, P, v)$ and $d_0 = d(z_f, P, v)$ via T2MT, as described in Section II. The process model is built via machine learning from a large set of experimental data with width and depth measurements in the lab. It represents the functional dependency of the customer goal on the parameters under the present conditions (e.g., initial laser head h_{init}) as $w(z_f, P, v|h_{init})$.

Under new conditions (e.g., new laser head) the process will behave differently and the model no longer be valid. As long as the physics of the process has not changed, the new process model can be most likely derived by a transformation of the initial model as in equation (8).

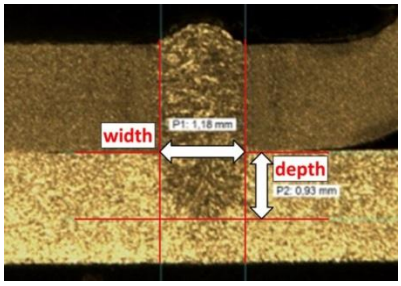

Figure 2. Cross section of two metal sheets joined by a welding seam from laser seam welding. With kind permission of AWL-Techniek B.V [5]

The initial model and only a few new experimental data with an exchanged laser head h_{exch} were used to estimate such transformation as depicted on the right column of Fig. 3. Just an affine mapping was required to transform the process model for capturing the new condition with sufficient accuracy (middle column of Fig. 3).

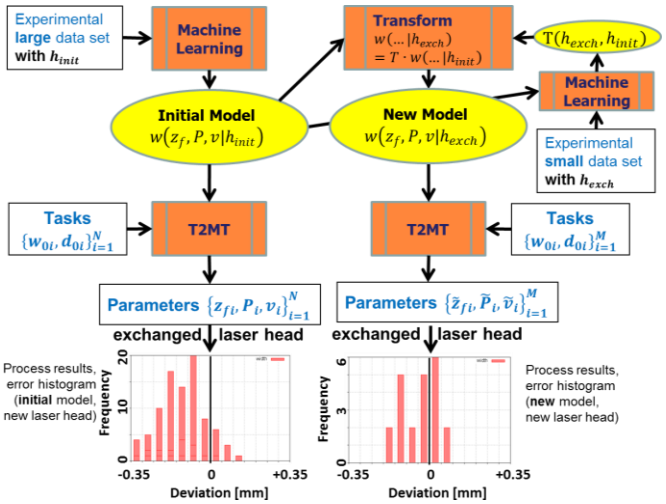

Figure 3. Transformation of laser seam welding process model from the initial laser head to an exchanged laser head.

The left column shows the large deviation of the process results with parameters derived from the initial model.

CONCLUSION

Instead of having to set-up a new model from hundreds of lab experiments, it is sufficient to estimate the transformation from only very few experiments. This can be generalized to a more generic hyper-model as in Section III to also include other conditions such as sheet material.

This way, hyper-modelling is enabling the re-use of existing models and minimizing efforts to explore and represent processes under new conditions. It is also an embedding of process-induced condition relations in the hyper-parameter space, which can be explored and exploited for the prediction of processes under modified conditions.

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