Process Chain Optimization using Universal State and Control Features

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***Abstract*—In order to obtain components with desired properties in production processes, it is necessary to consider all single process steps. The holistic view of a process chain enables the identification and the control of interactions between the single processes. In contrast to the description of a single process, state and control variables might not be consistent along the entire process chain. We propose a universal characterization of state and control features along the process chain that takes into account all relevant information and, at the same time, reduces the complexity in optimization. This allows us to optimize the entire process chain to obtain a desired product at the end under consideration of process noise, even for high dimensional state and control spaces.**

Keywords–process chains; optimization; feature extraction.

I. INTRODUCTION

A production process describes the transformation of a component from its initial to its final state (e.g., stresses in the material) which depends on applied process controls (e.g., forces) and unknown process noise (e.g., different friction conditions due to lubrication). The holistic view of a process chain allows to identify and to control interactions between the individual processes to obtain a desired product at the end of the process chain (e.g., compensate geometric imperfections with distortion engineering [1]). The linking of the single processes can be realized by forward and backward information exchange [2]. A statistical learning approach [3] enables the control of a single process [2] using radial basis functions to identify controls. For each time step, past process noise is taken into account by measurements of process quantities. However, future uncertainties are neglected in that approach, but are considered in optimal control as realized for deep drawing including process noise [4].

If the characteristic process state is not accessible during processing, state observers can be used to extract the state information by observable quantities that are measurable during process execution. State observers can be established by statistical learning approaches such as Artificial Neural Networks [5] and Symbolic Regression [6].

While we can use the same state and control variables within one process, the description among different processes is not necessarily consistent. There are properties that are meaningful for a specific process, but would be pointless for the entire process chain (e.g., cup height is a component property in deep drawing which is not applicable to rolling or heat treatment). We can find a common description along the entire process chain by expert knowledge (e.g., stresses in sheet metal forming) and / or use a universal description for state and control variables as proposed in this paper.

We introduce the concept of process chain optimization in Section II and give an example process chain in Section III.

II. PROCESS CHAIN OPTIMIZATION

We propose a universal description for state and control variables from which the characteristic features are automatically extracted for optimization and retransformed for application to the process.

A. Process chain modeling

Each process in the chain is characterized by its state during processing. A single process p_t transforms an initial state $\mathbf{x}_t$ to a final state $\mathbf{x}_{t+1}$ depending on the control variables $\mathbf{u}_t$ and the unknown process noise $\mathbf{v}_t$ as depicted in Figure 1. Each transformation is associated with local costs C_t (e.g., the production effort). The final costs C_{t+1} are added at the end of the process chain (e.g., the deviation of the actual state from a desired state). The Bellman equation [7] describes the optimal control problem for each process. The total costs J_t to be minimized comprise the local costs C_t and the successor costs J_{t+1}. The successor costs consist of the local costs of the remaining processes in the chain plus the final costs at the end. The Bellman equation can be solved by (Approximate) Dynamic Programming [7] (e.g., modeling successor costs and state transitions by nonlinear regression with Artificial Neural Networks from simulation data [4]).

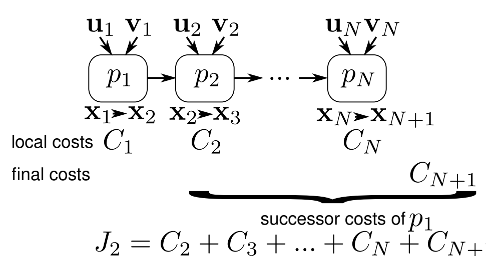

Figure 1. Process chain modeling.

The process data $\mathbf{u}_t, \mathbf{x}_t$ can be obtained by real experiments including uncertainty or by deterministic simulations without random noise. The local and final costs are defined by a human process expert.

B. Feature extraction and unwrapping

In order to obtain a characteristic description of the process chain, all relevant quantities are collected to represent

1) universal state variables $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N, \mathbf{x}_{N+1}$, (e.g., thickness and depth [8])
2) universal control variables $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N$.

Figure 2 points out how feature extracting and unwrapping is interconnected with optimization. We can either apply Principal Component Analysis (PCA) to state and control variables separately or use Partial Least Squares Regression (PLS) on

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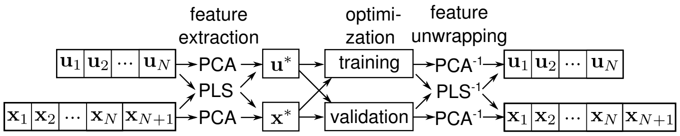

Figure 2. Feature extraction and unwrapping.

both simultaneously. PCA [3] allows dimension reduction from a higher dimensional to a lower dimensional space retaining most of the information (e.g., variance) in the data. PLS [3] enables a dimension reduction in input and output during regression. The features of the universal state and control variables are extracted: the control features $\mathbf{u}^*$ and the state features $\mathbf{x}^*$. The optimization problem (Bellman equation) is formulated and solved in the feature space. The training step establishes the models for state transitions and successor costs, whereas the validation step tests the established models with previously unseen data. Then the features are unwrapped (inverse PCA / PLS). The unwrapped features reveal the controls and states in its original space for process application and are interpretable.

This procedure allows to reduce the dimensionality in state and control spaces to handle the complexity in optimization (that grows exponentially with increasing spaces). Constant dimensions in state space (e.g., zero cup height in rolling) or control space indicate that these dimensions are not affected by any changes in the current process. They will be removed by dimension reduction.

C. From process data to chain optimization

A real life example for sheet metal forming is to obtain a homogeneous sheet thickness distribution at the end (final costs) under consideration of low production effort in each step (local costs). To realize the proposed concept, we recommend to implement the following procedure:

- record process data $\mathbf{u}_t, \mathbf{x}_t$ from simulations or experiments and optionally induce artificial process noise $\mathbf{v}_t$ if not contained in process data,
- define cost functions (local costs C_t and final costs C_{N+1}) based on $\mathbf{u}$ and $\mathbf{x}$,
- extract control features $\mathbf{u}^*$ and state features $\mathbf{x}^*$ along process chain from process data $\mathbf{u}_t, \mathbf{x}_t$,
- create cost mapping functions based on extracted features $C_t(\mathbf{u}^*, \mathbf{x}^*)$ and $C_{N+1}(\mathbf{u}^*, \mathbf{x}^*)$,
- build and validate process models for each step in chain by regression for (1) state transition, (2) costs, and (3) Bellman equation (after its solution),
- unwrap control features $\mathbf{u}$ and state features $\mathbf{x}$ along process chain from control features $\mathbf{u}^*$ and state features $\mathbf{x}^*$,
- evaluate process chain optimization.

III. Example process chain

An example process chain in sheet metal forming is given in Figure 3 [9]. It contains the processes rolling (forming a metal sheet from a metal block), annealing (heat treatment) and deep drawing (forming a cup-shaped workpiece from a metal sheet). The optimization objective is to compensate direction-dependent deformation which results in unwanted earing of the resulting cup. The holistic view of the process chain allows to

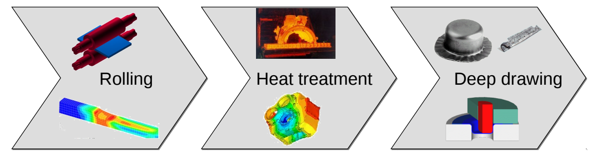

Figure 3. Example process chain "sheet metal forming" [9].

understand and to control the deformation behavior of the sheet metal components. The evolving microstructure (e.g., grain size and orientation of the crystalline structure of metals [10]) as the characteristic state of the metal sheet is controlled along forming, heat treatment and deep drawing operations to finally produce minimal earing. The proposed approach enables the handling of the complex microstructure.

IV. Conclusion

We introduced a universal characterization for state and control features in production process chains. This allows a consistent description along the entire process chain and, at the same time, a reduction of complexity in state and control spaces to realize an efficient process chain optimization. Future work deals with application of the proposed concept to different process chains. This allows us to compare it with conventional ways of process chain optimization.

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