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APPLICATION OF NEURO-PREDICTIVE CONTROL TO LASER BEAM WELDING

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Abstract: Welding with laser beams is an innovative technique, which is leads to higher penetration depth and a narrower seam compared to conventional welding techniques. One significant criterion of the quality of a junction is the penetration depth. Within this article a predictive control scheme is presented that optimises the process input laser power by taking the future welding speed into account. For modelling this non-linear process an Artificial Neural Network (*ANN*) is applied. The *GPC*-algorithm with a linear model obtained by instantaneous linearization of the network is used. First results of the application on a real laser welding system are described. *Copyright ©2002 IFAC*

Keywords: Neural networks, Predictive control, System identification, Linearization, On-line control

1. INTRODUCTION

Welding with laser beams is characterized by high specific power input into the workpiece. Thereby the material is not only molten, but also vaporized forming a capillary with plasma in it. The result is a narrow seam with a higher penetration depth compared to conventional welding techniques as the laser beam can penetrate the material through the capillary easily. As a result, a minimum of thermal stress of the workpiece can be maintained. The required energy density to vaporize the material is achieved by focussing the laser beam in the vicinity of the workpiece surface. After reaching a temperature high enough to vaporize the material a so-called keyhole is built and the deep welding process starts. From a control engineer's point of view laser beam welding is a complex multi-dimensional problem. Besides process parameters (e.g. laser power, welding speed, position of the focus, angle of incidence in 3D material processing, inert gas) also geometry parameters of the joint (e.g. material thickness, gap, surface properties) influence the seam quality.

Simple models of the process can be obtained from energy balances and approximate the static behaviour of the process. A detailed mathematical description of the process is extremely difficult as it has to take into account the sub-processes radiation absorption and multiple reflections, heat conduction, melting, hydrodynamics, evaporation and optical emission of plasma (Schulz *et al.* 2001). Analytical modelling of laser beam welding is a field of intensive research, but so far no self-contained model of the process covering all necessary details is found. As the dominating system input variables are welding speed and laser power, these are suited for controlling the penetration depth. In 3D laser beam welding the welding speed depends on the path planning, the machine dynamics and perhaps a seam tracking system and can therefore not be

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used for controlling purposes. The laser power, however, is instantaneously alterable; therefore it can be used as the manipulated variable. Further input variables mentioned above can be kept constant. As the future welding speed is known from the path planning and definitely has a not negligible influence on the penetration depth, the use of a predictive controller which takes future variations of the welding speed into account seems appropriate.

Model based predictive controllers (MPCs) belong to a class of model based control schemes that use a dynamic model of the controlled system to predict the future behaviour of variables of interest. Thereby the future impact of the actual system input variable values is estimated. The future deviation of the controlled variable is minimized by finding an optimal control sequence. The first element of that control sequence is then applied to the process and the optimization is carried out for the next sample step.

As the penetration depth cannot be measured without destroying the workpiece, the intensity of the plasma emission is used as the controlled variable instead. Temporally and spatially resolved observations of the keyhole are acquired with a CCD-camera and interpreted using physical insight (Kratzsch *et al.* 2000),(Schulz *et al.* 2001). The camera is mounted directly on the welding head and its optical path goes coaxial with the laser beam path through the focussing optic. The design of the system allows an easy adaption to both CO_2 and Nd:YAG laser optics. Simple control loops based on this controlled variable have already been realized (Kaierle *et al.* 1998).

In this article, a predictive controller taking the welding speed into account is introduced. As the fast, complex, non-linear process cannot be analytically described in a suitable way for MPC, experimental system identification is carried out to obtain a model for the controller.

2. IDENTIFICATION

The reduced data-driven model of the process has the two input variables laser beam power p and welding speed v. Its output variable is the (measurable) intensity of the plasma emission I. As the specific energy applied to the process is p/v, the process is expected to show non-linear behaviour. Identification of two linear *SISO*-models from p to I and v to I, respectively, will not result in a suitable model for the controller. To cover the whole operating range, a global non-linear model is needed. During different experiments measurements of the laser beam power p, the welding speed v and the intensity of the plasma emission I were collected.

Figure (1) shows a composition of different measurements of the static process behaviour as deviations from an operating point. Using a calibration curve, the

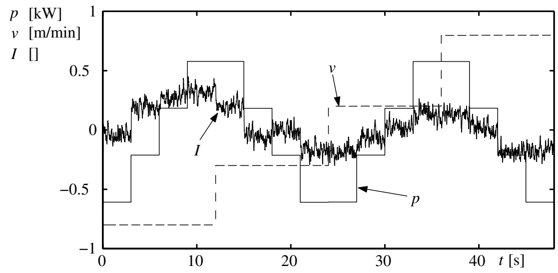

Fig. 1. Process behaviour

measured intensity can be mapped to the penetration depth to describe the quasi-steady penetration depth with time-averaged measurements. As the plasma in the capillary reacts faster to e.g. changes of the laser power than the penetration depth does, the dynamics have to be modelled separately. Like in the penetration depth estimation scheme presented in (Tu *et al.* 1997), where temperature measurements at the bottom surface of the workpiece, weld bead width, laser power and welding speed are used to estimate the penetration depth, an experimentally determined lag element is used to model the dynamics. With this element being considered to be part of the process, also a noise reduction is realized due to its low-pass behaviour. As the neural network is used to identify this element as well as the static mapping, further improvements of the measuring device that reveal the penetration depth's dynamics clearer will then not affect the controller's internal model structure.

Because of their approximation capabilities Artificial Neural Networks are well suited for system identification when a black-box model of a non-linear dynamic process is to be derived from measured data. In 1990, Narenda and Parathasarathy proposed the use of neural networks for system identification and control (Narenda and Parathasarathy 1990). Nowadays, neural networks are established as approximators in many fields. A widely-used type of network is a Multi-Layer Perceptron network (*MLP*) with one hidden layer of neurons with non-linear activation functions and one output layer with linear neurons. For the hidden layer neurons with the hyperbolic tangent activation function are frequently used. Non-linear time discrete dynamic systems can often be represented by non-linear difference equations. Therefore a tapped delay line *TDL* for *nb* by at least d samples delayed system input variables and *na* by at least one sample delayed output variables is used. These so-called *NARX*-structures (Non-linear AutoRegressive, eXogenous input) are intuitively deduced from linear system identification (Sjöberg *et al.* 1995), (Nelles 2001) and with neural networks often used to represent non-linear dynamic systems besides more complex structures with internal dynamics. Examples from various fields show their overall ability to approximate non-linear dynamic systems, e.g. (Previdi *et al.* 1999), (Lightbody and Irwin 1996).

Using neural networks in this framework means that two problems have to be dealt with: finding the right regression vector for the mapping (which means determining the system order) and finding a sufficient number of hidden neurons and determine optimal weights. The first problem is also known in linear system identification theory, the latter is a typical neural network training task. Starting with a considerably higher system order than the applied filter has, time series of p, v and I were arranged as regressors and presented to the network as training patterns. Using a Levenberg-Marquardt algorithm to adjust the network parameters, the one-step-ahead-prediction error was minimized (also referred to as *Prediction Error Method* and corresponds to figure (2), a), NARX). A number of $S_1 = 10$ neurons in the hidden layer gave good results during the training. To obtain a parsimonious model which does not tend to overfitting, the last delay terms were successively pruned and the network was retrained until a remaining system order of $na = 2$, $nb = 3$ and $d = 1$ for both system inputs was left. Further pruning of network inputs decreased considerably the network performance. For further hints see e.g. (Nørgaard *et al.* 2000) and (Gomm *et al.* 1997).

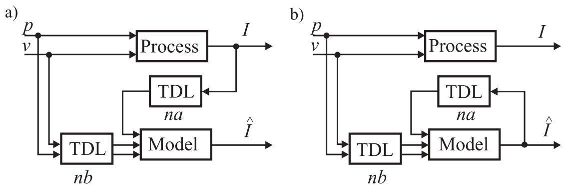

Fig. 2. Serial-parallel (a) and parallel (b) model

For predicting more than one step ahead, this NARX-structure cannot be used, and so for use in the controller the parallel model (cp. figure (2), b)), also called *NOE* (Non-linear Output Error), is mainly used. The resulting neural network has the structure depicted in figure (3).

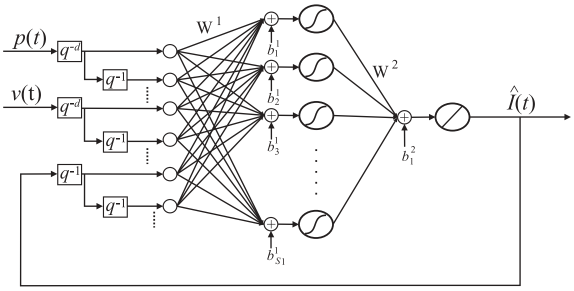

Fig. 3. MLP-network with external dynamics

The mapping of the network at discrete time t can be described by

$$\hat{I}(t) = \sum_{j=1}^{S_1} w_{1j}^2 \cdot \tanh\left(\sum_{i=1}^{na+2nb} w_{ji}^1 \varphi_i(t) + b_j^1\right) + b_1^2 \quad (1)$$

with the output of the hidden layer neurons

$$o_j^1(t) = \tanh\left(\sum_{i=1}^{na+2nb} w_{ji}^1 \varphi_i(t) + b_j^1\right) \quad , \quad (2)$$

where the network inputs for the prediction of time instant $t+k$ are given as a regression vector

$$\begin{aligned} \varphi(t+k) = [\ & p(t+k-d) \quad \dots \\ & p(t+k-d-nb+1) \\ & v(t+k-d) \quad \dots \\ & v(t+k-d-nb+1) \\ & \tilde{I}(t+k-1) \quad \dots \\ & \tilde{I}(t+k-na) \quad]^T \end{aligned} \quad (3)$$

in which the signals $\tilde{I}$ are measurements for time arguments negative with respect to t and predictions otherwise. The weight w_{ij}^k denotes the connection of the ith neuron in the kth layer to its jth input.

The validation of the network's performance as a 25-step-ahead predictor is shown in figure (4) with a sample time of 2.5 ms. The predictor starts in the serial-parallel mode and switches subsequently to the parallel mode approaching the upper prediction horizon N_2. Besides the dynamics of the applied filter, further low-pass behaviour is shown by the network.

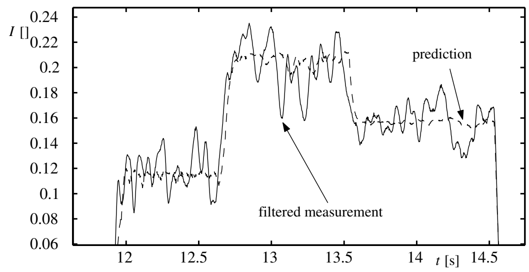

Fig. 4. Validation of the 25-step-ahead predictor

The non-linear network is able to predict the process output with sufficient accuracy in spite of the measurement noise.

3. PREDICTIVE CONTROL

Having an internal controller's model capable of modelling non-linear dynamic processes allows on one hand a wider operating range of the controller, on the other hand a demanding non-linear, perhaps constrained optimization problem has to be solved at every time instant. In e.g. (Sørensen *et al.* 1999) non-linear optimization is used with a neural network model applying a quasi-Newton algorithm, in (Botto and da Costa 1998), also feedback linearization is used to ease the optimization problem. In (Wang and Wan 2001) and (Galván and Zaldivar 1998), respectively, neural networks were also applied to learn the optimal solution instead of computing it analytically. As the computational burden is still high for those approaches and the time behaviour might even be not deterministic, a quite intuitive way, described in (Nørgaard *et al.* 2000) as approximate predictive control (*APC*) is followed for this application as short sample times of 2.5 ms are required due to the fast process dynamics. The approximate predictive controller uses a linear predictor. By instantaneous linearization at each sample step the good approximation capabilities of the neural network and the deterministic behaviour of a linear optimization are then combined.

By Taylor series expansion at time $t = \tau$ one receives as a linear approximation of eq. (1)

$$\hat{I}(t) \approx \hat{I}(\tau) + \left.\frac{\partial \hat{I}(t)}{\partial \varphi_1(t)}\right|_{t=\tau} (\varphi_1(t) - \varphi_1(\tau)) + \left.\frac{\partial \hat{I}(t)}{\partial \varphi_2(t)}\right|_{t=\tau} (\varphi_2(t) - \varphi_2(\tau)) + \ldots . \quad (4)$$

The partial derivatives are

$$\frac{\partial \hat{I}(t)}{\partial \varphi_k(t)} = \sum_{j=1}^{S_1} w_{1j}^2 \cdot \left(1 - \left(o_j^1(t)\right)^2\right) \cdot w_{jk}^1 \quad (5)$$

easily calculated from the non-linear prediction at time instant $t = \tau$ (cp. eq. (2)) and one obtains

$$b_i = \sum_{j=1}^{S_1} w_{1j}^2 \cdot \left(1 - (o_j^1(t))^2\right) \cdot w_{j,i+1}^1 = \frac{\partial \hat{I}(t)}{\partial p(t-d-i)}, \quad i = 0 \ldots nb-1, \quad (6)$$

$$c_i = \sum_{j=1}^{S_1} w_{1j}^2 \cdot \left(1 - (o_j^1(t))^2\right) \cdot w_{j,nb+i+1}^1 = \frac{\partial \hat{I}(t)}{\partial v(t-d-i)}, \quad i = 0 \ldots nb-1 \quad (7)$$

and

$$a_i = \sum_{j=1}^{S_1} -wij^2 \cdot \left(1 - (o_j^1(t))^2\right) \cdot w_{j,2nb+i}^1 = -\frac{\partial \hat{I}(t)}{\partial \tilde{I}(t-i)}, \quad i = 1 \ldots na \quad (8)$$

as coefficients for a linear ARX model and thereby

$$\hat{I}(t) \approx -\sum_{i=1}^{na} a_i \tilde{I}(t-i) + \sum_{i=0}^{nb-1} b_i p(t-d-i) + \sum_{i=0}^{nb-1} c_i v(t-d-i) + e(\tau) \quad (9)$$

approximates eq. (1) with

$$e(\tau) = \hat{I}(\tau) + \sum_{i=1}^{na} a_i \tilde{I}(\tau-i) - \sum_{i=0}^{nb-1} b_i p(\tau-d-i) - \sum_{i=0}^{nb-1} c_i v(\tau-d-i) \quad (10)$$

being the difference between non-linear and linearized model at τ resulting from the bias values of the network which is constant within the prediction horizon. The static non-linear behaviour will be covered quite exactly by the linearized model, while depending on the degree of nonlinearity transients will only be approximated. Therefore, care has to be taken in trusting the 'optimal' solution that can only be valid for the linear model. Setting the weighting factor ρ of future control changes in eq. (25) to a relative high value ensures a smoother control action that is not that strongly dependent on the properties of a single linearized model during one sample step.

The coefficients of the linearized model can be written in polynomial form

$$A\left(q^{-1}\right) = \left[1 + a_1 q^{-1} \ldots + a_{na} q^{-na}\right] \quad (11)$$

$$B\left(q^{-1}\right) = \left[b_0 + b_1 q^{-1} \ldots + b_{nb-1} q^{-nb+1}\right] \quad (12)$$

$$C\left(q^{-1}\right) = \left[c_0 + c_1 q^{-1} \ldots + c_{nb-1} q^{-nb+1}\right] \quad (13)$$

in the time shift operator q and one obtains

$$A\left(q^{-1}\right) \hat{I}(t) = q^{-d} B\left(q^{-1}\right) p(t) + q^{-d} C\left(q^{-1}\right) v(t) + e(\tau). \quad (14)$$

Using $\Delta = \left(1 - q^{-1}\right)$ on eq. (14) to achieve offset-free control action gives

$$\Delta A\left(q^{-1}\right) \hat{I}(t) = q^{-d} B\left(q^{-1}\right) \Delta p(t) + q^{-d} C\left(q^{-1}\right) \Delta v(t) + \Delta e(\tau) \quad , \quad (15)$$

and the *GPC*-algorithm (Clarke *et al.* 1987) for this *ARIX*-model (integrated ARX) can be executed for $N_1 = d$, which will be briefly outlined in the following. The first task is to rewrite the predictor in such a way that the contributions of the single future input signals to the predictions can be separated.

For the time instant $t + k$ applies for the predictor

$$\Delta A\left(q^{-1}\right) \hat{I}(t+k) = q^{-d} B\left(q^{-1}\right) \Delta p(t+k) + q^{-d} C\left(q^{-1}\right) \Delta v(t+k) \quad (16)$$

and by introduction of a diophantine equation

$$1 = \Delta A\left(q^{-1}\right) E_k\left(q^{-1}\right) + q^{-k} F_k\left(q^{-1}\right) \quad (17)$$

with

$$\deg E_k\left(q^{-1}\right) = k - 1 \quad \deg F_k\left(q^{-1}\right) = na \quad (18)$$

the predictions for the time instants $t + d \ldots t + N_2$ can be written as

$$\hat{I} = \Gamma_1 \tilde{P} + \Gamma_2 \tilde{V} + \Phi \quad , \quad (19)$$

where

$$\hat{I} = \left[\hat{I}(t+d)\,\hat{I}(t+d+1)\ldots\hat{I}(t+N_2)\right]^T \quad (20)$$

$$\tilde{P} = [\Delta p(t)\,\Delta p(t+1)\ldots\Delta p(t+N_u-1)]^T \quad (21)$$

$$\tilde{V} = [\Delta v(t)\,\Delta v(t+1)\ldots\Delta v(t+N_2-d)]^T \quad (22)$$

$$\Phi = [\varphi(t+d)\,\varphi(t+d+1)\ldots\varphi(t+N_2)]^T\,. \quad (23)$$

The components of the 'free' controlled variable are given by

$$\varphi(t+k) = F_k\left(q^{-1}\right)\tilde{I}(t) + \sum_{i=1}^{d+nb-2} g^1_{k-d+i}\Delta p(t-i) + \sum_{i=1}^{d+nb-2} g^2_{k-d+i}\Delta v(t-i) \quad (24)$$

where Γ_1 and Γ_2 are matrices of the size $(N_2-d+1)\times N_u$ and $(N_2-d+1)\times(N_2-d+1)$, respectively, containing the coefficients g^i_j of the respective step responses which result with the polynomial F_k from the recursion of the diophantine equation described in (Clarke *et al.* 1987). The 'free' controlled variable describes the prediction of the plasma intensity assuming constant future input variables. The expressions $\Gamma_1\tilde{P}$ and $\Gamma_2\tilde{V}$ show the impact of future changes in laser power and welding speed, respectively, and by defining a quadratic functional which contains the future reference values $r(t+i)$ and the predicted values of the plasma intensity

$$J(t,\tilde{P},\tilde{V},R) = \sum_{i=N_1}^{N_2}[r(t+i)-\hat{I}(t+i)]^2 + \rho\sum_{i=1}^{N_u}[\Delta p(t+i-1)]^2 \quad (25)$$

the laser power can be optimized. By collecting the reference values in the vector R and minimizing the functional by calculating

$$\frac{\partial J(t,\tilde{P},\tilde{V},R)}{\partial \tilde{P}} \stackrel{!}{=} 0 \quad (26)$$

one obtains the optimal solution for the future laser power

$$\tilde{P}_{\text{opt.}} = \left[\Gamma_1^T\Gamma_1+\rho I_{N_u}\right]^{-1}\Gamma_1^T(R-\Phi-\Gamma_2\tilde{V}) \quad . \quad (27)$$

With this approach for the predictive controller, the following scheme results for the closed control loop. The motion planning provides reference trajectories for the welding speed and the desired penetration depth. The latter is mapped to a desired intensity. The motion control loop of the welding system contains the drive dynamics and shows first order lagging behaviour. This is also considered by a prefilter to $\Delta\tilde{V}$ in the MPC. The MPC calculates the optimal laser power taking the future welding speed into account and passes $p_{\text{ref.}}$ as the first element of $\tilde{P}_{\text{opt.}}$ in eq.(27) as actual command value to the cascaded laser power control loop.

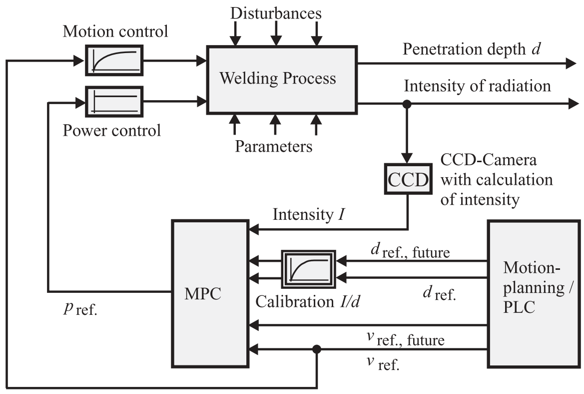

Fig. 5. Predictive control scheme

For practical application, a conservatively tuned *PI*-controller is operated in parallel to the predictive controller and is switched on if the process is leaving the domain covered by the training data.

4. APPLICATION

The described predictive control scheme has been implemented using a dSpace® DSP-system and Matlab®/ Simulink®, where the control scheme has been implemented graphically and the MPC-core being programmed in 'C'. A CCD-Camera (Kratzsch *et al.* 2000) was used to observe the plasma. A PC-system is processing the images from the camera and calculating the intensity value corresponding to the actual penetration depth. This intensity value, the welding speed and the desired penetration depth is then fed into the dSpace system to perform the control task. Various experiments have been conducted to investigate the predictive controller's performance. As one example the compensation of a step-like change of the welding speed by 1.6 m/min is shown. Figure (6) shows the change of the filtered measured intensity I, the welding speed v and the laser power p without controller. The longitudinal section of the weld shows the change in the penetration depth.

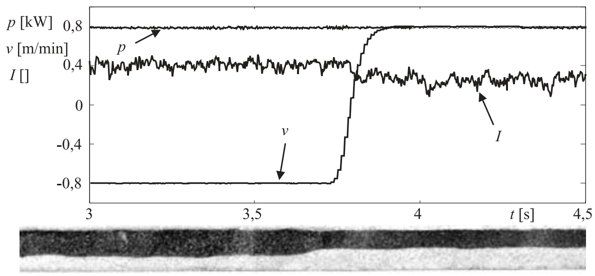

Fig. 6. Plasma intensity and penetration depth for an uncontrolled weld with constant laser power and change in welding speed

Figure (7) shows the filtered measured intensity, welding speed, laser power and a longitudinal section for an experiment with controller. Note that the penetration depth is almost constant as well as at a different level, as the reference value for the intensity was set to be lower than the resulting values in the experiment depicted in figure (6).

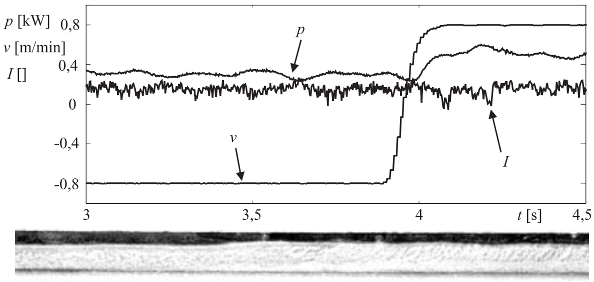

Fig. 7. Plasma intensity and penetration depth for a controlled weld with change in welding speed

5. SUMMARY

Welding with laser beams is an innovative technique for joining materials which experiences a strong increase in a wide variety of industrial applications (e.g. manufacturing car bodies) because of high welding speed and the good quality of the seam. As it is in fact a complex process, means and ways for monitoring and closed loop control have to be applied. Within this article, a predictive control scheme using a dynamic neural network as process model is introduced. The laser power is used to affect the process, taking the welding speed into consideration. For monitoring purposes a CCD-camera is used, calculating the penetration depth from the intensity of the spatially and temporally resolved emission of the plasma. A NARX-MLP-network with external dynamics is used to identify the process and provide parameters for the linear predictor of the controller. Thereby a non-linear neural network model and a well-known linear predictive control scheme are combined and used to control a very fast, non-linear process.

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