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CONTENTS:

Articles:

- Adaptive Process Control in Rubber Industry 253
Rüdiger W. Brause, Ulf Pietruschka
- Prediction of Musculoskeletal Discomfort in a Pick and Place Task
(A pilot study) 271
Claudia P. Kruizinga, Nico J. Delleman, Jan M.H. Schellekens
- Method for Evaluating Germicidal Ultraviolet Inactivation of
Biocontaminated Surfaces 287
*Emily L. Gorsuch, Sergey A. Grinshpun, Klaus Willeke,
Tiina Reponen, Clyde E. Moss, Paul A. Jensen*
- Identification of Ergonomic-Related Hazards in an Industrial
Sample Using the National Occupational Exposure Survey ... 299
Robert J. Biersner, Francis J. Winn, Jr.
- Artificial Neural Networks—Modern Systems for Safety Control 317
Robert A. Kosiński, Cezary Kozłowski
- A System for Measuring Vertical Concentration Profiles of Gaseous
Pollutants, Using Carbon Dioxide as a Case Study 333
Alfred Micallef, Chris N. Deuchar, Jeremy J. Colls
- A Comparison of Skin Temperatures and Clothing Microclimate
During Moderate Intermittent Exercise in the Cold Between One
and Two Layers of Cotton and Polypropylene Underwear ... 347
Minj a Ha, Hiromi Tokura, Kaori Yoden, Ingvar Holmér
- Measurement Accuracy of the Electrosensitive Protective Device
Response Time When Using the Double Penetration Method ... 363
Marek Dźwiarek
- Conference Announcement 385
- Contents Index to Volumes 1-3 I

Adaptive Process Control in Rubber Industry

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This paper describes the problems and an adaptive solution for process control in rubber industry. We show that the human and economical benefits of an adaptive solution for the approximation of process parameters are very attractive.

The modeling of the industrial problem is done by the means of artificial neural networks. For the example of the extrusion of a rubber profile in tire production our method shows good results even using only a few training samples.

extruder mask estimation nonlinear adaptive control neural networks
rubber production automatisisation knowledge accumulation

1. INTRODUCTION

In many industrial processes, the optimization of the process might reduce environmental damage and increase employee satisfaction as well as economical benefits. Here, the key problem lies in the optimal choice of the process parameters, which are typically not available due to several reasons. This contribution tries to show that adaptive methods are important alternatives to conventional solutions.

Let us study this idea in more detail for a concrete type of production: the rubber industry.

1.1. A Rubber Industry Production Problem

Process control in rubber industry has the smell of a "dirty" industrial branch. This branch is not only on the often very dull and dusty rubber

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and tire production rooms where the products are “baked” by heat and steam, but also on the fact that the macromolecular proportions of rubber are hard to predict due to their nonlinear character. When a rubber mixture leaves the extruder (the melting and form-giving machine) after being heated up to 110–140 °C, compressed to 7–14 MPa by a screw conveyor and pressed through a metal mask, the rubber relaxes, that is, it expands or shrinks, depending on the mixture, changing, therefore, its shape in a nonlinear manner by 10–20% up to 50%.

The basic production layout is shown for our example of tire profile production in Figure 1.

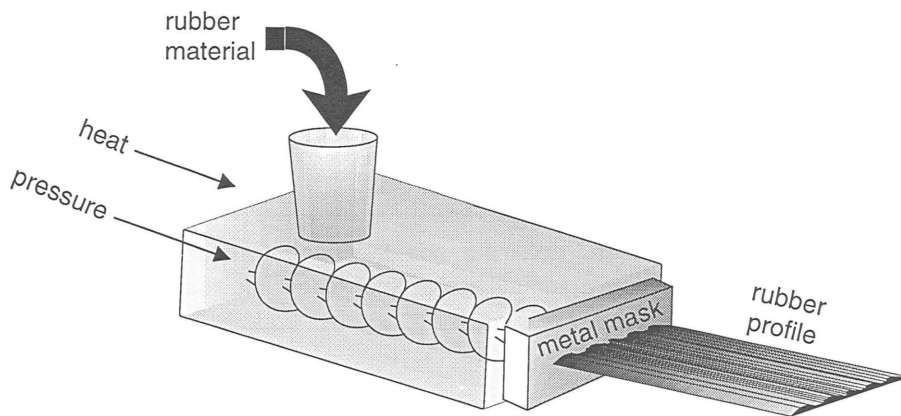


Figure 1. The tire profile extrusion is done by heating up a rubber mixture in a machine called an extruder, until it becomes liquid and then pressing it through a small opening called a metal mask. The outgoing rubber stream expands and solidifies after cooling down in the open air.

The task of process control consists of estimating the necessary extrusion parameters (in our case the unknown best shape of the extrusion metal mask) for an acceptable rubber product after relaxation. Up to now, due to the nonlinear nature of the macromolecular mixture this task can not be solved analytically. Instead, specialized people estimate the profile of the original metal mask by their experience with the subject and correct their estimates after experience. This gives a trial-and-error turnaround production cycle.

This kind of production causes severe disadvantages for the production business. For the management

- the start for a new product is delayed by the time for 2–3 turnarounds, each one taking 4–5 days to make a new mask, install it on the

extruder, make an extrusion try, measure the obtained rubber profile, and estimate a new metal mask;

- this delay does not only waste time, money, and natural resources, but also increases the production overhead and impedes, therefore, the production flexibility severely;
- in the case of illness of an employee or a change to another enterprise, the knowledge is no longer accessible. This causes major obstacles for the production.

Also from the employee's point of view, this kind of production is not satisfactory:

- The experienced employees are tied to this job (which is judged as boring) without the possibility of a change within the enterprise. The only possibility for a job change is to change to another enterprise, which is often not possible due to many economical and personal reasons. Thus, motivation and identification with the job is severely impeded.

In conclusion, there are very attractive benefits of a possible solution to this problem, both on the economical and the human labor side.

1.2. Adaptive Process Control

Now, this kind of parameter estimation problems can be overcome by adaptive process control methods. Generally, these methods are interesting in one of the following situations in industrial process control:

- The process control is analytically not solved. So, until now only crude human estimations or outdated practices have been available;
- In principle the problem can be solved analytically, but it is too expensive, or there is not enough time to do this for every variant of the problem, or there are no qualified people available to do this;
- In principle, the problem can be solved analytically and there are people ready and time available to do this, but the necessary internal parameters of the process can not be measured because either the measuring device will influence the process and, therefore, the measurements themselves, or the measurement is technically not feasible, or it is too difficult, or it is too expensive.

Contrary to the exact analytical solution, the adaptive methods will only update the parameters by an iteration process based purely on the

final, measured outcome data. Adaptive control methods are used in many industry branches, especially for system control and identification (see Narendra, 1986; White, 1992).

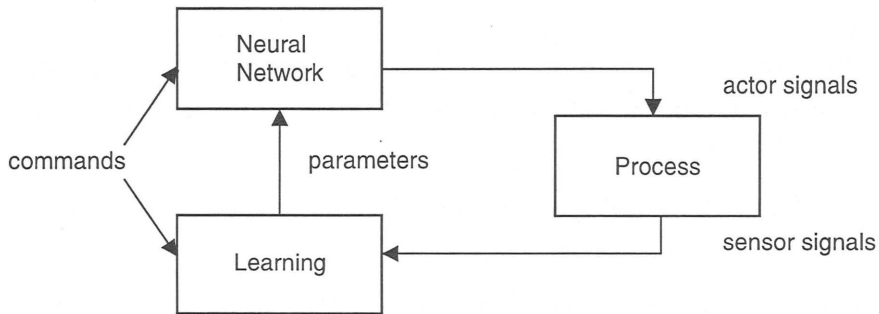


Figure 2. The main layout for adaptive control. The control commands are mapped to the actuator signals (e.g., to pumps, levers, and motors) by a neural network. The parameters controlling the network itself are updated by an adaptive algorithm, which uses the results of the actuator signals (the sensor signals) and the control commands as input. The preprocessing of the sensor signals and the learning may also be done by extra specialized neural networks.

This method is often used in conjunction with the paradigm of Artificial Neural Networks (see, e.g., Haykin, 1994) and Fuzzy Control (Buckley, 1992).

In this paper, we will show how this kind of approach can be used for the concrete problem of tire production. In the following, we consider the problem of approximating the necessary shape of the metal mask by means of an artificial neural network.

2. APPROXIMATING THE EXTRUSION PROCESS PARAMETERS

In order to apply adaptive parameter approximation algorithms, we have to model the industrial process, in our example the tire production. As it is described in the previous section, the main task consists of estimating the profile of a metal mask that extrudes the profile of a rubber band. This band is then cut into stripes of the perimeter length of a tire and then glued to the casing. The raw tire is then baked in a metal tire form for 20 min, which gives the preliminary profile its ultimate form.

2.1. Modeling the Process

Although the extruded rubber profile is a temporary form, its desired accuracy is 0.1 mm. This settles the upper limit for our approximation error. In Figure 3, a sample profile is shown.

The upper profile is the desired rubber profile, the lower one shows the corresponding rectangular metal mask. On the right-hand side, a cut through the metal (shaded area) shows the form of the opening (not shaded). The profile has a wider opening where the rubber flows in. This corresponds to the dotted line, which encircles the profile opening in the metal mask.

The modeling has to reflect the following facts:

- The profile of the extruded rubber band principally depends on the volume of the extruded rubber. The rubber expansion pressure and flow within the profile heavily depends on whether there is a huge amount of rubber, that is, the neighbor parts of the profile have a high level, or if we have very little rubber around, that is, the neighbor parts are low-level. This causes the rubber profile to be also a function of the profile height of the neighbor points;
- Additionally, the extruded rubber profile heights depend nonlinearly on the rubber mixture composition G , pressure P by the screw conveyor, temperature T , and extruder type E ;
- By the nonlinear form of the screw conveyor the pressure along the profile mask (along the axis of abscissae in Figure 3) decreases nonlinearly from the right to the left. This depends on the extruder machine type and on the profile type. Therefore, the rubber profile height also depends on the absolute position on the axis of abscissae of the metal mask.

Nevertheless, the whole system is deterministic: The same rubber mixture G with the same mask $g(x)$, temperature T , and pressure P result in the same rubber profile $r(x)$ on a different extruder machine of the same type E :

$$g(x) \xrightarrow{G, T, P, E} r(x)$$

The analytical treatment of the nonlinear dependencies is very difficult. Conventional assumptions about energy (i.e., enthalpy) conservation are not valid here, because the system is not closed and shows nonlinear molecule behavior. Also, the direct measurement of the

process parameters like temperature and pressure in the profile are practically limited. The sensors have to be incorporated in such a way that they do not constitute obstacles themselves, otherwise the pressure conditions will be immediately changed and give different results. This is practically impossible or very expensive.

In contrast to this, our adaptive approach models the system as a whole, avoiding all differential equations and constants that are hard to devise and to measure. Especially the model of a neural network with only locally distributed input for each neuron underlines the local character of the modeling.

We divided the whole profile, depending on the tire width, into 170–270 points, which are placed in the regular distance of δ mm. For the comparison of profiles with different width, the centers of the profiles were lined up and treated as the common middle point of the grid. Each point on the grid has a desired rubber profile height $r(i)$. As the profile data initially contain only points of profile change ($x_1, r(x_1), x_2, r(x_2), \dots$) the intermediate points are generated by interpolation (Figure 4).

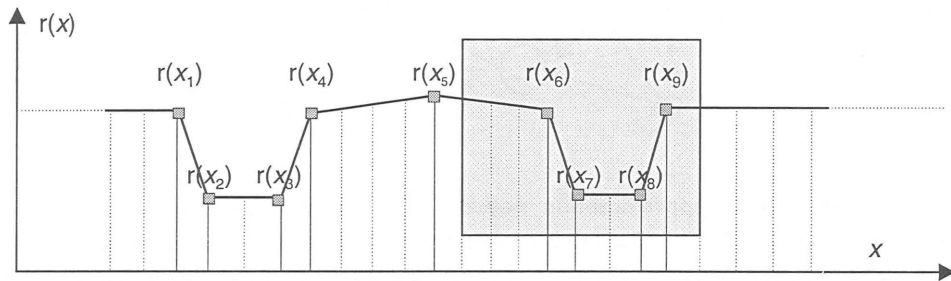


Figure 4. The interpolation of the rubber profile. The intermediate points are obtained by equidistant points and are denoted by dotted lines.

As the influence of the neighborhood is limited to a certain number s of sample points for a certain rubber profile height $r(i)$ we have only to consider $k = 2s + 1$ influencing sample points as parameters for the unknown metal mask function $g(x)$

$$g(x) = F(r_{i-s}, \dots, r_i, \dots, r_{i+s}, i, G, E, P, \dots) \equiv F(x_1, \dots, x_n)$$

In this model, we implement a neighborhood window, which uses $k = 2s + 1$ sampling points around location i . All values r_k for the sampling points outside the profile limits are set to zero.

3. THE APPROXIMATION NETWORK

In this section we want to derive an algorithm for approximating the exact extruder metal mask profile $f(\mathbf{x})$ at location $\mathbf{x} = (x_1, \dots, x_n)$ by a neural network, implementing the approximation function $F(\mathbf{x})$. The metal mask will, in turn, produce the desired rubber profile $r(\mathbf{x})$. It is well known that a two-layer neural network can approximate any continuous function to any degree of accuracy, provided that we have enough neurons in the first layer (see Hornik, Stinchcombe, & White, 1989; Xu, Krzyzak, & Yuille, 1994).

3.1. The Activity Network

Now, for our purpose, let us assume a two-layer network like the one in Figure 5.

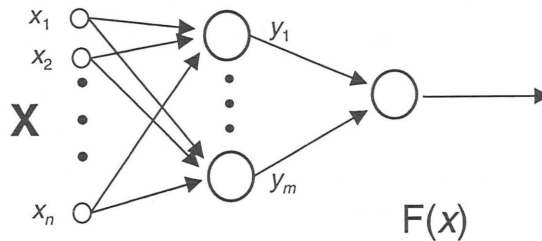


Figure 5. The activity approximation network. The input lines $\mathbf{x} = (x_1, \dots, x_n)$ are processed by special RBF (Radial Basis Functions) units, denoted as black circles. Their outputs y_i are linearly weighted, added together, and form the network output $F(\mathbf{x})$. All units with the same function are grouped vertically in one layer. Thus, we have two layers: m RBF units in the first layer and one unit as the second layer.

Each layer is composed of computational units called neurons. Each neuron computes a function $S(\mathbf{x}, \mathbf{w})$ of its input \mathbf{x} and its parameters \mathbf{w} .

Let us define the activity $\mathbf{y} = (y_1, \dots, y_m)$ of the first layer by the activity of the i -th unit

$$y_i = S_i(\mathbf{x}, \mathbf{c}_i) = e^{-d_i^2} \quad i = 1 \dots m \quad (1)$$

and the activity of the second layer by the linear function

$$F(\mathbf{x}) = F(\mathbf{y}(\mathbf{x})) = \sum_{j=1}^m w_j y_j = \mathbf{w}^T \mathbf{y} \quad y_0 \equiv 1, w_0 \cong \text{'bias'} \quad (2)$$

This models the approximation function $F(\mathbf{x})$ as a linear superposition (weighted sum) using m nonlinear basis functions S_i that depend only on the Mahalanobis distance d_i between the input \mathbf{x} and a neuronal center \mathbf{c}_i .

$$S_i(|\mathbf{x} - \mathbf{c}_i|) = S_i(d_i) \quad d^2 = |\mathbf{M}(\mathbf{x} - \mathbf{c})|^2 = (\mathbf{x} - \mathbf{c})^T \mathbf{M}^T \mathbf{M} (\mathbf{x} - \mathbf{c})$$

The fact that the activity $S(\cdot)$ depends only on the distance (radius) $|\mathbf{x} - \mathbf{c}_i|$ from a center gave them the name Radial Basis Functions (RBF).

For adapting and scaling the ellipsoidal input field controlled by the matrix \mathbf{M} , we used the scaling equation

$$\mathbf{M}^{\text{NEW}} = (\mathbf{I} - \gamma(1 - \alpha)(\mathbf{a}\mathbf{a}^T))\mathbf{M}^{\text{OLD}} \quad \mathbf{a} = (\mathbf{x} - \mathbf{c})/|\mathbf{x} - \mathbf{c}| \quad (3)$$

with the scaling factor α and the learning rate γ (see Pietruschka & Brause, 1996).

There are principally two approaches to train the network parameters: Either we train the two layers separately or as a whole.

The approach of treating the two layers separately, clustering the input space first and then optimizing the weights of the second layer, is fast, but it has some flaws. This gives us a high sample density of output values where we have clusters of input samples, not where the output error is high.

Therefore, we optimize both layers at the same time. To avoid the computational problems of the backpropagation (Rumelhart, Hinton, & Williams, 1986) approach, we choose a different strategy. We start with the lowest possible complexity of the network and gradually increase the number of neurons in the first layer until the error is sufficiently reduced. This was already proposed for RBF nets, for example, by Schiöler and Hartmann (1992). We insert the neuron at location \mathbf{x}_k , the k -th sample with the maximal error that has to be compensated by the new m -th neuron. We have to design the width \mathbf{M}_m such that it fits the new basis function in the context of all neighboring neuron basis functions. In contrast to the approach of Platt (1992) we do not use gradient descend technique to rearrange all other neurons and adapt all their receptive fields: This is computationally intensive and is the source of new errors. Instead, we stop the adaption process of the new neuron by the criterion of nonsignificant activation on a data point. Additionally, we reduce the long distance neighborhood influence by a learning rate $\gamma(d)$ which drops with increasing distance from \mathbf{c}_m , that is, with decreasing activity level (see Pietruschka & Kinder, 1995).

The whole growing and initialization learning algorithm, called GGRBF (growing generalized RBF), can be formulated in pseudo code. With the maximal tolerated Error TolErr end the maximal number m_{\max} of neurons we get

GGRBF:

```

m:=0; Errset(TrainingSet) :=f(Inputset);
WHILE ( max(Errset)>TolErr ) AND (m<mmax) DO
  x = coord(max(Errset))      (* location of maximal error *)
  InsertNeuron(x)
  AdaptTo1stNeighbor(Mm);    (* Equation 3 *)
  level:=1;  $\gamma$ :=1;          (* start with high activation level*)
  WHILE level>0.01 DO
    FOR i:=1 TO |TrainingSet| DO
      IF  $S_m(\mathbf{x}_i)$ >level THEN AdaptToNeighbor( $\gamma$ ,  $\mathbf{x}_i$ , Mm) ENDIF
    ENDFOR
     $\gamma$  :=  $\gamma$ *0.87;          (* diminuate learning rate *)
    level:=level-inc;         (* lower the attention level *)
  ENDWHILE
  m:=m+1                      (* new neuron installed *)
  computeErrset(TrainingSet); (*  $\Rightarrow$  new error landscape *)
ENDWHILE

```

4. SIMULATION RESULTS

The algorithm in section 3.1. was implemented and the approximation was simulated with real process data. An important key for the simulation performance turned out to be the two parameters: k , the number of neighborhood sampling points, and δ , the distance between the sampling points. The proper choice is determined by balancing the counteracting influences:

- If we choose δ too small, we increase the number of necessary sampling points for a certain neighborhood and increase, therefore, the dimension of the input space. As we have only a small limited number of training samples, the training becomes very difficult as the input space becomes very sparse. On the other hand, if we choose δ too big, important information can be lost due to undersampling the dependency function;

- If we choose k too big, we encounter the same problem of dimension inflation and training difficulties due to the sparseness of the training samples in the input space. Additionally, by increasing too much context information, the generalization ability of the network will be limited. On the other hand, if we limit the window too much, necessary context information that helps to distinguish between different situations is ignored, resulting in an unnecessarily randomized training.

From the theoretical point of view, this is an interesting situation. Nevertheless, we are not yet aware of an applicable method of determining the optimal δ and k to solve the problem of optimal training. Therefore, we decided to simulate different configurations in order to get an acceptable choice for the parameters.

We generated the training set by shifting a window (determined by δ and k) by an increment of 1 mm over the profile data of 5 profiles with the same values of G , E , and P . This generated 1346 training patterns. The sixth profile was used for the generation of test set of 271 test points. Our multidimensional approximated function became

$$g(i) = F(r_{i-s}, \dots, r_i, \dots, r_{i+s}, i, w)$$

with w being the weight per meter of the extruded rubber band. The simulation results generally showed only a very small influence of the position i . So, let us consider other dependencies.

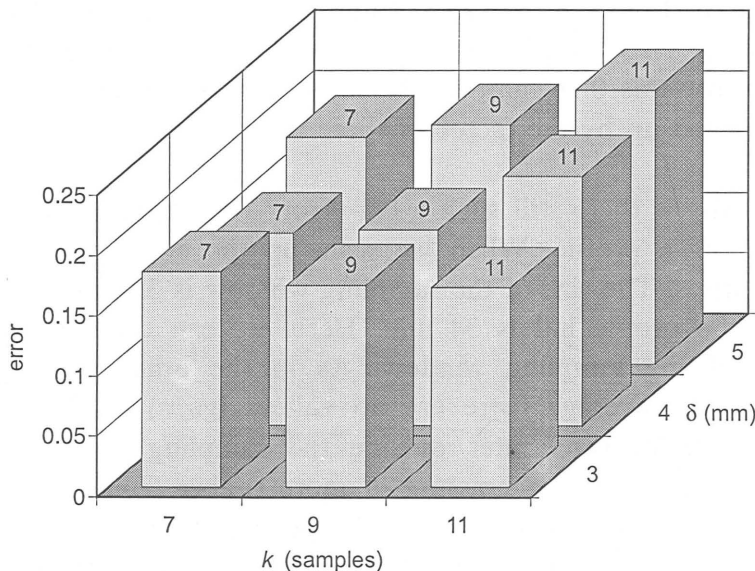


Figure 6. Error development for different parameter values of δ and k .

For the expected absolute error for 100 neurons we got different results. The best performance converged by training to the following expected absolute error, depending on the number of sampling points k and the interpoint distance δ . In Figure 6, this is shown for $k = 7, 9, 11$ for each of the intersample distances of $\delta = 3, 4, 5$ mm.

It is interesting to see that the error does not automatically decrease when we increase the number of sampling points. This is also valid if we consider instead the window size implied by the neighbor sample set size and the intersample distance δ (Figure 7).

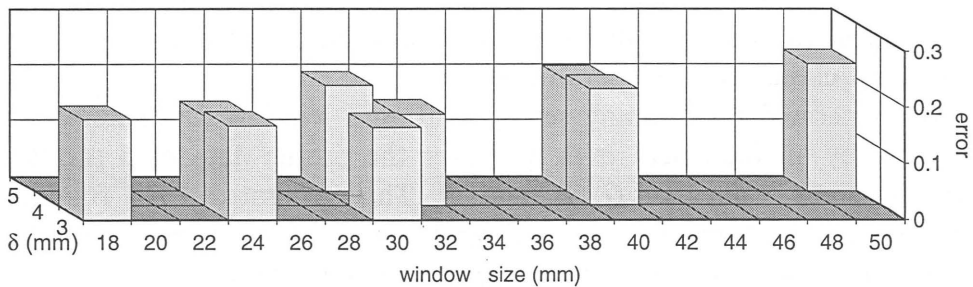


Figure 7. Error development and window size.

There is a configuration of the parameters where the balance is roughly met and the error becomes quite small. The best results are observed by $k = 9$ and $\delta = 4$ mm, which corresponds to a window size of 32 mm. In Figure 8, the test profile, the result of the network, and the resulting error are shown for this configuration. The expected absolute error was 0.16 mm, the maximal absolute error 0.56 mm. The y -axis is scaled up by the factor of three to enhance the visibility of the errors.

Now, why is there still such a big error? For example, let us regard the center of a profile. When we scale up the error, the drawing in Figure 9 arises. The size of the sampling window is 32 mm, whereas the width of the profile hill is 34 mm. Here, we can observe the typical influence of the sampling window: As in the other training profile samples in the average there are no valleys (gaps) on the right and left-hand side of the center outside the sampling window, the net "assumes" the expansion pressure of more rubber from the right- and left-hand side. This would increase the profile at the center. But here, this is not the case, so without the anticipated rubber neighbor pressure the desired height in the center is not reached and an error occurs.



Figure 8. The desired profile and the profile produced by the net for $k = 9$, $\delta = 4$. For visualization purposes, the y -axis (the profiles and the error) scaling is enlarged 3 times compared to the x -axis. One can clearly see that the error is especially increased in the neighborhood of strong changes in the profile.

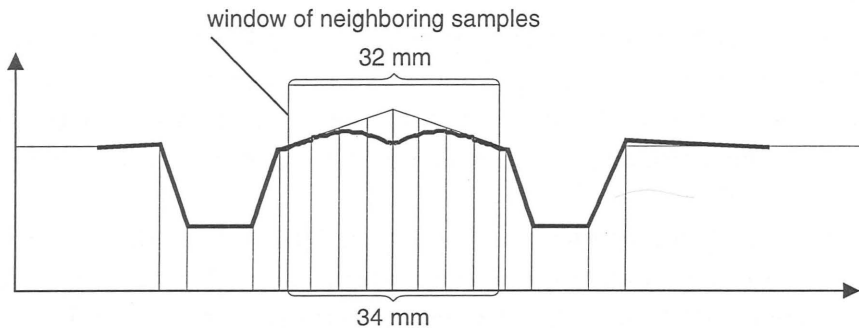


Figure 9. The error and the sampling window size ($k = 9$, $\delta = 4$). When the sampling window is too small, the deep ridges at the left- and right-hand side are not seen by the system and the prediction assumes too much rubber volume flow from the sides to the middle. This results in faulty estimation of the necessary metal profile in the middle.

In order to get rid of this effect, we have to enlarge the window and include the neighbor information about the desired gap, that is, about the lack of rubber material in the neighborhood. If we do this, we have experienced that the error will go up also. Why?

This can be explained by the following. All samples $r(j)$ near the point i of estimation in the profile are not completely independent of the value $r(i)$: The profile does not consist of random data. Thus, when we

add more or less correlated samples we do not automatically add information to the training. Instead, the interdependencies "confuse" the learning system. We have a sparse input space: If we enlarge the input space (by adding additional variables) without filling it with training patterns, the whole system learns less. This problem is known as the "curse of the dimensions" (Huber, 1985). The only remedy for this problem is either the augmentation of the number of training patterns (which is not available) or the appropriate deletion of unnecessary input lines, that is, variables. The current neural methods for the latter concept include weight pruning (see, e.g., Huberman, Rumelhart, & Weigend, 1991) or dimension reduction techniques by Kohonen maps (see, e.g., Bruske & Sommer, 1997). Nevertheless, to our knowledge, there exists no analytical method yet for a proper selection of the distances and related numbers of the necessary sample points.

5. DISCUSSION AND OUTLOOK

In the previous sections we have presented an adaptive solution for the problem of unknown process parameters in tire production. The proposed neural network learns the function that estimates the form of the metal profile for the extrusion of a rubber band when the rubber profile is given as a goal.

The learning algorithm uses no internal process variables or other intrinsic knowledge but only the measurable external process parameters as the weight per meter and the resulting rubber profile. In Figure 10, the layout of the adaptive control and the control migration from the human subject to the automatic system is shown.

In our case, the migration from the handmade mask specification to the automatic, net generated version can be made gradually and smoothly, leaving the control over the whole migration process always in the hand of the human.

In the beginning, the neural network profile prognosis is only used by the human operator as an additional information source. In Figure 10, this is shown by a solid arrow. When the net has learned sufficiently and the prognostic error has decreased, the switch to the automatic profile generation (dotted line in Figure 10) can be made. The human operator always has the full control over the usage of the adaptation process, which is a strong source of human acceptance for all automation projects.

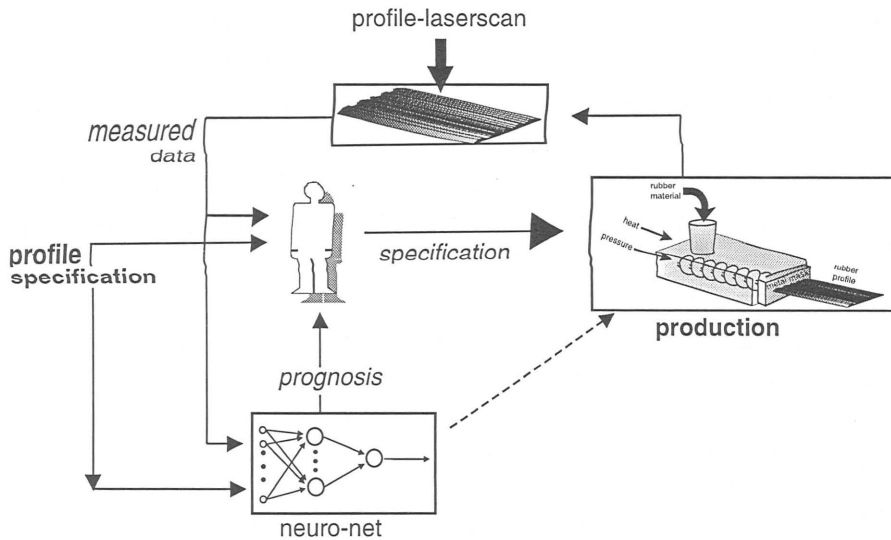


Figure 10. The principal feedback lines in the profile specification. The specification is initially tied to the human operator, who estimates the parameters for the conversion of the desired rubber profile to the metal mask profile. The produced rubber profile is then scanned and measured by a laser scan unit. This reveals an estimation error, which is corrected by the human operator. With a neural network system, the estimation and correction process is automatic. According to the performance error and the obtained accuracy, the migration of the profile specification from the operator (solid arrow) to the neural system (dashed arrow) can be controlled by the operator.

This approach has many technical advantages:

- There is no intrinsic system knowledge necessary like nonlinear dependencies or differential equations for modeling;
- The same adaptive program can be used even when the parameters change due to a change in the nonmodeled system background context;
- There is the theoretical possibility to obtain all necessary estimation parameter values for a new rubber mixture just by training with one standard profile. By the usage of a generalized adaptation, the initial parameters will determine the correct metal mask for all possible desired profiles.

This results in solid economic advantages:

- By involving a computer-based adaptive learning, the knowledge is automatically collected;

- The start for a tire production can be scheduled in a short time interval. This makes the production more flexible and competitive;
- The minimization of the trial-and-error cycles saves a lot of money and resources;
- The better profile estimations also save rubber material. It is estimated that saving 1 mm of rubber material on each profile will result in the saving of about US\$ 0.8 million per year. This is also interesting from the environmental point of view;
- The introduction of high-tech tires that contain multilayer rubber profiles is a new challenge for the human designers. Here, the automatic adaptive estimation technique can help a lot to produce high quality tires with a short setup period only.

Also, the human operator profits by the system:

- The task becomes less boring,
- The human operators are no longer tied exclusively to this production step.

Our work also shows that there are still several problems to be solved, for instance, a method to overcome the curse of dimensions by a proper method to select independent input sample points for the network.

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