Modelling and Control of the Web-Fed Offset Newspaper Printing Press

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Keywords: colour control, neural network, newsprint

Abstract: We present an approach to modelling and controlling the web-fed offset printing process. An image processing and artificial neural networks based device is used to measure the printing process output – the *observable variables*. The *observable variables* are measured on halftone areas and integrate information about both ink densities and dot sizes. From only one measurement the device is capable of estimating the actual relative amount of each cyan, magenta, yellow, and black ink dispersed on paper in the measuring area. We build and test linear and non-linear printing press models using the measured variables and other parameters characterising the press. The *observable variables* measured and the press model developed are then further used by a control unit for generating control signals – signals for controlling the ink keys – to compensate for colour deviation. The experimental investigations performed have shown that the non-linear model developed is accurate enough to be used in a control loop for controlling the printing process. The control accuracy – the tracking accuracy of the desired ink level – obtained from the controller was higher than that observed when controlling the press by the operator.

1. Introduction

In lithographic printing a key issue to produce a high quality print is to control the amount of ink dispersed on the paper. In web-fed offset, such as newspaper print, most parts of the process is highly automated. However, one step in the process, namely the control of the inking level is still mostly done manually.

The operator controls the amount of ink dispersed on the paper by controlling the flow of ink to the printing plates. The ink demand is determined by the inked area of the printing plate. The ink is fed from an ink tray by a special roller, ink ductor, through a small adjustable gap controlled by a metal plate – the ink key. These ink keys are divided into narrow areas – ink zones – across the printing press.

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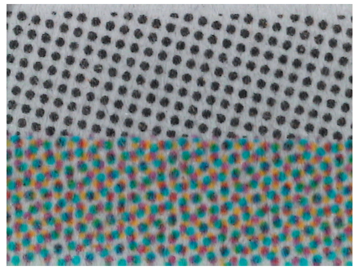

Fig 1. Sample of a grey-bar.

The operator controls the flow of ink, our *adjustable variables*, by adjusting the settings of the ink keys.

Three basic choices have to be made when attempting to automate the ink feed control. More specifically, one must choose the way *to quantify* the degree of deviation in the inking level from the desired one, the way *to model* the process, and the way *to control* the process.

To quantify colour deviation, traditionally solid ink density has been used in the graphic arts industry. However solid ink density, when used as a colour deviation measure, have some drawbacks, for example, it does not reflect the influence of water and other factors on halftone screens.

An ideal instrument would, when placed on a four-coloured print, show how the amount of cyan, magenta, yellow, and black ink need to be adjusted. To be able to determine the adjustment levels, the measured values have to be compared to desired ones. Two major problems then arise. One of determining the measuring position and one of determining the desired value.

Controlling colour by using grey balance have become popular. To do this, test-areas – grey-bars – composed of two halftone screen parts are used, as shown in figure 1. One part of such a bar is printed as a black halftone screen, and the other one as a balanced mix of cyan, magenta and yellow halftone screens to produce a neutral grey print of the same darkness. Grey-bars, originally developed for the naked eye, can also be used to measure on. Measuring on grey-bars does not pose the positioning problem.

We have recently developed an instrument called Malcolm for measuring the amount of ink on grey-bars (Malmqvist et al. 1999). The Malcolm instrument is a multi-functional instrument for print quality control in newspaper printing. The Malcolm instrument is equipped with four main tools for Measuring *Colour Impression*, *Dot Size*, *Density*, and *Registration*.

The *Colour Impression* is a quantity integrating information from both dot sizes and ink densities and yields the amount of ink in the measured area separately for cyan, magenta, yellow, and black.

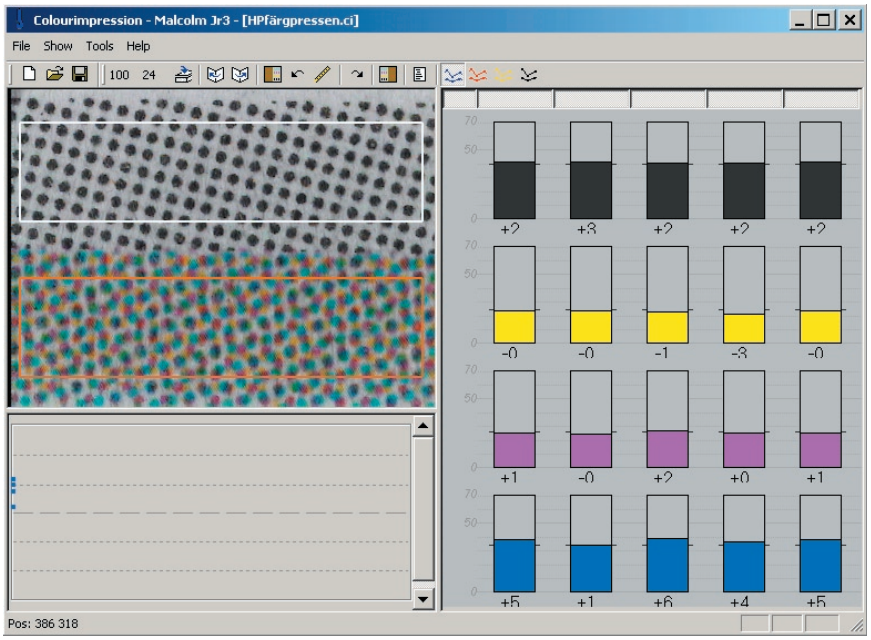

Fig 2. Malcolm screen showing the Color Impression values.

The Malcolm Instrument is optimized to measure *Colour Impression* on grey-bars. The *Colour Impression* values are provided separately for each ink. The values are independent of registration and overprint. *Colour Impression* values are normally presented to the operator as a difference between the value measured for the actual print and the reference print. Thus the values indicate if the operator should increase or decrease the amount of ink. Figure 2 illustrates the main window of the *Colour Impression* tool.

To model the printing process we use both linear and neural network based non linear models.

To control the process we build and test four different controllers: the press operator model based controller, the model predictive controller, the fuzzy logic controller, and the printing press inverse model based controller.

2. Related work

By measuring the amount of ink using a densitometer or the Malcolm Instrument the operator gets a hint on how to control the printing process. The operator has to do all the interpretation of the measured values and ”translate” them into what actions have to be done.

There have been several attempts to develop systems for controlling the ink flow process. The systems can be categorised into two groups, namely support systems and control systems.

A support system is an expert system used to guide the press operator in the decision process when minimizing the colour deviation in the printed result from the desired one. An example of such an operator support system is the system called CONES (Almutawa S. et al. 1999). The CONES system is a neural-network based expert system that was developed in order to model the behaviour of an experienced press operator taking actions to compensate for colour deviations. The CONES system has been designed to capture the expertise of an operator obtained on a specific machine. The CONES system consists of a neural network, and a rule based expert system.

The CONES system operates in Expert Mode or Novice Mode. In Expert Mode, the system is trained by following the on-line remedial control actions taken by an experienced operator. The purpose of training is to extract the relationship between the *observable* and *adjustable variables.* As an *observable variable* the CONES system uses solid ink density measured on control bars. Density is sampled from the match-print and the actual prints. In the Novice Mode the operator is given advice from the CONES how to adjust key settings to obtain recommended density.

The major conclusion drawn from the development of the CONES system is that the operator's knowledge was specific to the particular machine, where all tests had been made.

A control system is a system that is able to directly control the press. In this case, the measure of the inking level must be obtained on-line. In a semiautomatic control system, first, the press operator adjusts the inking level to the desired one, thereafter the control system keeps the level throughout the job run.

A fully automatic control system can control the inking level without the press operator have to intervene. An example of a control system was presented at TAGA 2000 by Pope (Pope B et al. 2000). The paper describes the results of an implementation of an on-line colour control device. The device was tested in a real-time environment and compared with an open-loop system.

The paper proposed three hypotheses. First the on-line closed-loop colour control system should reduce long-term drift in ink densities. Secondly, short-term variations should be reduced as well. The third hypothesis is that the system should be capable of running the press to programmed target densities during the printing process.

Experiments were run on a heatset press in a commercial printing shop. The system used a spectrophotometer and a video camera to measure solid ink density in bars on line.

The first hypotheses appears to be ”semi-true”, meaning that though long-term drifts are corrected by the closed-loop system, operators also manage to correct the drifts, though not as quickly as the closed-loop system. The second hypothesis is true. Short-term variations are strongly reduced by the closed-loop system. Even the third hypothesis has shown to be true. The closed-loop system drives the press, during make ready, to the desired densities.

Both the CONES and the closed loop system use solid ink density as *observable variables.* By contrast, to model and control the printing process we use the *Colour Impression* values.

3. Modelling the printing process

Building mathematical models of dynamical systems by observing input and output data (system identification), is a necessary step in investigating the system behaviour and constructing a controller.

3.1 Process variables

Numerous variables need to be measured or estimated for modelling the printing process. We categorize the process variables into three groups, namely *observable, adjustable*, and *additional variables.*

Our *observable variables*, the *Colour Impression* values, are measured on greybars.

The *adjustable variables* are the variables used to control the inking level. The only *adjustable variables* we use in this work is the ink key levels. In future work it may be necessary to control other press parameters such as ink ductor speed, dampening degree and others.

In addition to the *observable* and *adjustable variables* we use a set of *additional variables* characterising the printing process. Some of them are determined in advance and do not change during the job run, others constantly changes during the job run.

To ensure an even film of ink to the printing plate, ink is fed to the plate through a number of ink rollers. One or more of these rollers oscillates sideways to even out banks or traces of scratches. This causes ink to flow not only in the machine direction but also locally in the cross direction. In our models, we take this cross flow into consideration.

We obtain all our *observable variables* off-line after the job run. By taking samples both prior and after the operator changes of the *adjustable variables* we can take into account the press dynamics.

The whole set of variables needed for modelling the printing process is listed below:

x_1, x_2 – the copy number, and the printing speed in copies per hour, respectively.

x_3, x_4 – the ink ductor speed, and the ink tray level, respectively. In most presses the ink ductor speed is changed when print speed is changed in order to compensate for the change in ink flow due to the speed. The level of ink in the ink tray influences the pressure at the outlet and therefore it does influence the ink flow in the press. We have chosen not to use x_3 and x_4 in the tests we present here, since our tests were done during the relatively short job runs at a constant speed.

x_5 – the CTP dot size error compensation. The parameter used to compensate for errors in dot sizes on the printing plate depending on the behaviour of the CTP. We have chosen not to use x_5 in the tests we present here, because we used the same CTP to produce all the plates, and the behaviour of the CTP did not change during the relatively short period of the tests.

x_6, x_7, x_8 – the estimated *ink demand* – the desired amount of ink for a given area (ink zone). *The parameters* x_6 and x_8 are *ink demands* for the left-adjacent and the right-adjacent ink zone, respectively. The estimated *ink demand* depends on the job and does not change during the job run.

x_9, x_{11}, x_{13} – the ink key settings prior to the change of an *adjustable variable*. The parameters x_9 and x_{13} are obtained from the left-adjacent and the right-adjacent ink key, respectively.

x_{15} – the *Colour Impression*, our *observable variable,* from the previous time step (prior to the change of an *adjustable variable*).

x_{10}, x_{12}, x_{14}, and x_{16} – are given by x_9, x_{11}, x_{13}, and x_{15} after the changes of the *adjustable variables.*

3.2 Linear model

In the linear model, the output variable y – the *observable variable* (the *Colour Impression* in our case) – linearly depends on the input variables x_i characterizing the printing process:

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + ... + w_nx_n \qquad (1)$$

were w_i are the parameters of the model and n is the number of model parameters. We find the parameters of the model by minimizing the sum of squared errors.

To examine the importance of each variable and to get information if any variable can be excluded from the model, we use the so called Z-score test (Hastie T. 2001).

3.3 Non linear neural network based model

If the relationship between the process input and output is not linear we need a

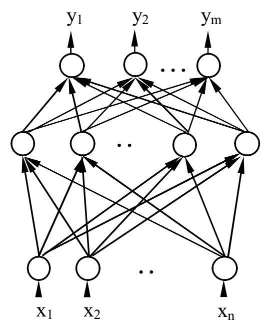

Fig 3. Example of a feedforward neural network.

non linear model for modelling the process. To build non linear models, we use neural network based methods which have proven themselves to be very good at modelling non linear systems. Neural network based methods do not require any apriori knowledge about the data distributions.

A neural network is a parallel, distributed information processing structure of processing elements interconnected via signal channels called connections. The strength of the connections are characterised by weight values. Most known neural networks have their processing elements divided into subsets called layers. Fig. 4 shows a typical feed forward (no recurrent connections) neural network with explicit division of processing elements into three layers. The layer related to the input, $x, x_2 ... x_n$, is called an input layer and that related to the output, $y, y_2 ... y_m$, is called an output layer. The internal layers are referred to as hidden layers. The type of function performed by a network of a given structure depends on values of weights that are determined by minimising some error functional. The estimation process of network weights, which is most often done by using the error back-propagation algorithm (Bishop 1997), is called learning or training. See for example (Bishop 1997) for a deeper study of feed forward neural networks. In our work, we use feed-forward neural networks with one hidden layer, such as the one shown in Figure 3.

4. Controlling the printing process

We can use different approaches when building our controller. The controller can be based on a forward model which predicts the *observable variables*, or an inverse model which predicts the *adjustable variables.*

An open loop controller predicts a control signal independent of the process current value. A closed loop controller acts upon changes in the process and therefore depend on the status of the process. We can choose to build either an open loop or closed loop controller because we have values both before and after changes of our *adjustable variables.*

We have built and tested four different controllers. The model predictive controller – controller which has been recognized as being an effective tool for tackling some of the difficult control problems in industry, the fuzzy logic based controller, the inverse press model based controller, and the press operator model based controller.

We have chosen to present here the test results obtained from two controllers. The press operator model based controller was chosen because it is interesting to model the behaviour of the printing press operator. We can assume that a press operator models, to some extent, the inverse behaviour of the printing press. Therefore the inverse press model based controller was included to. We have tested these two controllers using both linear and neural network based non-linear models.

4.1 The press operator model based controller

The press operator model based controller is an example of an inverse model based controller. The model predicts the required control signal. Based on the *observable variables* and other variables influencing the printed result, the operator takes a decision how to adjust the inking level. The press operator model based controller is trained to extract the relationship between the *observable*, *adjustable*, and *additional variables* by observing the actions performed by an experienced operator when adjusting for colour deviations. Both linear and non linear models have been implemented and tested. We can expect that the behaviour of the press operator model based controller will be highly dependent on the operator/operators involved and their skills. Such a controller can hardly perform better than the operator. It is also known that operator's knowledge of an offset printing press is specific to the particular press.

The variables x_1, x_2, $x_6 - x_9$, x_{11}, x_{13}, and x_{15} are the input variables used for modelling the operator behaviour. The variable x_{12} is the output variable of the operator model and the controller.

4.2 Inverse model based controller

The press operator model based controller models the behaviour of the press operator, while the inverse model based controller models the inverse dynamics of

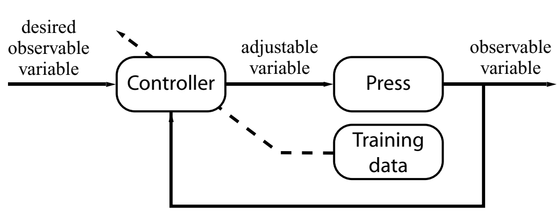

Fig 4. Flowchart of an inverse model based controler.

the press. There is an analogy between these two controllers. An ideal operator would behave as a good inverse model based controller. Figure 4 shows the flowchart of the inverse model based control configuration.

The variables x_1, x_2, $x_6 - x_9$, x_{11}, x_{13}, x_{15}, and x_{16} are the input variables to the controller, and the variable x_{12} is the output variable from the inverse printing press model and the inverse model based controller.

5. Experiments

5.1 Experimental setup

Before our experiments started, the press was investigated and adjusted. All ink keys where adjusted according to the manufacturers instructions to ensure that all ink key settings are comparable.

The dampening system of the press consists of spray ramps with eight valves and nozzles each. The amount of water emitted from each individual valve/nozzle was measured for different settings. In this way it was possible to give each valve an individual setting to ensure that the same amount of water was emitted from each valve.

The reaction of the printing press to changes in ink key settings was investigated in order to ensure that samples are taken as soon as possible after adjustments in ink key settings, but not before the changes of the *observable variables* caused by the adjustments of ink key settings fade away. The investigations showed that the *ink demand* has a big influence on the reaction time. The reaction time is short at high or medium *ink demand* and increases at low *ink demand*. Problems occur when decreasing the ink key settings at very low *ink demands.* In such a case, it can take a very long time to "get rid of the ink in the press". If we exclude cases with very low *ink demand,* two minutes is a sufficient, but not to long waiting time to take a sample after a change of ink key setting.

The experimental tests were done in ordinary production on a four high offset newspaper printing press. The press has 38 ink zones for each cylinder. Each ink zone is approximately 42 mm wide. Samples were collected at 12 occasions during the first part of the job runs, during approximately one hour of production each. During the 12 job runs the same type of newspaper was printed, and the same type of paper was used.

All the print runs started off with a "cold" press. The press used, uses a preset system to adjust the ink key settings prior to production. This reduces the workload of the press operator and decreases the number of adjustments the press operator has to do during the start-up. This was unfortunate for us, because we got fewer data samples per job run, and less variations in our data set.

5.2 Data collection

We used a log system to record all our variables during the 12 job runs. The log system recorded the *ink demand* for each ink zone and ink, and all the changes of the variables x_1, x_2, $x_6 – x_{13}$ for each ink and ink zone during the job runs.

All adjustments made by the press operator during the job runs were followed by the log system and the page number where the adjustments have occurred was recorded. Every time the log system recorded a "new" change for a page, a change of setting of any ink key for any ink, one sample – one newspaper copy – was collected. When no more changes were recorded for that page by the log system during the two minutes delay time a new sample was taken. In this way, it was possible to obtain the *Colour Impression values* before and after the changes.

The sampled newspapers were measured off-line with the Malcolm Instrument after the job runs. The data collected consisted of the *observable variables* – CMYK values – measured on the grey-bars printed along the edge of each newspaper page, and the *adjustable* and *additional variables* recorded by the log system.

In total 672, 621, 678, and 618 data points were collected for cyan, magenta, yellow, and black ink, respectively.

The data collected were normalized to ZERO mean and variance ONE, according to the following equations:

$$x_{norm} = \frac{(x_i - \overline{x})}{\sigma} \tag{2}$$

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2 \tag{3}$$

were N is the number of data points, x_i is the variable before normalization, $\overline{x}$ is the mean value of x_i, and σ^2 is the variance of x.

6. Results

Our data sets contain data with rather small variations, so we have to take special care when removing outliers. Outliers are erroneous data values due to noise and press operator errors. We have chosen to define and remove outliers from our collected data set in two different ways, and therefore we got two different data sets. In the first data set – SET I we define the outliers in a more restrictive way and get a data set with low noise and small variations. In the second data set – SET II we define the outliers in a less restrictive way and get a data set with larger variations and higher noise.

TABLE 1. LINEAR PRINTING PRESS MODEL TEST RESULTS FOR THE *SET I* DATA SET.

Data/Training set #	*Maximum error*	*MSE error*	*Mean error*
1	*5.58*	*2.10*	*1.11*
2	*4.80*	*2.18*	*1.12*
3	*4.91*	*2.46*	*1.22*
4	*8.91*	*2.82*	*1.13*
5	*7.51*	*2.81*	*1.13*
6	*7.25*	*2.05*	*1.03*
7	*6.85*	*2.48*	*1.21*
8	*6.71*	*2.25*	*1.16*
9	*7.82*	*3.95*	*1.30*
10	*6.90*	*2.79*	*1.19*
Mean	*6.72*	*2.59*	*1.16*

Our data sets were randomly dived into learning, validation, and test data sets according to the following proportions: 0.7 – 0.1 – 0.2. The learning data set was used to estimate the parameters of the linear and non linear models. The validation set was used to compare the different models. The test data set was used to test the models chosen.

We tested our models using both SET I and SET II data sets. Table 1 shows prediction error for the test set data for the linear model, and Table 2 shows the test data set prediction error for the non linear neural network based model. In both cases, the SET I data set was used. The experiment was repeated 10 times with different

TABLE 2. NEURAL NETWORK BASED PRINTING PRESS MODEL TEST RESULTS FOR THE *SET I* DATA SET.

Data/Training set #	*Maximum error*	*MSE error*	*Mean error*
1	*5.77*	*1.95*	*1.08*
2	*6.30*	*2.73*	*1.25*
3	*5.79*	*2.77*	*1.24*
4	*8.21*	*2.77*	*1.16*
5	*7.02*	*2.72*	*1.17*
6	*4.93*	*1.86*	*1.02*
7	*5.01*	*2.26*	*1.19*
8	*5.26*	*2.03*	*1.14*
9	*7.03*	*2.76*	*1.12*
10	*4.17*	*2.08*	*1.17*
Mean	*5.95*	*2.39*	*1.15*

random divisions of the data set available into the learning, validation, and the test data sets. A press operator normally accepts errors up to 2 or 3 units, thus the errors obtained are quite acceptable.

When we used the SET II data set, the linear model showed errors twice as big as the ones obtained from the non linear neural network based model. Our tests have also shown that there is a significant difference in the results obtained for the different colours.

TABLE 3. TEST DATA SET PREDICTION ERROR FOR THE LINEAR OPERATOR MODEL.

Data/Training set #	*Maximum error*	*MSE error*	*Mean error*
1	*3.79*	*1.39*	*0.80*
2	*5.70*	*1.75*	*0.86*
3	*4.06*	*1.34*	*0.77*
4	*6.62*	*1.92*	*0.89*
5	*5.13*	*1.66*	*0.82*
6	*5,93*	*1.78*	*0.82*
7	*5.96*	*1.31*	*0.79*
8	*8.37*	*1.74*	*0.79*
9	*3.69*	*1.23*	*0.78*
10	*5.68*	*1.33*	*0.79*
Mean	*5.60*	*1.55*	*0.81*

TABLE 4. TEST DATA SET PREDICTION ERROR FOR THE NEURAL NETWORK OPERATOR MODEL.

Data/Training set #	*Maximum error*	*MSE error*	*Mean error*
1	*3.92*	*1.46*	*0.85*
2	*5.58*	*1.88*	*0.93*
3	*4.26*	*1.43*	*0.79*
4	*6.97*	*2.15*	*0.96*
5	*5.53*	*1.78*	*0.94*
6	*5,98*	*1.84*	*0.86*
7	*5.58*	*1.28*	*0.78*
8	*11.11*	*2.37*	*0.82*
9	*3.88*	*1.63*	*0.93*
10	*6.01*	*1.67*	*0.87*
Mean	*5.89*	*1.75*	*0.87*

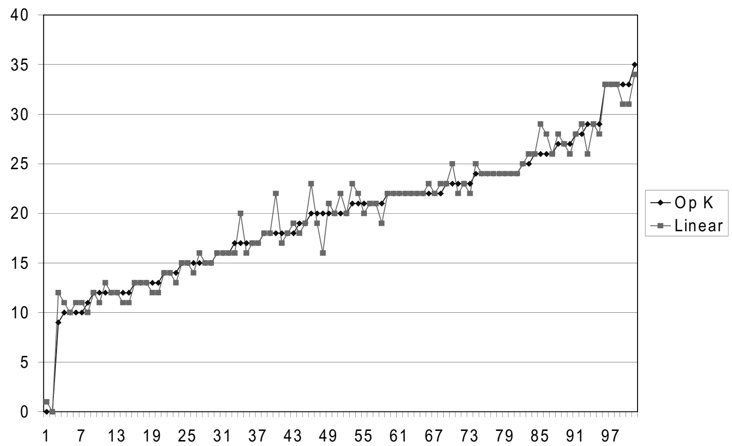

Fig 5. Ink-key levels set by the operator (Op K) and the linear operator model based controller (Linear).

6.1 The press operator model based controller

If the operator modelling task is a non-linear problem, the neural network based press operator model should perform better than the linear one. Tables 3 and 4 presenting the test data set prediction error for the linear an non linear operator model, show that there is no benefit in choosing a neural network for designing the operator model.

The press operator model based controller performed well on the test set data. However such a controller can hardly perform better than the operator. The results show that the operator is moderate in his adjustments to avoid over-inked printing. This is an obstacle for increasing the operator model based controller performance.

Figure 5 shows one hundred different ink-key levels set by the operator and the linear press operator model based controller. As can be seen in Figure 5, the con-

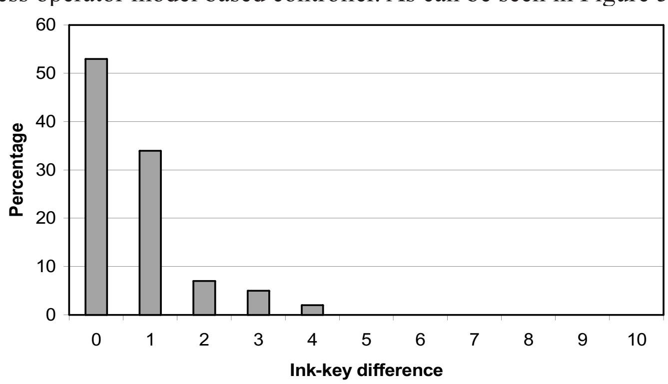

Fig 6. Distribution of the difference between the operator and the linear operator model predictions of ink-key settings.

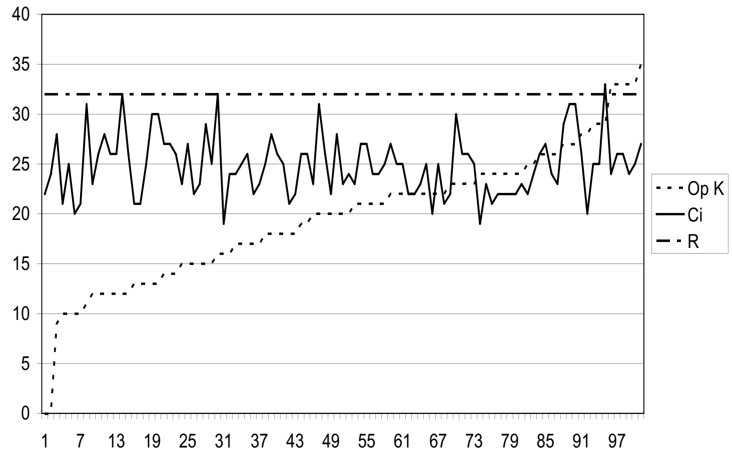

Fig 7. Ink-key level (Op K) as set by the operator, the colour impression value (Ci) and the reference colour impression (R). Data are sorted to obtaion a set of increasing ink key values.

troller predictions follow the operator settings quite well. The histogram of the difference between the operator ink-key settings and the corresponding linear press operator model based controller predictions, shown in Figure 6, indicates that 87 % of the predictions have an error of not more than 1 unit.

Ink key settings are dependent of the *ink demand*. In Figure 7, *Colour Impression* values (Ci) for the test data set and the ink key levels set by the operator (Op K) are shown. The figure shows that there is no clear correlation between the *Colour Impression* values and the ink-key settings. This is due to the fact that the *ink demand* is different for the different data points. As can be seen in Figure 7, the *Colour Impression* (Ci) has a negative bias to the desired *Colour Impression*

Table 5. Test data set prediction error for the inverse printing press model.

Data/Training set #	*Maximum error*	*MSE error*	*Mean error*
1	*3.24*	*1.30*	*0.82*
2	*4.03*	*1.21*	*0.78*
3	*3.49*	*1.16*	*0.79*
4	*4.88*	*1.29*	*0.80*
5	*5.43*	*1.91*	*0.97*
6	*4.00*	*1.10*	*0.70*
7	*4.68*	*1.11*	*0.76*
8	*6.10*	*1.20*	*0.70*
9	*3.77*	*1.50*	*0.93*
10	*5.85*	*1.61*	*0.82*
Mean	*4.55*	*1.34*	*0.81*

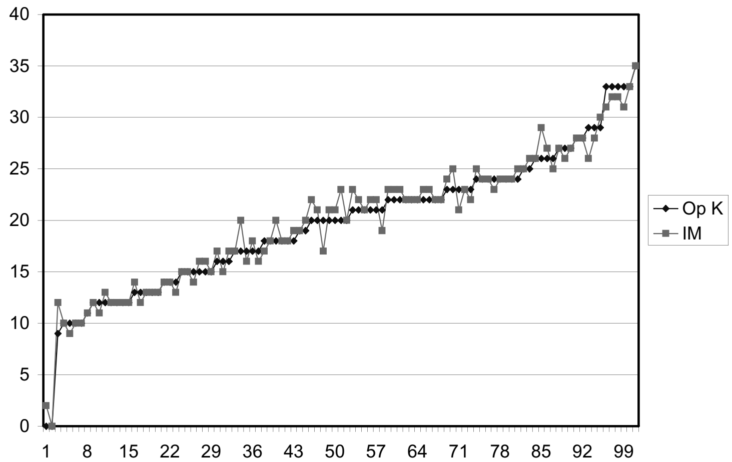

Fig 8. Correct ink-key level (OpK) and the level predicted by the inverse model (IM) based controller.

value (R). This negative bias makes it difficult for the press operator model based controller to perform better than the operator.

6.2 Inverse printing press model based controller

The inverse model predicts the ink-key level required. Table 5 illustrates the prediction accuracy of the model. The predicted ink key values follow the correct ink-key levels in the test data set quite well, as it can be seen from Figure 8. The histogram of the difference between the ink-key levels set by the operator and the corresponding inverse model based controller predictions, shown in Figure 9, indicates that 44% of the predictions have no error, and 42% of the predictions have an error of 1 unit. The maximum error of 3 units and the mean error of 0.77 units have been observed.

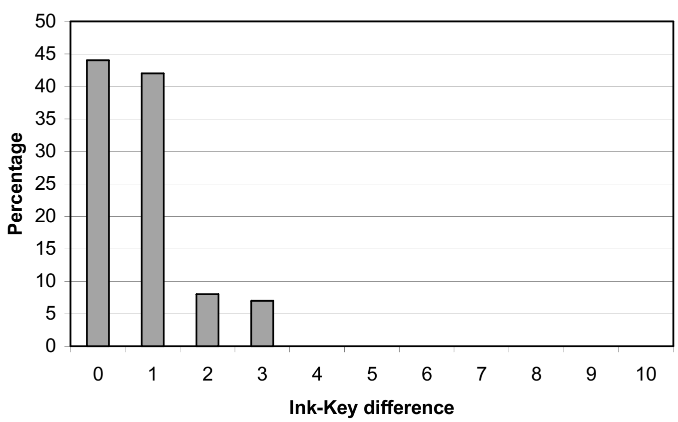

Fig 9. Distribution of the difference between the correct ink-key level and the level predicted by the inverse model.

7. Conclusions and discussion

The printing press modelling results have shown that it is possible to build models to be used for controlling ink flow in a newspaper printing process. The non linear neural network based models have shown better performance than the linear ones.

Improving the prediction accuracy of our models can be done by averaging predictions from multiple models and by averaging measurements from several samples.

The performance of the press operator model based controller depends of the skill and experience of the press operators participating in the training process.

Inverse printing press model based controller has shown the best performance among all the four controllers tested. The obtained controlling accuracy of the ink flow process was higher than that obtained from the experienced printing press operator.

In future work we are going to take steps toward implementing the colour control system on line.

Acknowledgments

The authors wish to thank the staff of the VTAB printing plant in Halmstad, Stora Enso Newsprint Hylte Mill, Hallandsposten AB, and the KK-foundation of Sweden for founding this project. Special thanks to EAE (Ewert Ahrensburg Electronic) GmbH.

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