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Neural network modelling and prediction of the flotation deinking behaviour of industrial paper recycling processes

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SUMMARY: The removal of ink from recovered papers by flotation deinking is considered to be the "heart" of the paper recycling process. Attempts to model the deinking flotation process from first principles has resulted in complex and not readily usable models. Artificial neural networks are adept at modelling complex and poorly understood phenomena.

Based on data generated in a laboratory, artificial neural network models were developed for the flotation deinking process. Representative samples of recycled newsprint, magazines and fine papers were pulped and deinked by flotation in the laboratory, under a wide variety of practical conditions. The brightness, residual ink concentration and the yield were measured and used to train artificial neural networks. Regressions of approximately 0.95, 0.85 and 0.79 respectively were obtained.

These models were validated using actual plant data from three different deinking plants manufacturing seven different grades of recycled pulp. It was found that the brightness and residual ink concentration could be predicted with correlations in excess of 0.9. Lower correlations of ca. 0.43 were obtained for the flotation yield.

It is intended to use the data to develop predictive models to facilitate the management and optimization of commercial flotation deinking processes with respect to recycled paper inputs and process conditions.

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In 2007, the global paper industry recovered an estimated 208 million tons of paper, compared to an estimated total pulp production of 188 million tons (RISI 2008a and b). These figures show that recycled fibre now constitutes the largest proportion of the fibre used in today's paper industry. Recent figures have suggested that in Europe and America the waste utilisation rates have even exceeded earlier projections ("European Declaration on Paper Recycling 2006 – 2010. Monitoring Report" 2007; '2006 Recovered Paper Annual Statistics" 2006).

In developed countries, growing mountains of waste material, limited landfill capacity, increasing costs of waste disposal and growing environmental awareness by the general public has driven the promulgation of waste paper related environmental legislation. This legislation typically aims to limit the amount of waste produced by domestic households and industrial operations.

South Africa has lagged these legislative trends, but has nevertheless achieved a recovery rate of 43% in 2008 (PRASA 2009). Pending legislation will target a 70% reduction in waste dumped in landfills by 2022, which will thus boost the supply of waste paper in South Africa (PAMSA 2007). Thus, most of the future source of recycled paper will be post-consumer waste originating from domestic households. This waste is difficult to collect and needs extensive sorting into useable fractions. Even after sorting, the resultant recycled paper in not uniform and presents processing challenges to paper recycling plants. The steadily increasing quality problems experienced by paper recyclers in South Africa have been attributed to this deteriorating recycled paper supply situation (Andrew 2007; Govender 2008; Steyn 2008).

In preliminary work (Pauck *et al.* 2012), the local deinking industry was surveyed to identify process parameters commonly used to control deinking plants, and were assessed to determine the most effective control variables. It was found that that residence time in the float cell, flotation consistency, system alkalinity and addition of hydrogen peroxide were most influential on the floatation outcome. Other parameters such as surfactant additions, pulping time, flotation pH and temperature in the floatation cell had minor to negligible effects on the flotation outcome.

In order to better equip recyclers to process this increasingly variable raw material, it was intended to develop an Artificial Neural Network (ANN) to model the effect of various recycled paper grades and selected process parameters (Pauck *et al.* 2012) on the deinking processes. Such a model could be used for model-based predictive control of such processes to allow for optimal response to changing incoming waste paper conditions. A neural network modelling methodology was chosen in preference to a mechanistic approach; due to ease of application and an ability to model multiple unit operations with completely unrelated physical process parameters.

Process technology of deinking plants

By considering the typical process technologies commonly encountered in newsprint deinking plants, a number of potential process modelling parameters emerge:

Batch pulping: carried out under alkaline conditions (pH 9 to 10.5), medium consistency (10-15%) and temperatures ranging from 45 °C to 60 °C (Ali *et. al.* 1994). Sodium hydroxide, sodium silicate, hydrogen peroxide, chelants and surfactant are usually added into the pulper (Goettsching and Pakarinen 2000: 241-258). The effect of the consistency in the pulper on the deinking process has been studied by various researchers (Bennington *et al.* 1998; Ackerman *et al,* 1999). Generally, pulpers do not have the flexibility to operate out of their design consistency range, thus consistency is not a good modelling variable. Pulping pH is merely a function of chemical additions. However pulping temperature, addition of hydrogen peroxide, sodium silicate, sodium hydroxide and surfactant are all potential modelling variables.

Centrifugal cleaning: removes contaminants of high or low relative density. Cleaning does not contribute significantly to deinking.

Screening: removes contaminants using size exclusion. Screen apertures as low as 0.1 mm are in common use in the paper recycling industry. Screening can contribute to deinking by removing large ink particles.

Froth flotation: is commonly used to remove ink. Fine air bubbles are introduced into a low consistency (0.8-1.5%), alkaline (pH 8-9) fibre slurry under intense agitation. The air bubbles attract hydrophobic ink particles as they rise to the top of the fibre slurry. The froth, bearing ink and other fine hydrophobic contaminants is mechanically removed from the fibre slurry. Surfactants called collectors are added to assist in ink dispersion and attachment to air bubbles. Hence, flotation consistency, pH, temperature and surfactant addition are all potential modelling variables. In addition, agitation speed and air flow rates have been shown to greatly affect the brightness and yield of the flotation process (Hunold *et al,* 1997; Carrasco *et al,* 1999; Peters *et al.* 2007). However, agitation conditions and air flow rates are often not adjustable on commercial flotation plants, but are rather a function of the original plant design. None of the deinking mills in South Africa and the several mills in the United States that the authors are familiar with use air flow or froth layer thickness as a manipulated control variable.

Peters *et al,* (2007) stated that the Specific Air Volume (SAV, Litres air/kg solids), defined as the volume of air applied to a flotation line per kilogram of solids in the feed determines the flotation efficiency. Thus for a laboratory batch cell:

$$SAV_{lab} = \frac{qt_f}{Vc} \qquad [1]$$

where V = cell volume, c = consistency, q = air flow rate and t_f = flotation time.

Similarly, for a continuous flotation cell, where Q_s is the flow rate of the stock:

$$SAV_{plant} = \frac{q}{cQ_s} \qquad [2]$$

But, the hydraulic retention time $t_{HR} = V/Q_s$

Substituting into *Eq 2* and rearranging produces:

$$SAV_{plant} = \frac{qt_{HR}}{Vc} \qquad [3]$$

Under industrial conditions the air flow, although not measured would be maintained constant. *Eq 1* and *3* show that the terms flotation time t_f and hydraulic retention time t_{HR} can be used to relate the performance of batch and continuous flotation cells. Thus, t_{HR} was calculated for the plant data, and related to t_f for the batch cell.

Hence, air flow rates and agitation conditions were not considered as modelling parameters, but rather the hydraulic residence time in the flotation cell (flotation time) was chosen as a modelling parameter.

The levels of addition of process chemicals are normally not changed

Washing: removes particles that are too fine to remove by flotation. Washing is usually performed on a dewatering device such as a disc filter or wash press. The theoretical efficiency of washing is determined by the increase in consistency from inlet to outlet. The inlet and outlet consistencies are determined by the nature and design of the equipment, and are not varied outside of the design range. Hence, there are no independent control parameters around the washing process.

Dispersion: is used to reduce the size of dirt particles to below the limit of human visibility (about 50 microns). Dispersion takes place in disc dispergers or kneaders at temperatures between 40° and 95°C. This typically results in a greying of the pulp.

Bleaching: Oxidative and/or reductive bleaching is performed to overcome the greying induced by dispersion and to remove any yellowing that was produced by the alkaline pulping stage and/or colour that was liberated by the printing inks.

Recycled office paper is deinked in a similar way, except that it is usually carried out under neutral or near-neutral conditions, which means that the sodium hydroxide and/or sodium silicate and hydrogen peroxide are omitted.

The final outcome of the deinking process is typically measured by the brightness of the pulp. Additional measures of ink removal, such as residual ink concentration (ERIC) or dirt count are sometimes used. In addition, the yield is often monitored, as it impacts the economics of the process.

In more advanced processing plants (double-loop processes), secondary stages of flotation, washing, dispersion and bleaching may be used.

Process control of deinking plants

Deinking lines generally offer few opportunities to make adjustments to the process if the quality of the output changes. The usual strategy is to vary the ratio of the grades of recycled paper fed to the deinking plant. Grades of waste with a high intrinsic brightness (for example old magazines in newsprint deinking) are employed to control the final brightness. Thus, the grade of recycled paper is a major control variable in the deinking process.

Often, low quality deinked pulp is bled back into the process, as a wasteful way of controlling the final pulp quality.

However, these approaches are becoming less viable due to constrained availability of high quality feedstocks. The deinking mills will have to make use of lower grade and more variable waste.

Potential control parameters

A useful *control variable* is one that can influence the outcome of the process without throwing the process out of balance, reducing the capacity of the plant or requiring considerable operating or capital expenditure. Variables having a significant effect on the process but simultaneously causing process disruptions are not practical control variables. They would still need to be optimized, and would be considered to be an *optimisation variable*.

A number of possible control variables for deinking plants were identified, and screened for their net effect on the complete deinking process (Pauck *et.al.* 2012). Arising out of this study, the following were considered as practical control variables, which would be suitable for modelling the deinking process, in addition to the grades of recycled paper:

Chemical additions: Level of addition of sodium hydroxide, sodium silicate, hydrogen peroxide and surfactant.

Process variables: pulping time, pulping temperature, flotation residence time, flotation temperature, flotation consistency and flotation pH.

Process variables such as pulping consistency, flotation air flow rate and froth height were not considered to be good modelling variables, as they were equipment specific and often not adjustable in practice.

Neural networks

Artificial Neural Networks (ANN's) are mathematical constructs which were inspired by the vast interconnected network structure of nerve cells found in the human brain. ANN's have developed to become useful tools in scientific and engineering applications such as regression, pattern recognition and classification. Traditional computing applications rely on sequential or serial processing, but a neural network is a highly interconnected parallel processing structure which is able to perform complex modelling functions (Dayhoff 1990).

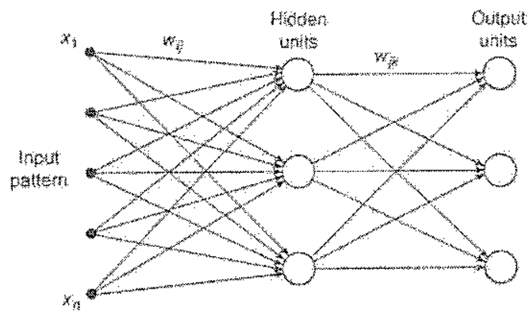

Fig 1 - A two-layer perceptron structure. (Tarassenko 1998:15)

The basic processing unit of an ANN is called a neuron or *peceptron* (Tarasenko, 1998). These processing units are interconnected to other, similar units in the manner shown in *Fig 1*. The first layer consists of input units. Data is inputted into the network in the form of an input vector. With reference to *Fig 2*, for each neuron the values of the input vector (x_n) are multiplied by the connection weights (w_{kn}) and summed. The sum, v_k is operated on by the activation function f_h (usually tan-sigmoid) to produce an output Y. Neurons in the output layer usually have a linear activation function. The output is compared to a target value t and an error is computed. In the process of network training, the values of the connection weights are obtained by various mathematical techniques so that the output of the network matches or closely approximates the target answers. Typically, the error function is minimized by gradient descent by differentiating it with respect to every weight w_k in the network (Tarassenko 1998) in a process called error back-propagation. Also, the ideal number of processing units and layers needs to be selected.

Network training

The training process consists of finding the optimum number of hidden units *j*, with the associated first-layer weights w_{ij} and second-layer weights w_{jk} (*Fig 1*). Network training normally occurs in three distinct steps, each requiring its own data. (Tarassenko 1998:17)

Step 1: Training: present the network with input-output data. The method of error back propagation is commonly used to determine w_{ij} and w_{jk}.

Step 2 – Validation: the validation set is presented to the network not to further adjust w_{ij} or w_{jk} but to determine the error of the output. Training is stopped when the error is at a minimum, and the weights are fixed. This is referred to as *early stopping*.

Step 3 – Testing: the generalisation of the network is assessed by applying a test set.

The three-step process described above is termed *supervised learning*.

The use of neural networks in flotation processes

The effects of various separation unit operations, process chemicals and waste types have been extensively studied by many researchers. In particular, attempts have been

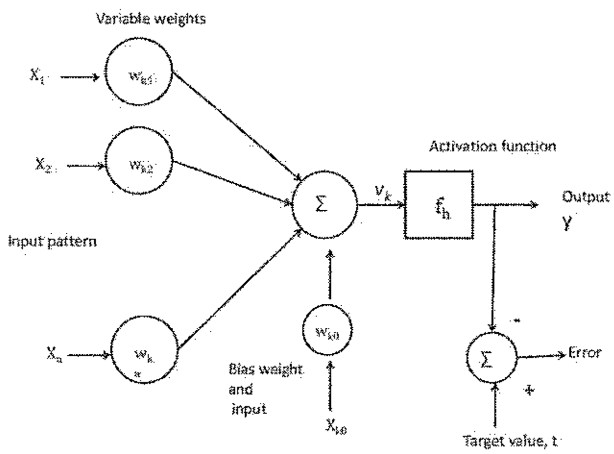

Fig 2 - Nonlinear model of a single neuron. (Tarassenko 1998; Haykin 1994) made (Beneventi et al. 2006; Bloom 2006; Heindel 1999; Julian Saint Amand 1999; Bloom and Heindel 1997) to model flotation deinking processes from first principles.

However, there remains a great deal of uncertainty around what exactly happens in a flotation cell (Labidi et al. 2007). These theoretical models are complex and difficult to apply in practice (Hodouin et al. 2001).

Thus, attempts have been made to use Artificial Intelligence based systems to model and control modern flotation plants in the field of mineral flotation, and to a much lesser extent in deinking flotation. Flotation deinking plants share many similarities to the problems faced in mineral flotation plants viz. complex raw material, measurement difficulties, complex physical processes, a small number of outputs measuring the process but a large number of inputs, and many interactions. (Singh et al. 2003; Hodouin et al. 2001)

An ANN model of a copper/lead flotation plant was developed by Forouzi and Meech (1999), and used to predict the assays of the concentrate streams. Cubillos and Lima (1997) used a combination of a physical model (mass, energy, momentum) and an ANN model to predict certain process parameters. Gupta et al. (1999) developed an ANN to predict flotation rate constants from operating variables, and thereafter used these constants in a first principles model to predict the performance of a phosphate flotation column.

Rughooputh and Rughooputh (2002) describe the application of ANN's to analyse the visual attributes of the froth in a flotation cell to make deductions about the state of flotation process. .

Labidi *et al.* (2007) studied the effects of flotation consistency, airflow rate and agitation speed, at various flotation times, on the rate of ink removal. An ANN was developed which effectively modelled the brightness and ERIC out of the flotation cell.

In a practical plant study, Smith and Broeren (1996) reported on the use of an ANN to analyse and optimise a newsprint deinking facility, which recycled a mixture of old newsprint and magazines. Time-stamped plant operating data was acquired and fed into an ANN. A vector of 66 variables was inputted, and the influence of a large number of process variables was analysed and ranked in order of influence. As a result, cost savings were achieved in terms of reduced pulper chemical additions.

An ideal is to have an algorithm or strategy to find new optimum process conditions, rather than an "unguided hunt" for the new conditions (Singh *et al.* 2003). In line with this thinking, the objective of the current work was to develop an artificial neural network model of a general deinking system, based on mixtures of four commonly recycled grades of printing and writing papers (detailed later), and a selection of practical, non-equipment-specific process parameters, and to evaluate the validity of this model against a number of commercial deinking processes. The networks were trained using deinking data generated in a laboratory, as only in a laboratory was it possible to evaluate the process parameters within a wide enough range.

Materials and Methods

The objective of this research was to model the combined processes of pulping, deinking and washing with respect to raw material changes and process parameters. It was decided to use neural networks to accomplish this modelling due to their relative ease of use and the fact that commercial software is readily available. Neural networks are better able to model a combination of unit operations, whereas mechanistic models are restricted to particular unit operations. For example, it would be difficult to model the combined effect of pulping and flotation with a unified mechanistic model. The output parameters that were modelled were brightness, residual ink concentration and flotation yield. The methodology was as follows:

1) The general deinking conditions in the South African tissue and newsprint deinking industry were established. The practical ranges are detailed in *Table 1*.
2) The industrial processes were modelled in the laboratory. Experimental work was performed with a wide range of different recycled paper raw material blends and selected control parameters to generate the data.
3) The neural networks were trained using the laboratory data.
4) A selection of the best neural network models were validated using plant data to determine how well the model generalizes and predicts outputs on a plant scale.
5) Based on the validation results, a useable predictive model/s to control deinking plants was selected.

Raw materials

The four main grades of recycled paper pertinent to deinking in South Africa were represented by the following standard mixtures:

Old newsprint (ONP): A random selection of South African newspapers less than 6 months old with all inserts removed.

Old magazines (OMG): A blend of *ca.* 33% heavy weight coated glossy magazines, *ca.* 33% lightweight coated and *ca.* 33% uncoated magazine grades, all less than 6 months old.

White office papers (HL1): A blend of 80% Xerographic printed paper (laser printer and photocopier) and 20% inkjet printed paper.

Pastel coloured office papers (HL2): Mixed office papers comprising 44% white or grey papers and the balance a blend of yellow, green, blue and red pastel shades of paper.

The recycled paper used in the experiments was torn into strips, mixed well and stored under standard conditions of 22 °C and 50% relative humidity.

A data base of nearly 500 laboratory deinking runs was constructed as described below. The recycled paper grades and process parameters were varied within the ranges listed in *Table 1*. This data base served as the training data for the neural networks.

Laboratory methods

Water at 200 ppm calcium hardness, 0.2% Chelant, pulping chemicals according to the range of addition levels in *Table 1* and recycled paper were charged to a laboratory pulper (Laboratory Hydra Pulper model UEC 2020, Universal Engineering Corporation, India) and allowed to soak for 10 minutes. Hydrogen peroxide (*Table 1*) was added and the mix was then pulped at a constant 8-10% consistency at the specified temperature and time (*Table 1*). A sample was taken and 200gm^{-2} pulp pads were formed on a Rapid-Koethen sheet former with reduced dilution (2l instead of 7l), based on the method Tappi 218 om-91: Forming handsheets for the reflectance testing of pulp. The pulp pads were measured for brightness (GE brightness, UV included, D65, 10°) and Effective Residual Ink Concentration (ERIC, C, 2°) on a Technidyne ColorTouch PC Spetrophotometer. In all cases each quadrant of the pad was measured on both sides and the average taken to represent the brightness of the pad.

The pulped mass was allowed to stand for 1 hour, and then a sample was withdrawn, transferred to the 15 litre flotation cell (Flotation Cell model UEC 2026, Universal Engineering Corporation, India), made up to the required consistency with 200 ppm calcium hardness water and floated at 1550 to 1600 rpm at the conditions specified in *Table 1*. At the end of the float, the contents of the cell were collected quantitatively, filtered and weighed to determine the yield (dry mass of fibre out/dry mass of fibre in). A sample of the floated pulp was formed into 200gm^{-2} pads and measured for brightness and ERIC, as above.

The floated pulp was used to form 60 gm^{-2} handsheets on the Rapid Koethen former, according to a method based on Tappi 205 sp-95: Formation of handsheets for physical testing of pulp. The process of dilution and filtering allowed considerable quantities of fine material, including ink particles, to be washed through the screen. The brightness and ERIC of both sides of the pads or sheets were measured and the average was taken. The washing out effect that occurs in the preparation of the handsheets was used in this study to simulate the washing process in a deinking plant. These final samples were thus designated as *washed* pulp.

Training methodology

A commercial software package, MATLAB Version R2009a Neural Network toolbox was used to implement the neural network model of the laboratory deinking data. The number of input units corresponds to the number of variables in the input vector, and the number of output units corresponds to the number of outputs. In this work, a single output (either brightness, ERIC or yield) was chosen so as to minimise the amount of data required to train the networks. The number of neurons required in the hidden layer was determined by iteration. The greater the number of layers or neurons, the more complex is the function which can be approximated. On the other hand, more layers or neurons require more data and can also lead to over-fitting of a function (Demuth *et al.* 2009:1-8). The neural networks were restricted to one hidden layer and one output layer, as this is considered adequate to model any function (Tarassenko 1998: 89).

Table 1 - Ranges of deinking parameters used to construct deinking data base.

Variable	Range of parameter
%ONP	0-100
%OMG	0-100
%HL1	0-100
%HL2	0-100
%NaOH	0 – 1.5
% Sodium silicate	0 - 3
% H_2O_2	0 - 2
%Surfactant in pulper	0.25 – 1.0
Pulping time, mins	5 - 15
Pulping temperature, °C	35, 43 and 50
Flotation temperature, °C	30, 38 and 45
Flotation consistency, %	0.8 – 1.5
Flotation pH	7 -10
% Surfactant in flotation cell	0 – 0.25
Flotation time, mins	2 - 20

The following settings were used for training networks for function fitting:

- The input vectors were divided randomly upon initialisation into three sets as follows: 70% of the data for training; 15% of the data for validation and 15% for independent testing.
- The network was initialized with random values close to zero and the data was presented as a batch (*viz.* batch training).
- The performance of the network was determined by computing the mean-square-error (MSE) of all the sets.
- The technique of *early stopping* was used to avoid over-fitting so as to ensure good generalisation (Demuth et al., 2009).
- Once the training was complete, the regressions of the training, validation and test sets were calculated and ranked.

Plant validation

The collection of plant data was fraught with difficulties. Not all input parameters were monitored or recorded at all times. Considerable variation around set points existed, and the output data showed a large scatter. This has also been the experience of other researchers (Moe and RØring 2001).

Plant data corresponding to the variables listed in *Table 1* were collected from a single-loop newsprint deinking mill, a double-loop office paper deinking mill and a single-loop office paper deinking mill, making in total eight different grades of recycled pulp. The processes can be summarised as follows;

Newsprint single-loop: **[alkaline pulping** – cleaning – screening – **flotation** – cleaning – screening – **washing]**– dispersion – storage and reductive bleaching.

Double-loop office paper: **[neutral pulping** – cleaning – screening – **flotation 1** –cleaning – screening – **washing** dispersion (reductive bleaching) – **flotation 2 – washing]** – storage.

Single-loop office paper: **[neutral pulping** – cleaning – screening – **flotation** – cleaning – screening – **washing]** – thickening (reductive bleaching) - storage.

The process steps in bold above denote those modelled in the laboratory. The process steps enclosed in square brackets were compared to the laboratory models. Generally, the process conditions and outputs were recorded variably on an 8 hour to 24 hour basis. Depending on the process intervals, the process inputs were averaged to produce one process record per brightness test. In some cases, process conditions were either not recorded or recorded sporadically. In these cases average values were inserted for the missing data, or the data was estimated using correlations or interpolations.

The yield data for the plants was available on the basis of total yield, across all the unit operations. On the other hand, the laboratory yield data corresponded to the flotation yield only. Thus, the flotation yield had to be deduced from the total plant yield, by estimating the losses due to heavy media separation (staples, metals, grit), cleaning losses and ink sludge removed from the plants. These estimates were obtained from the masses of waste material sent by the recycling plants to the landfill sites. However, the different plants measured yield in different ways (either from paper produced or by integrating flows), and eliminated contaminants in different ways (*viz.* either as a slurry or as a solid effluent), which made it difficult to get reliable and consistent estimates of flotation yield.

Only the newsprint recycling plant routinely measured the ERIC. As was the case with brightness, averages were inserted for missing data. For the plants which did not routinely measure the ERIC, the average of a limited number of samples was taken, and applied to all of the process data.

Alignment of plant and laboratory flotation processes

Laboratory cells can and have been used to successfully simulate plant processes (Beneventi *et al.* 2007; Dionne 1994) and are useful for comparisons and trends (Borchardt 1993). Laboratory tests do not produce absolute values, as they do not take into account factors such as recirculation of contaminants in back-water systems (Ferguson 1993). Because the neural networks were trained on laboratory data, it was to be expected that there would be a "gap" between laboratory and plant scale processes.

Solids loss has often been used as a basis for comparing laboratory flotation results to plant flotation performance (Goettsching and Pakarinen 2000:167). The ultimate efficiency of a deinking process can be determined by a process called "infinite flotation" (McCool 1993). However in this study solids or yield loss was not used as the basis for comparison, as it was not possible to accurately determine the solids losses across the commercial flotation cells.

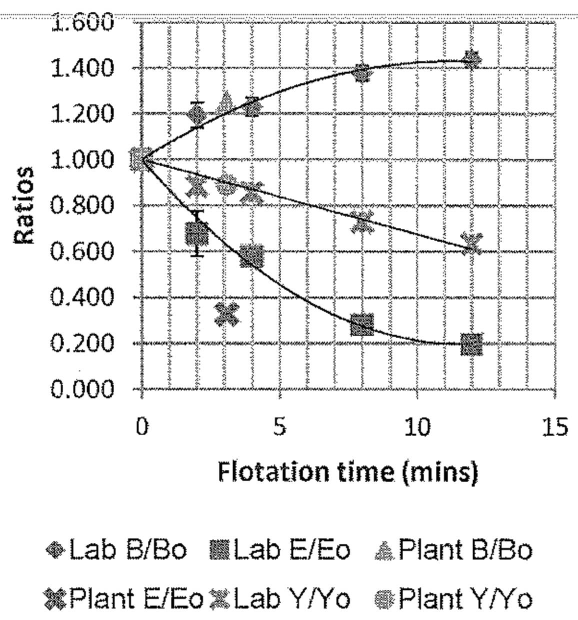

Fig 3 - Comparison of brightness (B), ERIC (E) and yield (Y) for laboratory to single-loop newsprint deinking plant flotation.

A more convenient basis for comparison was the flotation time in a laboratory batch cell compared to the hydraulic residence time in a continuous plant flotation cell, as explained in the section under Froth Flotation. However, the plant hydraulic residence time was not directly equated to the laboratory flotation time, because the flotation dynamics and efficiency in a large commercial flotation cell are very different to a laboratory cell. Accordingly, a flotation efficiency comparison was carried out. A pulper sample from the plant was floated in the laboratory under average conditions and the outputs (brightness, ERIC and yield) were compared to the average plant results. An example for a single-loop newsprint deinking plant is shown in *Fig 3*.

The changes in brightness (B), ERIC (E) and yield (Y) were expressed as ratios (*eg.* B/Bo) relative to the pulper properties. The pulper properties (Bo, Eo, Yo) were taken as flotation time zero. The ratios are shown graphically for newsprint flotation in *Fig 3* for brightness, ERIC and yield respectively.

Thus, with reference to *Fig 3*, for brightness a plant hydraulic residence time of 3.1 minutes was equivalent to a laboratory flotation time of *ca.* 3.7 minutes, *viz.* a scaling factor of *ca.* 1.2. For ERIC, a plant hydraulic residence time of 3.1 minutes was equivalent to a laboratory flotation time of *ca.*6.3 minutes, *viz.* a scaling factor of *ca.* 2.0. For the yield, a plant hydraulic residence time of 3.1 minutes was equivalent to a laboratory flotation time of *ca.* 3 minutes, thus a scaling factor of *ca.* 1.

This alignment process was repeated for all the plants and grades, by modifying the plant hydraulic residence times for the specific outputs as described above, before inputting into the neural networks. In all cases, the ERIC results required the greatest adjustment in residence times.

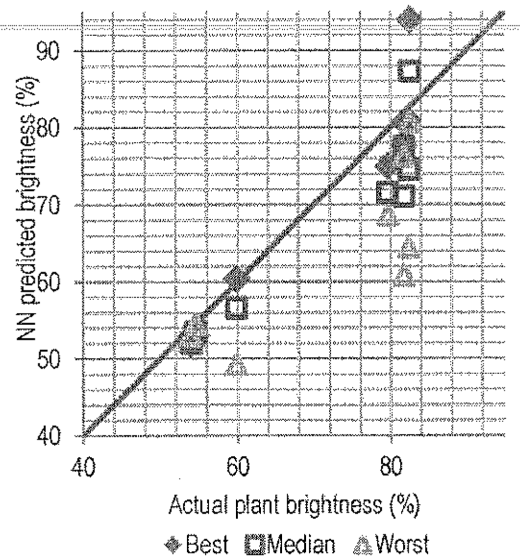

Fig 4 - Brightness prediction performance of best, median and worst ranked neural networks.

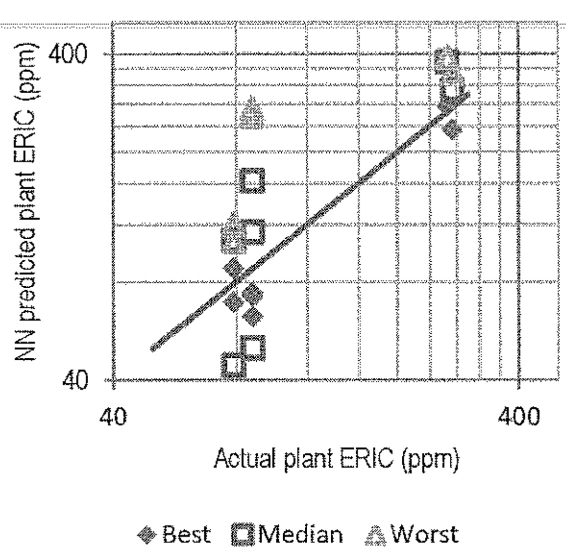

Fig 5 - Residual ink prediction performance of best, median and worst ranked neural networks.

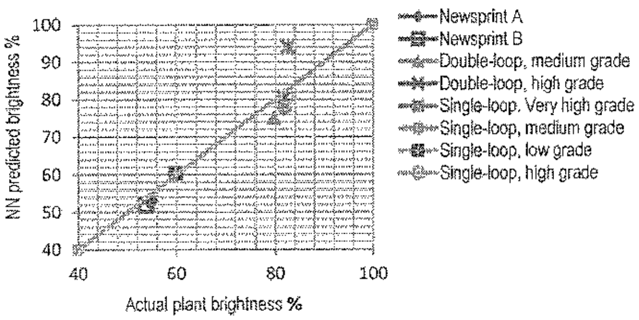

Fig 6 - Brightness prediction performance of best ranked network for different recycled paper grades and processing plants.

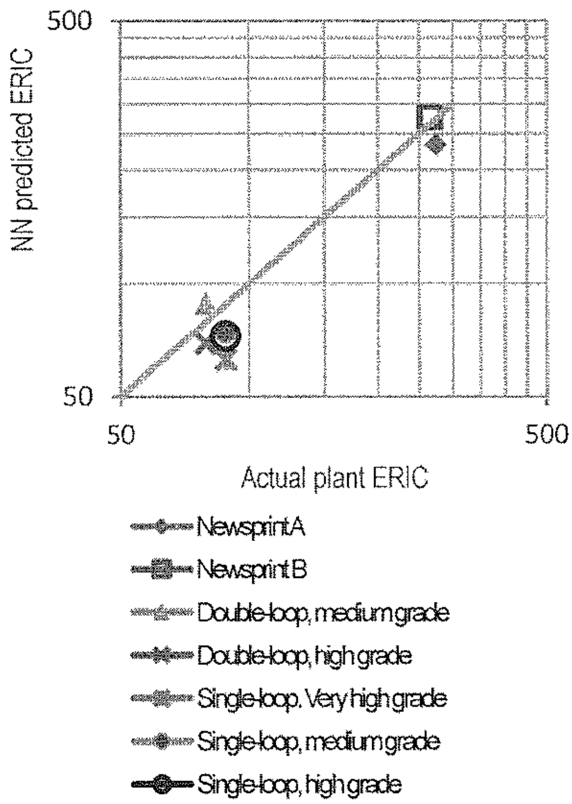

Fig 7 - ERIC prediction performance of best ranked network for different recycled paper grades and processing plants.

Selection of neural networks

The neural networks were trained using the laboratory data set, as outlined in the Training Methodology section above. A total of eighty networks (number of neurons 1 – 20, four networks each) were generated. The performance of the trained networks was determined by feeding the modified plant inputs into the networks and comparing the predicted values to the actual plant output data. The correlations and mean square errors of predicted versus actual plant values were determined. The top ten networks were retained as possible final models.

Results and discussion

The best, median and worst networks (selected according to correlation coefficient R and mean square error MSE) and their prediction performances for brightness, ERIC and flotation yield are tabulated in Appendix 1, and summarised in *Table 2*.

The neural networks effectively modelled the laboratory data (*Table 2*, column 2), with R values ranging from 0.790 up to 0.954. The predictions of aggregate plant brightness (R = 0.940) and ERIC (R = 0.934) were high, but the prediction of plant flotation yield was poor (R = 0.425).

Table 2 - Summary of neural network performance (Appendix 1)

Property modelled	Correlations with lab data (R)	Predictions of plant data (R)	Prediction of plant data (MSE)
Brightness %	0.954	0.940	26.0
ERIC ppm	0.853	0.934	1021
Flotation yield %	0.790	0.425	101.2

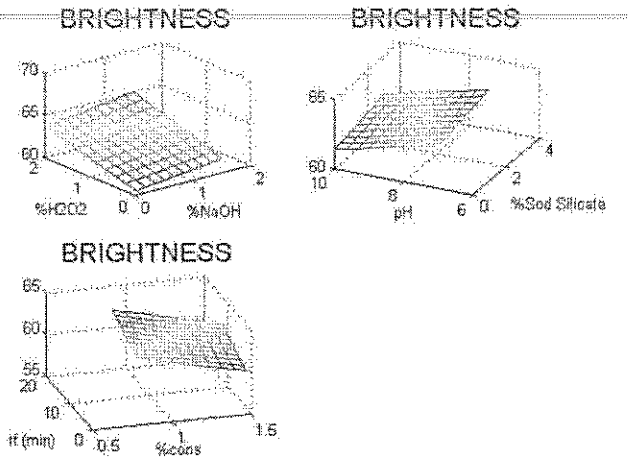

Fig 8 - Best network brightness response surface for a mixture of all recycled paper grades as a function of the most influential control variables. (Grade mix ONP 25%, OMG 25%, HL1 25%, HL2 25%)

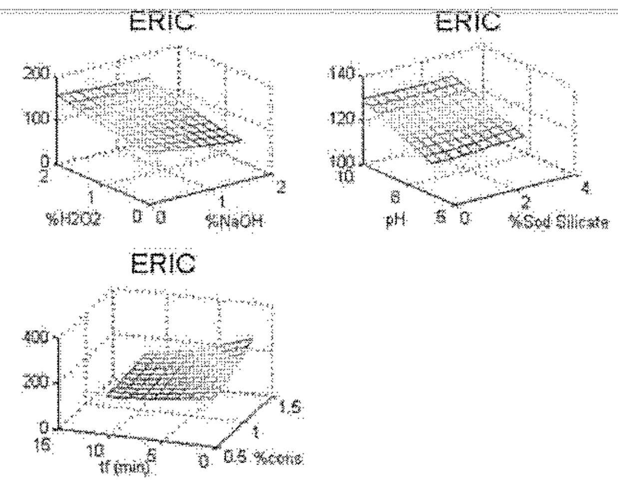

Fig 9 - Best network ERIC response surface for a mixture of all recycled paper grades as a function of the most influential control variables. (Grade mix ONP 25%, OMG 25%, HL1 25%, HL2 25%)

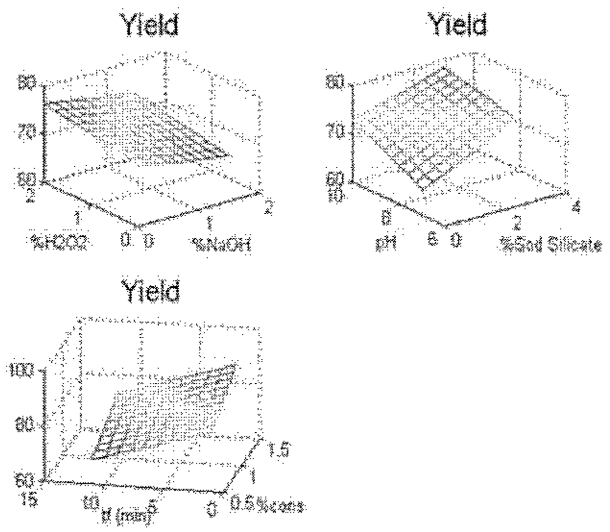

Fig 10 - Best network flotation yield response surface for a mixture of all recycled paper grades as a function of the most influential control variables. (Grade mix ONP 25%, OMG 25%, HL1 25%, HL2 25%)

Ink removal

The performance (predicted *vs.* actual) of the best, median and worst ranked networks for brightness and ERIC are shown in *Fig 4* and *5* respectively. The Y = X line denoting perfect prediction is also shown in the figures. It can be noted visually that the prediction performance varies considerably between the best and worst ranked network. Visually, prediction in the low brightness/high ERIC region (corresponding to newsprint and low brightness office paper deinking) is better than the predictions in the high brightness/low ERIC region (*viz.* high brightness office paper deinking).

Fig 6 and *7* show the brightness and ERIC predication performance of the best network across all the grades and recycling plants evaluated. The actual plant brightness exceeded the model predicted brightness by about 2 points for newsprint deinking and about 5 points for office paper deinking (*Fig 6*). It is to be expected that plant brightness would exceed the laboratory model-based predicted brightness because of the greater complexity of the full scale plants and hence their higher deinking efficiencies. There was one anomaly at the very highest brightness level. This corresponded to the manufacture of a small-volume high quality grade on a single-loop office paper deinking plant. The optimum potential of this grade was probably not achieved on the plant due to contaminated water re-circulation loops decreasing the brightness.

In *Fig 7*, the plant ERIC values are higher than the predicted ERIC values, particularly for the high brightness tissue deinking papers. This suggests an inferior ink removal, contradicting the trends shown in *Fig 6*. However, very little plant ERIC data was available for the office paper recycling plants, and more data might show otherwise.

The network response surfaces for brightness and ERIC are shown in *Fig 8* and *9* respectively. The response surfaces are shown as a function of the most influential process parameters (*viz.* hydrogen peroxide concentration, alkalinity comprising sodium hydroxide and sodium silicate, flotation time, consistency and flotation pH), as identified in Pauck *et al.* (2012). It can be noted that the responses are linear or slightly curved in nature.

With reference to *Fig 8*, the slopes of the response surfaces agree with known behaviour, *viz.* brightness increases with increasing alkalinity, hydrogen peroxide, and flotation time and decreases with flotation consistency. The flotation pH was adjusted independently of the pulping alkalinity in the training data. The models suggest that increasing flotation pH negatively affects brightness and ink removal. Lower flotation pH leads to greater ink agglomeration and thus better removal by flotation.

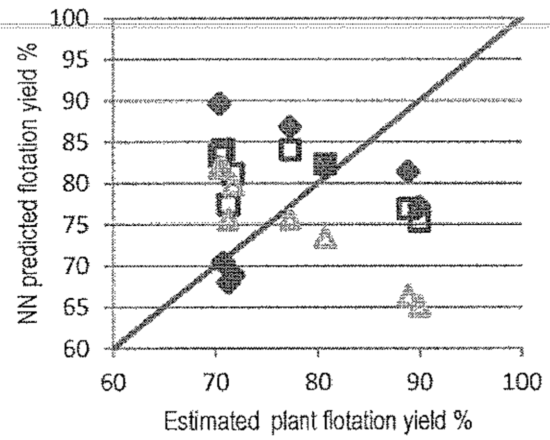

Fig 11 - Plant flotation yield prediction performance of best, median and worst ranked neural networks.

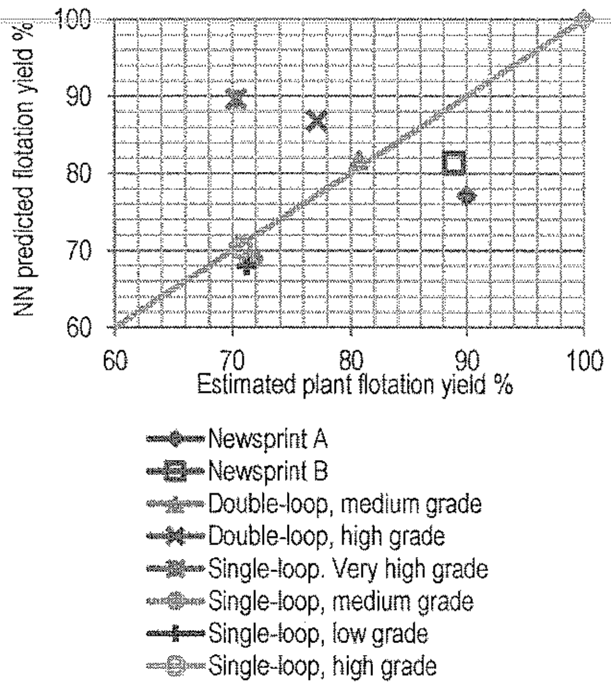

Fig 12 - Flotation yield prediction performance of best ranked network for different recycled paper grades and processing plants.

With reference to *Fig 9*, the models confirm that ink removal improves (*viz.* lower ERIC) with flotation time and alkalinity from sodium hydroxide, and is adversely affected by flotation consistency and flotation pH.

The models suggest that hydrogen peroxide negatively affects ink removal (*Fig 9*). This is anomalous, but it can be speculated that hydrogen peroxide somehow initiates cross-linking between ink binders and the underlying fibre, which results in less ink removal (viz. higher ERIC), but overall net higher brightness due to the dominant bleaching effect on the fibres (*Fig 8*).

Yield

The neural networks modelled the laboratory flotation yield data fairly well, achieving correlations of 0.790 for flotation yield (Appendix 1 and *Table 2*). The models predict that increasing sodium silicate, flotation pH and flotation consistency all decrease yield losses, whereas increasing flotation time increases yield losses (*Fig 10*).

However, the predictions of plant flotation yield were much poorer (*Table 2* and *Fig 11*). It appears that the estimates of flotation yield made from the plant total yield data were too approximate, with the resultant poor predictions. These data collection difficulties were discussed in the section on plant validation, above.

In can be seen in *Fig 12* that all of the plants (newsprint, single-loop office paper and double-loop office paper) produced good and bad correlations, which suggests generally poor plant flotation yield data.

Conclusions

The neural networks were able to model the brightness, ERIC and yield of the laboratory processes with high correlations (*Table 2*). The predictions of aggregate plant brightness ($R = 0.94$) and ERIC ($R = 0.93$) were high, but the prediction of plant flotation yield was poor ($R = 0.42$) due to the fact that the flotation yield had to be estimated from the unreliable plant yield data.

The predicted brightness values ranged from 4.7 points lower to 11 points above the actual plant values (*Fig 6*), and the predicted ERIC values were between 10 points higher and 40 points lower than the actual plant values (*Fig 7*), depending on the plant and paper grades. This was ascribed to the generally greater deinking efficiencies of the production plants. It would be possible to close this "gap" by introducing a mathematical correction to the otherwise linear relationship between predicted and plant brightness.

Further work and applications

Unresolved questions

The main unresolved question in this research was the "gap" between the laboratory based model predictions and the plant brightness values. This was indicated by the deviations of the neural network predictions from the Y = X lines. A partially successful attempt was made to bridge this gap by relating the laboratory-based data to the plant data through the flotation performance curve of brightness verses flotation residence time (*Fig 3*).

Most of the "gaps" occurred with the predictions for the office paper deinking plants, where the plant brightness was higher than the predicted brightness by up to 4.7 brightness points (*Fig 6*), and the ink removal was lower by up to 10 points (*Fig 7*). It is known that toner inks produce large, difficult to float particles. The office paper recycling plants had extra equipment (screens, cleaners and dispersers) to eliminate the large ink particles. This equipment was not simulated in the laboratory, and hence not modelled. This could account for the consistent under-estimation of the final brightness by the models. This limitation needs to be taken into account when applying the models. It would be possible to apply a mathematical correction or bias to the output of the models to bring the predictions in line with the actual values.

Another unresolved issue was the lack of sufficient plant ERIC data, particularly for the office paper recycling plants, to obtain a good test of the models against plant data. This was due to the fact that the ERIC was not measured by these plants, and practical obstacles prevented a large amount of data being collected.

The last unresolved question was the quality of the yield data from the plants. The plant yield data incorporated the general and combined yield losses of the plants, and not just the flotation yield. Data corresponding to flotation yield had to be teased out of the data using indirect means and estimates, which negatively affected the quality of the data. It would be instructive for further work to obtain high quality data from the plants for ERIC and yield, and to re-test the models, to try to find a better fitting neural network.

Applications

The models developed in this research could be used for deinking plant process optimisation and troubleshooting exercises. The models represent "standard" or average conditions, and deviations from predicted values can be indicative of some malfunctioning equipment or other process deviation. As an example, the very high grade tissue pulp manufactured on the single-loop process showed an anomalously low plant brightness for the high quality raw material used (*Fig 6*), compared to the neural network predicted brightness. It is possible that this could have been due to the low volumes manufactured and the effect of recirculating contaminated back water. Another example was the yield deviations of some of the processes, as shown in *Fig 12*. This suggests that there are perhaps undetected yield leakages from the system.

The models could also be used to pre-empt the results of trials. An actual mill trial carried out in the newsprint mill with a different ratio of magazine to newsprint yielded only a marginal increase in brightness, despite the change in furnish composition. This marginal change was also predicted by the neural networks. The use of the models pre-trial would have avoided the unnecessary costs and disruptions of trials on production plants.

Recycling plants are sometimes confronted with sudden raw material changes. A particular grade of recycled paper could suddenly become unavailable, and the plant is confronted with the need to change the ratio or even the grade mix of recycled paper raw material. These changes could be fed into the models to predict the outcome. In addition, the corresponding changes to the alkalinity or bleaching regime required to maintain the output quality could be determined in a short period of time. This would enable plant management to make a rapid decision on the processing conditions for changed incoming raw materials.

Practical Implementation

In order to develop a desk-top model which would enable plant personnel to proactively anticipate quality and process adjustments in response to changing recycled paper raw material conditions, a process of development would be required, which would involve the following steps: (Tarassenko, 1998: 46-48):

- Implement the prototype on mill hardware and software by programming user-friendly interfaces for use by plant personnel.
- The models must be tested on plant data over a longer period of time and variety of conditions. This would make it possible to quantify confidence limits for the model. It would be advisable to repeat the laboratory-plant flotation alignment processes (as discussed above), specific to the plant on which the model is being implemented.
- The use of these models to troubleshoot or optimise processes must be combined with extensive knowledge and experience in deinking processes. The models rely heavily on the underlying data base of laboratory work. An understanding of this data base and its limitations is essential to make effective use of the neural network models.
- Lastly, the system would need to be maintained. Bugs could develop and the operating environment could change, necessitating revisions and enhancements.

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APPENDIX 1: Neural Network training and prediction performance

	Training Performance mean square error (MSE)			Training Performance correlation (R)				Prediction *vs.* plant data	
Ranking	Training	Validation	Test	Training R	Validation R	Test R	Total R	Correlation R	MSE
BRIGHTNESS (%)									
Best	5845	992	601	0.950	0.966	0.957	0.954	0.940	26
Median	5777	924	891	0.950	0.963	0.957	0.953	0.924	69
Worst	3756	1146	582	0.966	0.960	0.971	0.965	0.740	217
ERIC (ppm)									
Best	1974668	319646	332271	0.867	0.832	0.806	0.853	0.934	1021
Median	461843	276934	293051	0.957	0.879	0.874	0.933	0.871	6798
Worst	881200	266974	504903	0.922	0.908	0.603	0.890	0.712	20667
FLOTATION YIELD (%)									
Best	21063	10013	2786	0.825	0.598	0.816	0.790	0.425	101
Median	39937	8241	3282	0.688	0.673	0.647	0.679	-0.401	153
Worst	57041	10986	6865	0.502	0.447	0.633	0.499	-0.711	240