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PAPER MILL PROCESS SIMULATION AND DATA-MINING CONCEPTS, AND INTEGRATION INTO A SYSTEM-WIDE APPROACH FOR PREDICTIVE CONTROL

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ABSTRACT: Detailed real-time dynamic simulators are an ideal tool for examining the co-operation of the papermaking process and its automation during normal and exceptional operating conditions, and disturbances due to equipment or automation malfunctions, operator actions, or raw material quality variations.

Dynamic real-time models are an excellent tool for advanced control development. A systematic use of multi-functional dynamic simulators over the entire process life-cycle can bring substantial benefits both to the pulp and paper companies, to the equipment and automation manufacturers, and engineering companies. As an example, the risks related to process and automation renewals can be reduced by using detailed real-time dynamic simulators in design quality assurance and rigorous automation testing. The same simulator can further be used for high-quality operator training. Altogether, this subsequent utilisation of the simulator substantially helps in achieving trouble-free commissioning and start-up savings. Cumulative benefits can be gained after start-up, when the simulator is kept consistent with the real process and its actual automation by continuous system updates. The self-adaptive neural network-based simulator is an ideal tool both for continuous improvement of mill personnel skills and mill operating strategies, and as the foundation for a system-wide predictive control system.

Application: Models, simulation and optimisation are important because they can enable the achievement of the following:

- reduced manufacturing costs
- reduced research, development and engineering times
- increased efficiency
- greater understanding of the problem
- decision support & risk reduction
- reusability and reproducibility
- knowledge management
- technology transfer
- ability to handle complex problems
- reduce pollution
- improve the safety of the plants
- bring new products to market faster
- operator training (also for hazardous situations)
- reduce waste in process development
- reduce need for potentially hazardous experiments
- improve product quality.

BACKGROUND

At the moment, the paper industry faces many challenges. Shareholders expect more return on investment; the markets set increasing store on cost-effective production and environmental issues, as well as sustainable development, all of which need to be taken into account. Moreover, better profitability is achieved by introducing new knowledge-based specialty products. Mathematical modelling, real-time simulation and data-mining provide tools that can be used to respond to these challenges.

Pulp and paper processes have traditionally been thought of as containing sufficient complexity as to contain a major element of “art” as opposed to scientific understanding. Much has changed in recent decades, not least of which is the availability and power of modern computers. This has lead to developments of powerful distributed control systems and advances in large database numerical analysis techniques. Recent advances have enabled the creation of virtual paper mill control systems offering system-wide predictive control, in real-time, and with the capability to predict the physical performance characteristics of pulp and paper mill process systems with great accuracy. Furthermore, these systems can be operated in a self-adaptive way – i.e. they will automatically learn and adapt to changes in the process, in real-time.

Traditionally, and in the majority of mill cases, relatively simple static material and energy balances have been employed for process design and, perhaps, some degree of optimisation. However, new techniques and methods are available to model linear and non-linear paper mill processes with exceptional accuracy, in real-time if required, and even when variables are not directly measured. Critical product qualities such as tensiles, bulk, grammage variation, smoothness and porosity can be forecast and optimised using the vast volume of data usually stored within a mill’s own DCS and QCS systems.

Appropriate non-linear modelling techniques, when coupled with sophisticated data-mining technology such as neural networks, and applied using detailed mill process knowledge as an integrated approach offer mills many opportunities to gain competitive advantage.

Mathematics, numerical analysis, modelling and process programming will become more and more important in the design and optimisation of pulp and paper mill operations for those mills wanting to maximise the potential of their existing assets, and ensuring right first time delivery of design outputs for new investments. The ultimate form this will take is in the form of real-time, system-wide predictive distributed control systems containing in-built adaptive neural network and similar capabilities. All this technology already exists, and the ultimate predictive control system capable of self-adaptive learning and control optimisation has become a reality.

CONVERGING TECHNOLOGIES

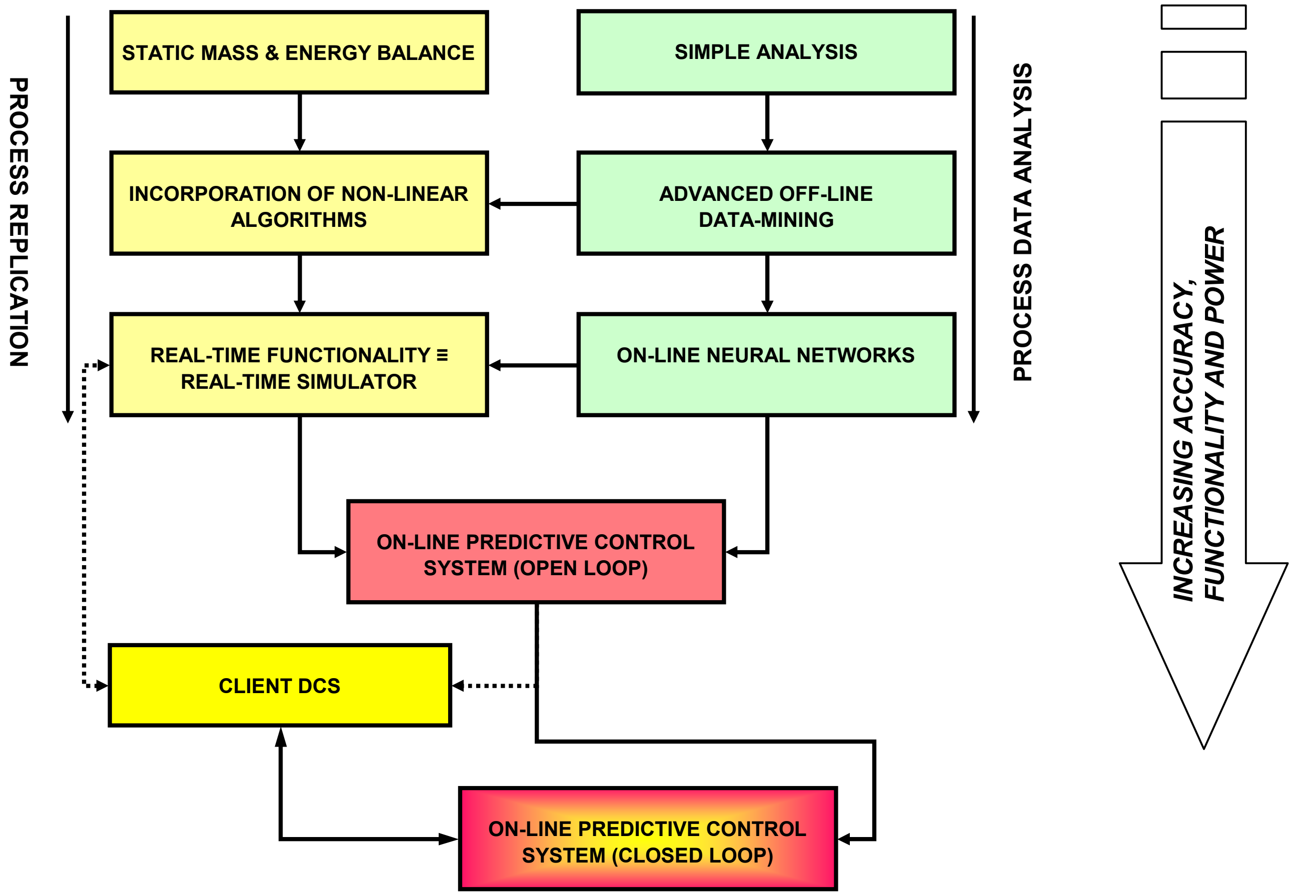


Figure 1. Development and convergence of process simulation, data-mining and distributed control systems [Clearwater Paper Technology 2003]

Convergent technologies are:

Mathematical modelling & simulation
Data-mining & neural networks
Distributed Control Systems

Mathematical Process Modelling

Commercial materials and energy balance software, or paper mill specific can be used. However, the key is the ability to combine process knowledge with accurate calculation of unit operation variables. Clearwater has successfully used specific mathematical replication of paper mill processes to generate the algorithms that determine the outcomes of unit operation modelling. By creating process mathematical models in an Excel / VBA environment it is possible to run all mill models on any modern desktop PC with Microsoft Excel installed.

Conventional modelling is restricted to equilibrium material and energy balances. Often, such balances use simple linear equations to derive output variables from each unit operation calculation block. Such models are frequently run at steady-state equilibrium and maximum design output. As such they can be useful for initial scoping of equipment size ranges. However, real process problems and significant inaccuracies will occur if some degree of precision is not applied to the variable determinant equations (which are usually non-linear functions of multiple variables) in each unit operation, and to non-steady state events within the process. In particular, discrete throughput turndown conditions are not always adequately simulated, with corresponding process balance issues resulting in the real process.

The Clearwater Paper Technology (CPT) “Pro-SIM”™ modelling system has the capability to:

- Model all pulp and paper mill unit operations
- Handle multiple non-linear variables – eg. pressure screen thickening factors, 1st pass retention.
- Provides a graphical user interface (GUI) which is intuitive for spreadsheet literate users.
- Runs multiple operating scanerios, including non steady-state events and process excursions

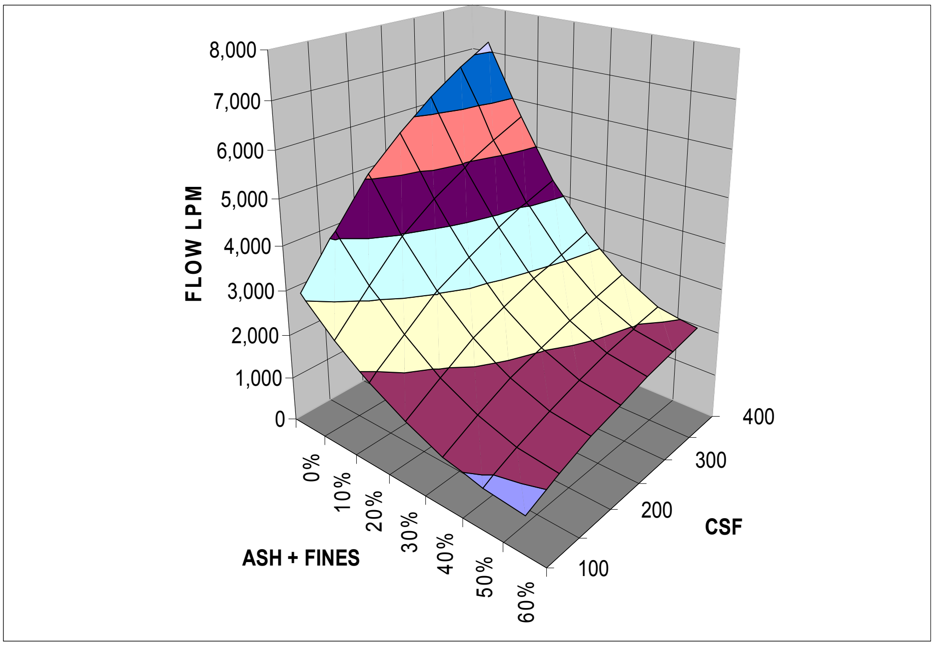


Figure 2. Algorithm surface map of two variable non-linear function of thickener filtrate flow as a function of freeness and ash+fines components.

Data-mining

Appropriate data-mining techniques offer the opportunity to derive very precise and highly specific non-linear equations for mill unit operations. These equations have the great advantage of being derived from real mill data, as opposed to micro-, or molecular-scale calculations based on first principles (such as thermodynamics and fluid dynamics). Careful selection of the correct data-mining technique is key to the successful analysis of mill process data. In addition, the application of sophisticated dynamic filtering techniques becomes essential to eliminate high levels of signal noise, almost always present in raw mill DCS and QCS data. However, when properly applied, algorithms which define every unit operation with great precision can be achieved.

Neural networks have been used with excellent results, to generate precise (but highly complex) algorithms which can define multiple variable interactions and their effects both on the process and the products. Applied neural networks provide the non-linear, mill and unit operation specific algorithms essential for precision modelling of every element of the process – and hence the entire system model.

Once a true non-linear model has been created it can be used for many different purposes. For example: process design, process de-bottlenecking, yield analysis, energy auditing. Such a model can now be used as the foundation for a true (virtual reality) real-time simulator of the entire paper mill process. This is achieved by integrating the VBA-based model (containing the data-mining derived non-linear algorithms) with a specially created process control platform with the relevant communications protocols to enable two-way communication with the mill's own DCS system.

Thus, it is possible to "fool" the DCS into communicating with the virtual paper mill system instead of the real one (which may still be in the construction stage). The advantages of this approach become very clear when building a new stock preparation and / or paper machine system. As well as providing the basis for fundamental process design, this "Integrated Simulation Solution" (or "I.S.S"™.) technology provides the ultimate in Factory and Site Acceptance Tests (FATs and SATs) for a new DCS – since all loops, starts and sequences can be replicated with high levels of fidelity.

For example, it becomes possible to detect sub-optimal matching of centrifugal pumps and downstream control valves before anything is even purchased or installed in the real process. Following on from FAT and SAT duties, the Clearwater I.S.S.™ real-time simulator provides an extremely efficient method of training operational personnel – i.e. trainees use the DCS and control environment weeks or months before a project start-up - in a manner analogous to a flight training simulator (the DCS is the real thing, but the whole paper machine and all processes are virtual).

The fact is that it is possible to devote huge resources on modelling from first principles what happens in each unit operation. Instead, CPT uses neural network and other data-mining techniques to construct precise algorithms of each unit operation on a customer's site from the customer's own data. These algorithms are a fundamentally accurate virtual-reality replica of the real process. They offer greater fidelity, and far superior cost-effectiveness than equations developed from first principles.

Data driven analysis

The data generated from a paper manufacturing process has a number of characteristics that have a big impact on the modelling process. These characteristics cause the modelling process to be particularly intricate and quite challenging with regards to data mining of variable behaviour for example. Some of these specific characteristics are:

- Time-varying process dynamics.
  The production and conditions for the paper manufacturing process are under constant changes; a generated predictive model will lose accuracy over time because of changes in the dynamics, conditions and production. Approximation functions in general are sensitive towards changes in the production, target quality and other process conditions. In order to utilise predictive models on a continuous basis a predictive model has to be frequently updated with the latest data available.

- Various sources of disturbances
  There are a large number of disturbances in a paper process to consider when analysing process data. The measured flow for example during a week may include disturbances such as equipment degradation, sensor failure, unexpected interruptions, cyclic disturbances and random behaviour. Figure 3 shows the type of disturbances that can be embedded in a measured signal. The disturbances occur with various levels of intensity but in general there are high levels of noise in measured data from paper process data. In order to capture the actual process dynamics and build an effective online control strategy based on linear and non-linear predictive models it is of great importance to isolate, understand and decrease the levels of noise in the measured data.

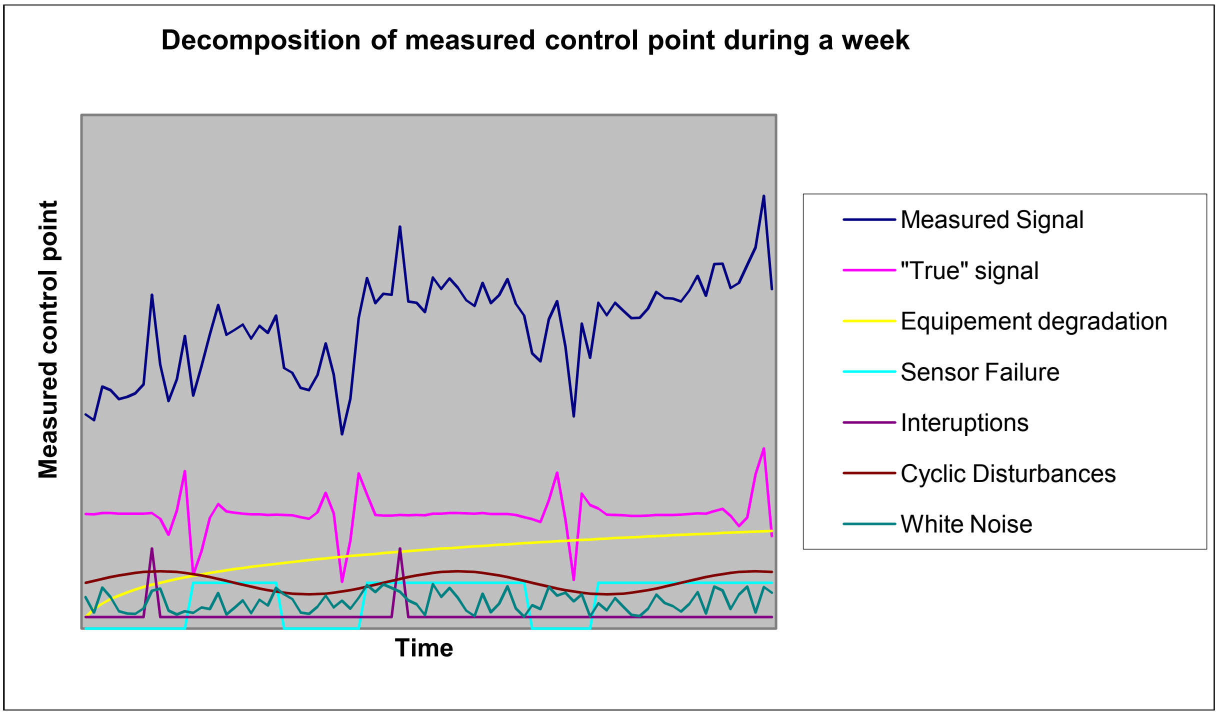


Figure 3. A signal from a possible control point and its possible components. The blue “Measured Signal” is made up by all the other components.

- Linear dependencies combined with a high degree of non-linearity.

The dynamics within a paper process line are highly non-linear with a very complex interaction with known linear dependencies. If these dynamics are not explicitly determined, the most cost and resource effective ways to model these is to find an approximate function that fits historical data.

- High degree correlations in the data.

The availability of data from several thousand control points creates a problem when conducting data-mining of complex dynamic data. Many nearby control points are closely correlated even though they may measure different things. A predictive model that is based upon similar control points will be unstable and not useful when applied in an on-line scenario. Another problem with process modelling in general is that data from control points are primarily used for control purposes but may not provide sufficient information for predictive modelling. With the amount of data available there are endless numbers of combinations and calculations that can be performed.

Data pre-processing

The objective of the data pre-processing step is primarily to make a pre-judgement of which information not to include in the modelling among the several thousands control points available. Simple univariate and bivariate analysis in combination with regression methods and decision trees gives a set of variables to continue modelling with. A separate correlation analysis will show which variables are "measuring the same thing" and how to combine them in order to maximise the stability of a predictive model. Further data transformations in order to highlight possible discrepancies and deviations from the normal are also done.

In order to increase the accuracy and precision of the model it is important to create a "clean" signal with a minimum level of noise. The data pre-processing also involves sequential non-linear filtering in order separate the noise from the actual dynamics. This is done by filtering the data, identify disturbances and removing them from the data. The filters are designed to capture sharp changes in a piece-wise continuous signal as well as "background noise" which usually has low amplitude and high frequency

Figure 4 and figure 5 show the measured paper basis weight during a week, sampled at five minute intervals. The green graph is the original paper basis weight and the red superimposed graph is the filtered paper basis weight. The target basis weight during this period was 45 g/m^2 and this paper machine clearly suffers from significant instability of the paper basis weight. These two filters accomplish two objectives; identification of the key quality drivers; and identification of the key instability drivers. The filter in figure 4 captures the main trend of the basis weight. The further analysis of this data was concentrated to identify the key drivers of the quality and to develop a strategy to balance this. The filter in figure 5 captures the main instabilities of the basis weight and further modelling was concentrated to identify the sources for instabilities and develop a strategy to minimise those.

These graphs demonstrate the ability to design and adapt the filter to accomplish specific data which is a necessity when dealing with live on-line data.

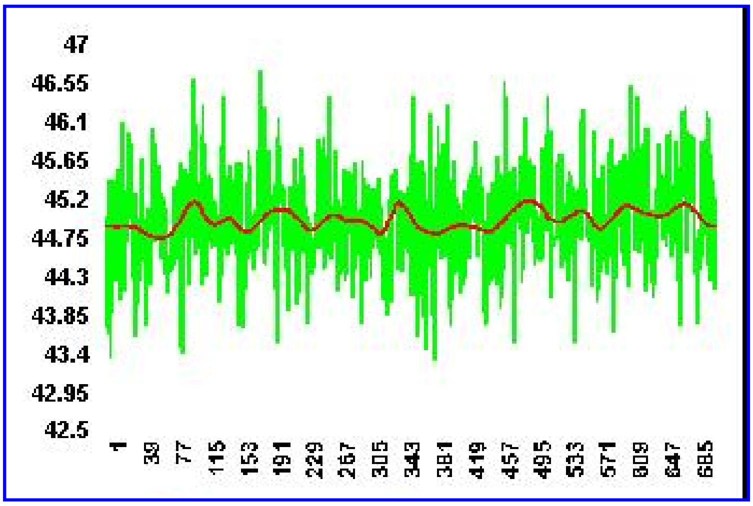


Figure 4. The paper basis weight measured during a week. The green graph is the actual paper basis weight whereas the red graph is the filtered weight highlighting the general trends and cycles.

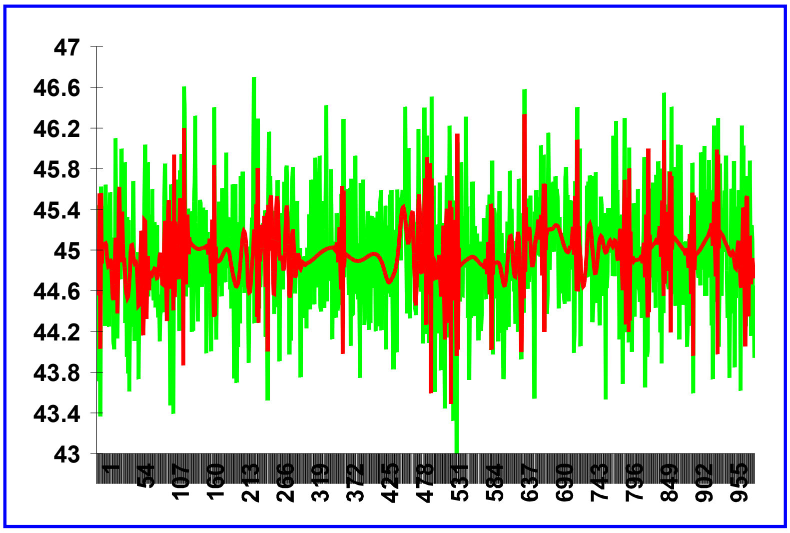


Figure 5. The paper basis weight measured during a one week period. The green graph is the actual paper basis weight whereas the red graph is the filtered weight highlighting the instabilities in weight.

Off-line modelling

Neural networks are named after the cells in the human brain that perform intelligent operations. The brain is made up of billions of neuron cells. Each of these cells is like a tiny computer with extremely limited capabilities; however, connected together, these cells form the most intelligent system known. Neural networks are formed from hundreds or thousands of simulated neurons connected together in much the same way as the brain's neurons.

Just like people, neural networks learn from experience, not from programming. Neural networks are good at pattern recognition, generalization, and trend prediction. They are fast, tolerant of imperfect data, and do not need formulas or rules. Neural networks are trained by repeatedly presenting examples to the network. Each example includes both inputs (information you would use to make a decision) and outputs (the resulting decision, prediction, or response).

The network tries to learn each of the examples in turn, calculating its output based on the inputs you provided. If the network output doesn't match the target output, “DATA-Pro” corrects the network by changing its internal connections. This trial-and-error process continues until the network reaches your specified level of accuracy. Once the network is trained and tested, you can give it new input information, and it will produce a prediction. Designing the neural network is largely a matter of identifying which data is input, and what you want to predict, assess, classify, or recognise. However, the high-degree of complexity and interactions between variables means that a supercomputer would be needed to process all the data with any accuracy. This is where specially designed dynamic numerical filtering techniques have been developed and applied by CPT. Results have shown that the use of this technique can eliminate “noise” from the database and allow the neural network to learn a complex set of relationships with much improved efficiency. This equates to reduced computation time and faster, more robust results.

The multi-layer perceptron neural net has proven to be successful in a number of off-line applications within paper processing. This network is composed of an input layer, one or more hidden layers and an output layer that predicts paper quality, as can be seen in figure 6. The input layer is made up by nodes that represent input variables, the hidden layers are intermediate variables that are made up by weighted sums of the previous layer and the output layer is the final predicted quality. The type of weighting combined with the interactions between the nodes creates a powerful approximation function able to capture any non-linear dynamics. There are a number of variations of neural networks available for application for non-linear process algorithm generation.

During the training phase of the neural network deployment, historical data is passed through the neural net and the weights in the hidden layer are adjusted in order to fit predicted outcome to the actual outcome. The accuracy of the neural is heavily dependent upon the availability of historical data; more historical data usually makes the training more efficient. Neural nets can easily be “over-trained” but this is addressed through validation and test procedure where the predictability is controlled. Once a neural network has been trained the layers are “fixed” and can be used as an on-line predictive model.

Multi-layer Perceptron Neural Net

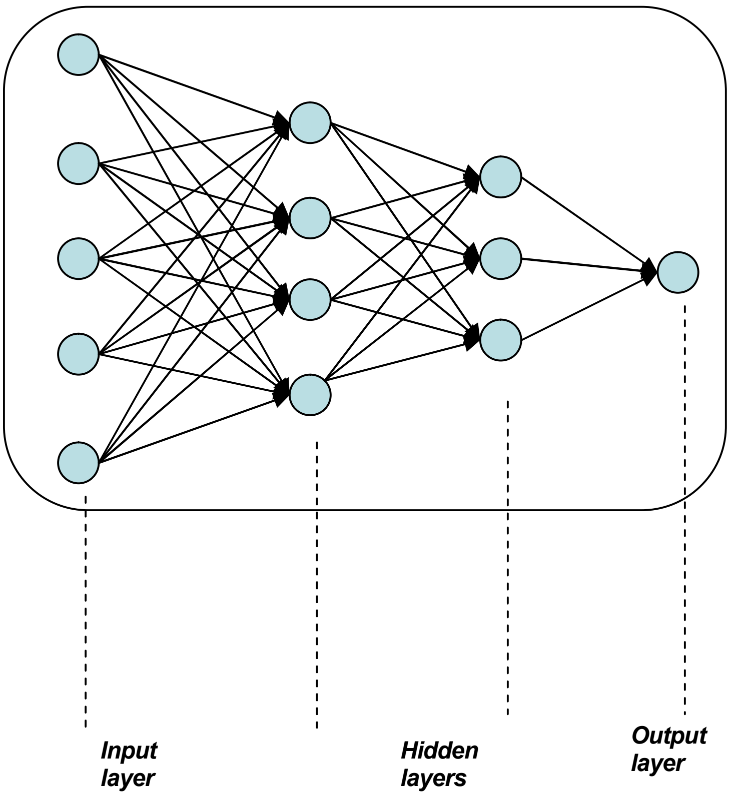
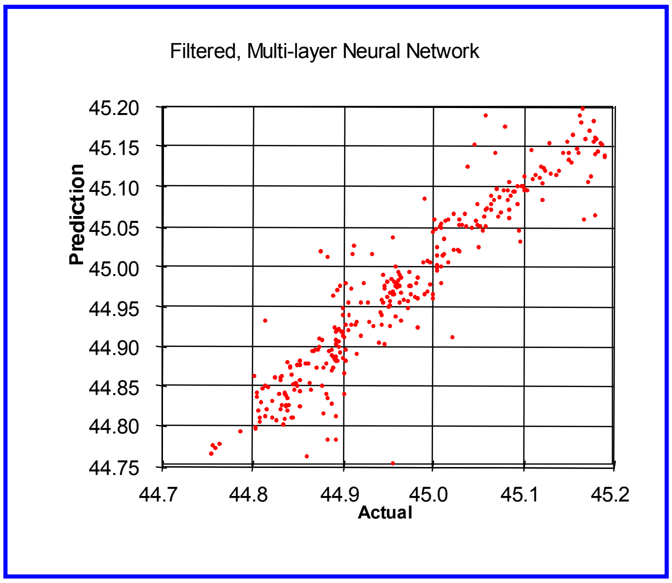


Figure 6. Data modelling includes a data transformation step that mainly includes normalisation, creation of new aggregated variables, correlation and difference variables. A selection of variables to include in the neural net modelling is also done. The variables are entered in the input layer, processed through the hidden layers and is finally aggregated to a final prediction in the output layer.

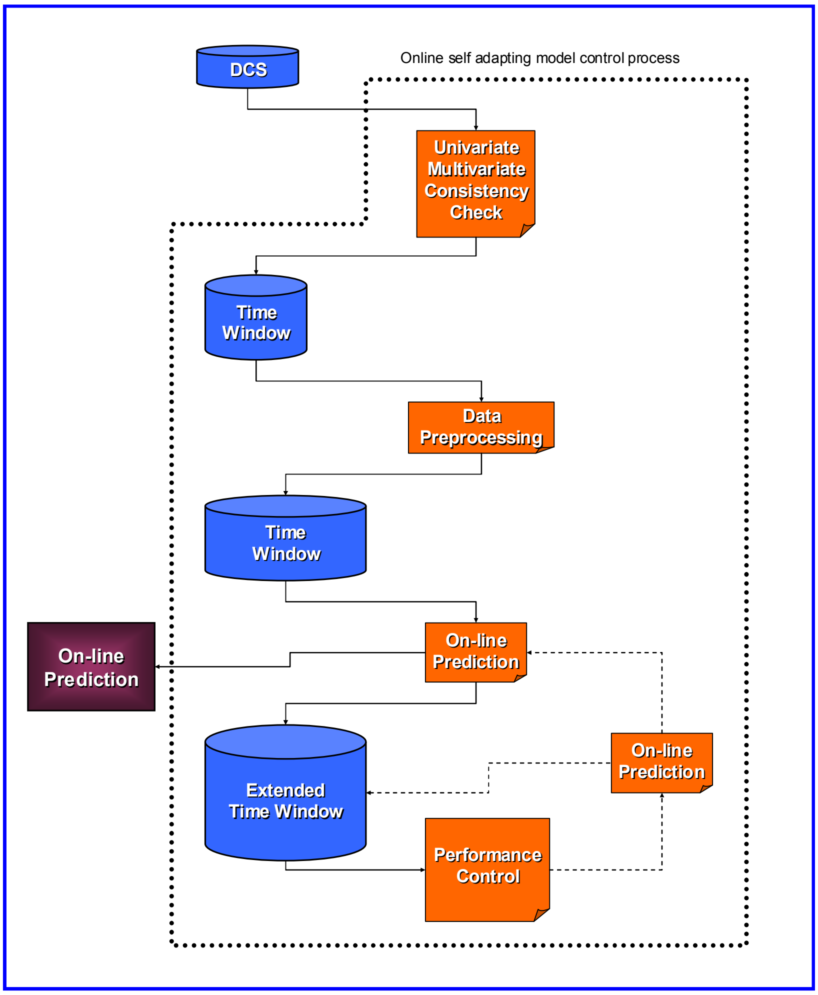
Figure 7 shows an implementation of such a neural network predicting the paper basis weight. There is a very good predictability with an R^2 exceeding 90%. The model is based upon the filtered data in figure 5 above. This is an expected effect from the filtering; neural networks are very capable of finding very complex relationships <u>if the data is reliable</u>. If there is too much noise in the data then the neural net will be blurred and unstable.



Self Adaptive Online Modelling

The described process of pre-processing data, training neural networks and prediction can be automated by adding two sub-processes; a data consistency check that makes sure that the model is not extrapolating; and a performance control process that decides when the model needs to be re-trained. Also, the modules needs to have a short history available in intermediate databases in order to perform quick and effective data pre-processing, performance control and re-training. An overview of such a process is shown in figure 8.

Figure 8. Schematic view of a self-adapting process for online prediction



1. Data from the DCS is entered into the online control process and passed through a univariate and multivariate consistency check module. This module will warn the performance control module if there is risk for univariate or multivariate extrapolation which will decrease the precision of the neural network. It will also do a pure data consistency check. Warnings will be stored in extended time window database.

2. The online data is stored in an intermediate database that keeps the most current data within a determined time window. The data is processed through the data processing module that will filter, aggregate and transform the variables. New variables will be added to the stored time window. Any warnings from the processing are stored in the database.

3. The processed data will be stored and processed in a new time window database and the neural network will be applied directly onto the new time window database. The predicted outcome will be outputted back to the system and stored in a database with extended time window.

4. The extended time window database includes the history for performance control and re-training purposes

5. The performance control module controls the performance and the warnings and trigger re-training of the neural network if the performance drops. The re-training will be based upon the extended time window database and the resulting model will replace the current model.

PREDICTIVE CONTROL

Predictive control is broadly defined as feed-forward control based upon the use of predictive algorithms.

Today, most commercially available predictive control operates on the basis of the adaptation and optimisation of individual, discrete conventional control loops. By using a virtual reality model of the paper machine and all its systems, it is possible to create an entire system-wide predictive control system, fully integrated, and functioning in symbiosis with an existing DCS. Self-adapting neural networks are embedded into the kernel of the virtual system thus imparting a degree of artificial intelligence to the control of the paper mill processes.

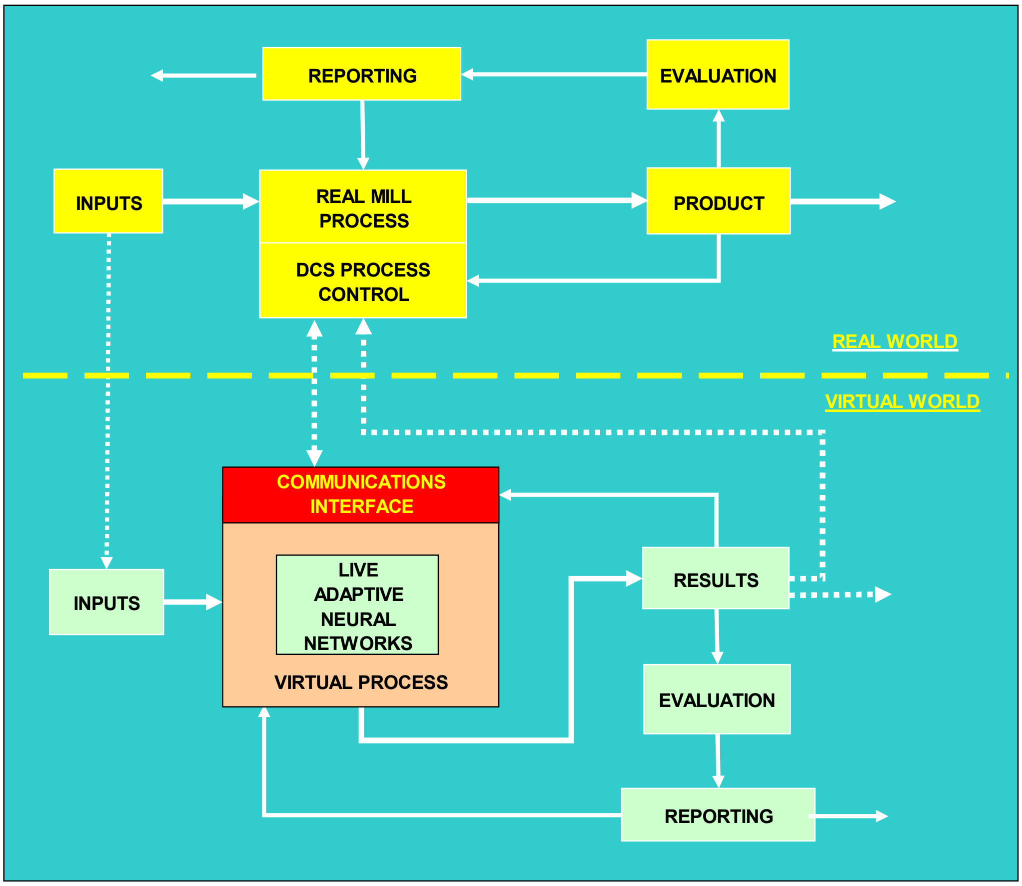


Figure 9. Analogy and function of system-wide predictive control system based on virtual process simulation

CONCLUSIONS

Modern computing power, data-mining techniques, neural network development and non-linear simulation technology, when coupled to distributed control systems, can provide the means to achieve true, system-wide predictive (feed-forward) process control. Process design, optimisation, de-bottlenecking, operator training, and quality control can all be enhanced by the application of the same technologies.

No matter how good the mathematical modelling, simulation and data-mining, it can only be regarded as of limited value if the application and use of these tools does not reflect the complexities of the particular production process. Good process and chemical engineering skills, not to mention knowledge of the pulp and paper production processes, are essential to the effective deployment of these technologies. When deployed by experienced personnel using accurate and adaptive simulation and analysis tools, these technologies can make the difference between a successful mill and a failing mill.

Key points:

- Mathematical modelling and simulation in the paper industry have for a long time been based on the unit operations approach, and although still very important this field of process modelling can be considered as mature.
- New techniques such as genetic algorithms, case-based and rule-based reasoning, neural networks and fuzzy logic should be put to more active use.
- Modelling tools that support innovative utilisation of deep knowledge of chemical engineering science should be developed. One example is the use of specific simulators in innovative process development.
- Integration of the modelling tools should be enhanced. Tools and models that support technology transfer such as operator training and support systems should be further developed.
- Knowledge management will continue to become more and more important.

References:

1. Principles of Data Mining (Adaptive Computation & Machine Learning): David Hand, Heikki Mannila & Padhraic Smyth – M.I.T. 2001.
2. State of Mathematical Modelling and Simulation in the Finnish Process Industry, Universities and Research Centres - Kimmo Klemola & Ilkka Turunen - Lappeenranta University of Technology, Department of Chemical Technology
3. Asprey Steven, Dynamic process simulation – A Quick Overview, 1998, http://www.pse.res.titech.ac.jp/~asprey/Dynamic/tsld001.htm.
4. Benyahia F., Flowsheeting packages: reliable or fictitious process models. Trans IChemE, Vol 78, Part A, September 2000.
5. Björkqvist Jerker, Comments on BSched 12.02.2001. CFD-RES, What is CFD?, 2000, http://www.cfdres.com.au/whatcfd/index.html.
6. Dagani R., Building from the bottom up, Chemical and Engineering News, October 2000, Vol.78, No.42.
7. Douglas J. M., Conceptual design of chemical processes, McGraw- Hill, 1988.
8. Elliott David H., What is CFD?, Cranfield University, 1995, http://www.cranfield.ac.uk/sme/cfd/david/pages/whatiscfd.html.
9. Eudoxus Systems Ltd, What is optimization? 2000, http://www.eudoxus.com/what.html.
10. Gani Rafiqul, Kraslawski Andrej, Process synthesis – state of art, CAPE.NET 2000 Seminar & Exhibition, 22-23 June 2000, London.
11. Neural Networks, Deterministic Method of Analysis. Steve Ellacot and Deb Bose. 1996 International Thomson Computer Press
12. Machine Learning. Tom M. Mitchell. The McGraw-Hill Companies, Inc
13. Optimization and Simulation of Quality Properties in a Paper Machine with Neural Networks. Jouko Lampinen, Member IEEE and Ossi Taipale. 1994.
14. Predictive control of nonlinear systems based on fuzzy and neural models. R Babuska, J.M. Sousa, H.B.Verbruggen.
15. Chemical process identification with multiple neural networks. Wen Yu. International Journal of Computational Engineering Science. 2002