Development and application of a real-time recovery boiler expert system

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A millwide information system, an expert system shell, statistical process control, and real-time process simulation were combined to form a prototype advisory system.

The recovery boiler, although often a bottleneck, is an integral part of any kraft mill. Maximizing production while maintaining safe operation are primary concerns. Statistical process control (SPC) and simulation are powerful tools for addressing these problems. SPC is useful for maintaining stable operation, whereas off-line simulation has proven useful to evaluate various operating strategies (*1*). Real-time integration of these methods has also been proposed (*2*). This paper describes integration of a millwide information system, an expert system shell, SPC, and real-time process simulation into a prototype advisory system for recovery boiler operation.

System topology

Figure 1 shows a general representation of the mill computer system as it is now configured. Real-time process data are available to all system components via the data highway. Since the simulation is computationally intensive, the calculations are performed on a dedicated microcomputer. The simulation output is entered into the millwide database and is treated as a typical process variable. Consequently, the expert system is able to address both measured and calculated data. Expert system output, in the form of messages, is relayed to remote terminals and computers. Messages can easily be routed to operators, engineers, or managers.

Model description

The recovery boiler model is based on the General Energy and Material Balance System (GEMS) (*3*) steady-state modular simulator developed by Shiang and Edwards (*4*). **Figure 2**, which presents the GEMS block diagram, is included to show the level of detail addressed by the model.

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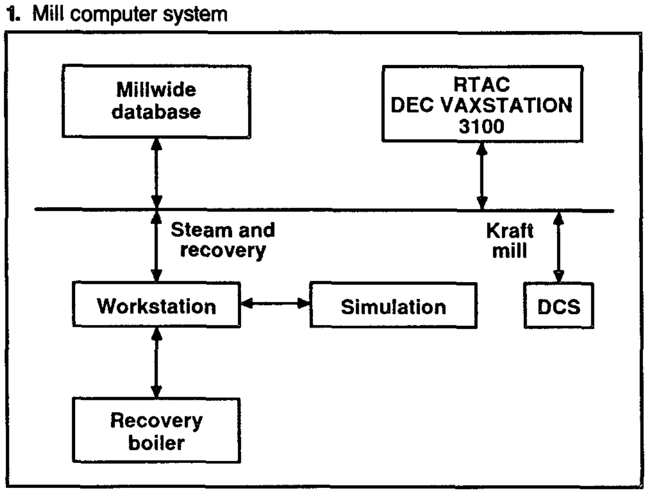
1. Mill computer system

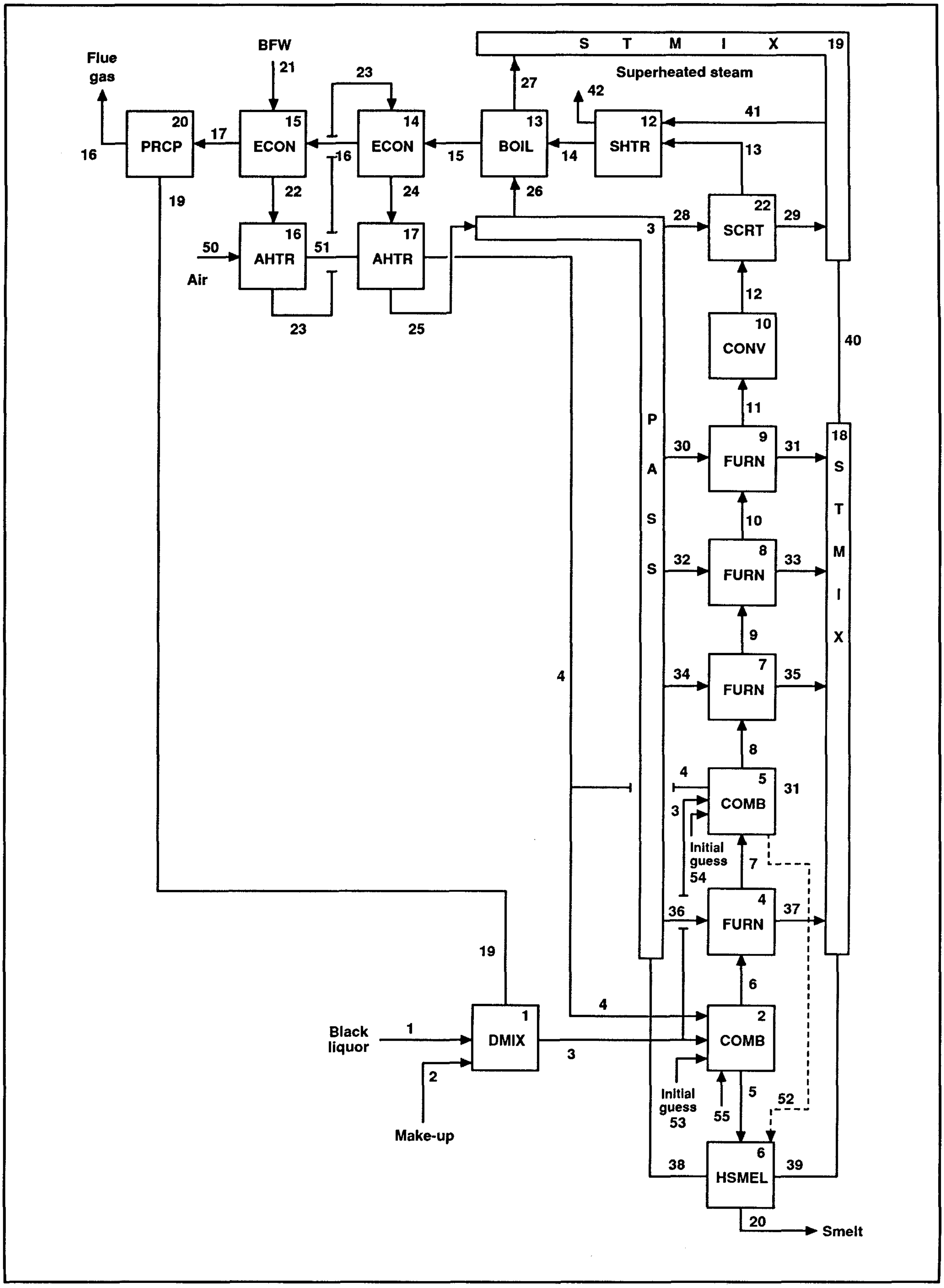


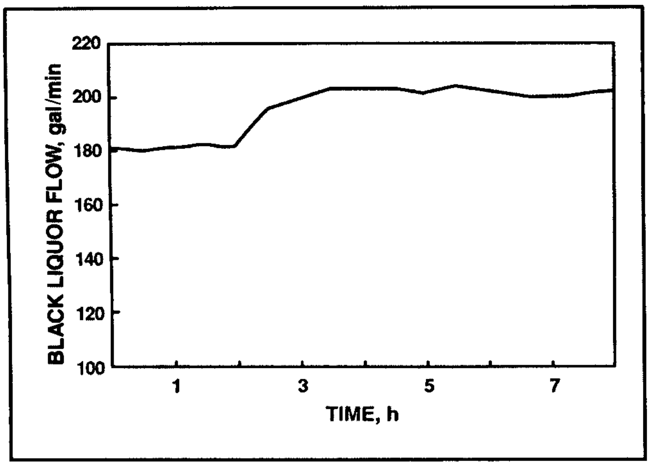
Briefly, conditions in the combustion zone are predicted by an adiabatic free energy calculation. Both radiative and convective heat transfer modes are used to model the firebox and individual tube sections. Furnace temperature profile, heat fluxes, and dust accumulation are estimated, along with a complete material and energy balance.

Since char bed dynamics are an important aspect of recovery boiler operation, an on-line estimate of bed mass variation would have great benefit. It is not intuitively obvious how a steady-state simulator can be used for this purpose. By definition, steady-state calculations do not include material accumulation. However, consider the following mill process data. Black liquor, total air, and superheated steam flow rates are shown in **Figs. 3-5**, respectively. Although not plotted, the black liquor solids fraction remains constant over the given time period. Additionally, flue gas temperature and composition are measured as well as steam pressure and temperature.

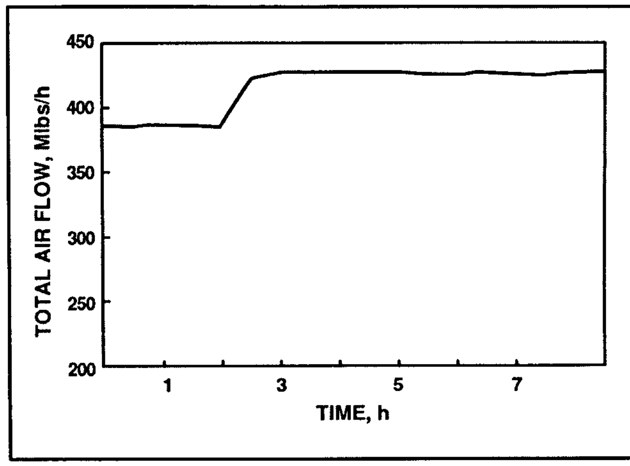
After two hours, black liquor and air flow to the boiler are increased. As a result, steam flow also increases by some proportional amount. If an instantaneous GEMS material and energy balance calculation is performed

2. GEMS recovery boiler block diagram.

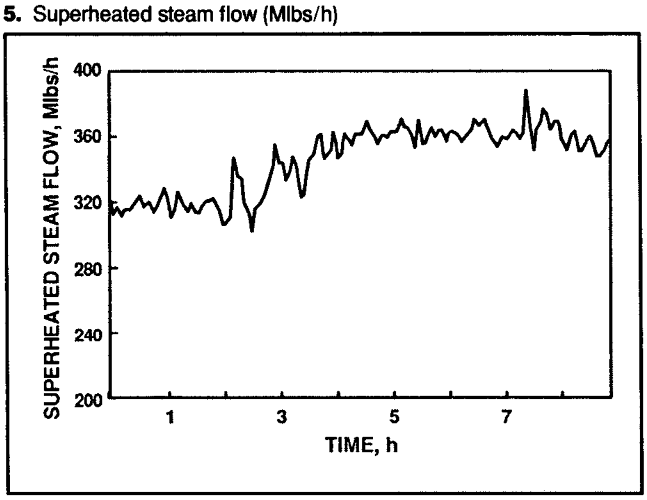




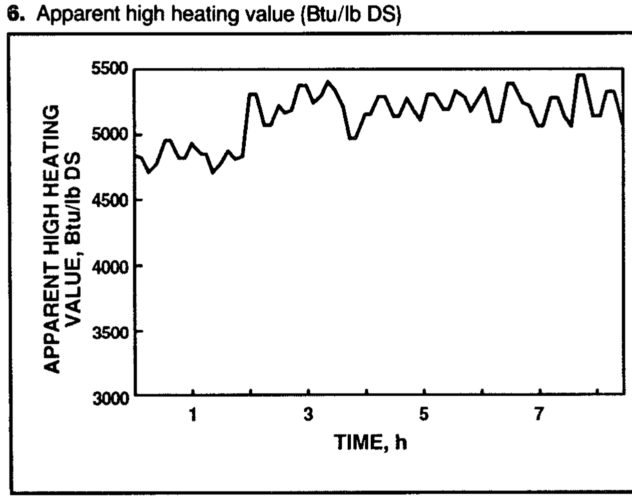
3. Black liquor flow (gal/min)



4. Total air flow (Mlbs/h)



5. Superheated steam flow (Mlbs/h)



6. Apparent high heating value (Btu/lb DS)

which matches inlet and outlet conditions, an apparent high heating value (HHV) can be estimated for the black liquor. In other words, the overall balance is computed with HHV as the dependent variable. The result of this updating calculation is shown in **Fig. 6.** If all the additional black liquor solids were combusted, an overall balance would generate the same apparent HHV. However, examination of Fig. 6 shows a positive step change in apparent HHV synchronized with the firing rate adjustment. The increase must be attributed to complete combustion of the incremental solids plus some of the char bed. Variability of black liquor composition can also cause the computed HHV to change. However, mixing of liquor in storage tanks prior to firing would cause a first- or higher-order response rather than a step change.

A trend plot of the apparent heating value can therefore be a relative indication of bed building or burning. Increases in apparent HHV are associated with bed depletion, whereas char accumulation is indicated by decreasing apparent heating value. Since the GEMS material and energy balance is updated on a 3-5 min cycle, operating personnel receive char bed accumulation information much faster than is possible visually from bed cameras. Work is currently underway to shorten the calculation time and hence increase the update frequency.

Real-time expert system

The recovery boiler has a large number of process variables and associated information. Mentally interpreting all this data in real-time, particularly during a severe process upset, is a difficult task. Presentation of additional simulated process variables provides process insight but also compounds the problem of information overload. A solution is to off-load part of the data analysis to a real-time expert system.

The Real Time Advisory Control (RTAC) (*5*) software product by Mitech Corp. is a central component of the recovery boiler advisory system. RTAC integrates process knowledge, in the form of rules and simulated values from GEMS, with process data. The software, which is capable of processing approximately 2700 rules per second, continually monitors for operating abnormalities. Once a disturbance is detected, explanatory messages are routed over the data highway to appropriate computer consoles.

Rapid identification of process upsets is a significant aspect of an advisory system. However, correctly detecting a disturbance is equally important. Rules must be developed which not only identify abnormal conditions but screen spurious sensor signals as well. Here, statistical process control plays a crucial role. SPC is ideally suited for determining if a process variable is in an abnormal condition. Embedding SPC in RTAC provides a real-time, easily understood method for detecting sensor problems as well as process upsets. The SPC criteria include one, two, and three sigma confidence intervals for both sample average and range. A rule to detect the shift of the sample mean is also incorporated.

Presently, all SPC confidence intervals are a function of black liquor solids flow rate. Clearly, different sets of SPC limits must be used over the range of solids firing rates. This is analogous to using grade-based SPC intervals. A single set of SPC limits would be too wide to distinguish all but the most severe process abnormalities.

Expert system details

Process variables and sensors are considered to be either in normal or abnormal states. For clarity, "process variable" refers to data, whereas "sensor" refers to the physical instrument. As an example, if the current excess O_2 measurement does not violate any SPC limit, the oxygen reading is judged normal. However, if the present O_2 value is outside any SPC confidence interval, the O_2 value is in an abnormal state. An abnormal process variable state is an indication of either a disturbance or faulty sensor. The problem at hand is to determine the situation correctly. Analyzing combinations of abnormal and normal states can enable one to differentiate between an upset process and a defective sensor.

Consider first the problem of sensor validation. **Table I** shows a sample rule for checking the state of the excess O_2 sensor. If the excess O_2 reading is abnormal for the given solids flow rate, any of five different systems could be responsible. Process upsets in primary air, secondary air, natural gas, fuel oil, or char bed dynamics could each cause fluctuations in excess O_2. However, if all five measurements are in a normal state, then the rule concludes that the O_2 sensor must be defective. This rule executes every two minutes, and a message is sent to the operator if the meter is faulty. The proper functioning of sensors should be verified before data are used in subsequent rules, since erroneous data can cause incorrect conclusions to be drawn.

Once confidence in instrumentation has been achieved, general process trends can be analyzed by the expert advisory system. For instance, a blackout is easy to detect once it happens. However, from an operations standpoint, it is essential to identify conditions which may lead to a blackout and thereby avoid the situation. **Table II** presents a rule which attempts to recognize these circumstances. The first three rule clauses confirm that pertinent sensors are operating correctly. Process trends preceding a blackout are then checked by the last four rule clauses. Since the black liquor is not burning correctly, CO, TRS, and O_2 can all be expected to increase and steam flow to decrease. Additionally, the apparent HHV would decrease as an indication of bed building. Again, a message is sent to the operator if the rule conditions are satisfied.

The advisory system monitors the process for several additional disturbances. These include tube rupture, firing solids variability, and liquor nozzle pluggage, to name a few. Presently, system messages notify users of process upsets but do not offer advice for resolving the problem. More operating experience is required before adding this feature.

I. Sample rule for oxygen sensor validation

Define rule: Excess O_2 chk If state of Excess O_2 is abnormal and state of Prim Air Flow is normal and state of Sec Air Flow is normal and state of Calc HHV is normal and state of Nat Gas Flow is normal and state of Fuel Oil Flow is normal then conclude Meter of Excess O_2 is abnormal and send (operator, "Excess O_2 sensor is defective") Scan = 2 minutes

II. Impending blackout analysis

Define rule: Partial blackout chk If meter of Excess O_2 is normal and meter of CO is normal and meter of TRS is normal and rate of CO is increasing and rate of TRS is increasing and rate of O_2 is increasing and rate of Stm flow is decreasing and rate of Calc HHV is decreasing then conclude Partial blackout is TRUE and send (operator, "Blackout is approaching") Scan = 2 minutes

Conclusions

A great deal of effort has been expended in developing millwide information systems. However, the act of data collection does not in itself improve operations. Operational improvements are achieved by innovative presentation and application of available data. Here, the millwide system serves as the foundation for integrating advanced process analysis tools such as expert systems, simulation, and statistical process control.□

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