ON-LINE OPTIMIZATION OF MSF DESALINATION PLANTS

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Contents

Summary

In this paper, the real-time (or on-line) optimization (RTO) of the control system set points for MSF desalination plants is addressed. The recomputation of set points is necessary to counter slowly varying disturbances which move the process from optimal operating conditions. Typically, RTO is implemented using a modular structure. Since RTO is based on steady-state models, its results are only reliable if steady-state data are used. Here, a method based on wavelets is used for steady-state detection. To improve the quality of the steady-state data, data reconciliation and gross error detection are used. The reconciliation is generally formulated as a constrained minimization problem. Once the data are validated, new set points are computed such that an economic objective is optimized.

In this work, RTO was implemented in a simulation environment for MSF plants using powerful commercial tools, i.e. SPEEDUP for data reconciliation and optimization and Matlab for steady-state detection. The coordination and data exchange module between the different tasks of the optimization scheme was implemented based on the communication mechanism EDI (External Data Interface) of SPEEDUP. A distributed client and server architecture was chosen to map the partial problems of the full RTO

problem to independent and self-sustained software processes. The communication between client and server processes is based on remote procedure calls.

1. Introduction

The operating conditions of industrial plants are essentially computed to optimize some economic objective, e.g. to maximize profit. Optimal operating conditions would be obtained with a centralized optimizing controller, which uses on-line dynamic optimization based on a non-linear dynamic model of the complete plant. However, this solution is not used in practice for a number of reasons, which include the difficulty of controller design, its maintenance and modification, robustness problems, operator acceptance, and lack of computer power.

In today's practice, operations optimization is achieved using a two-layer hierarchical structure of the automation system (Skogestad and Postlethwaite 1996): (a) an optimization layer, which computes appropriate operating conditions and (b) a control layer, which keeps the controlled variables at the specified set points. Within the optimization layer, the computation tends to be performed open loop based on non-linear steady-state process models. The control layer is mainly based on feedback information and relies on linear dynamic models. Process dynamics can be accommodated for in a more rigorous manner by several modifications of this base structure as suggested in Helbig et al. (1998).

During plant operation, even if the controlled variables are kept at the set points, these disturbances may change the plant optimum over time. Slowly varying disturbances, result from variations in the environmental conditions (e.g. quality of the feed rates), uncertainties, and changes in the process parameters (e.g. heat transfer coefficients) as well as changes in the market conditions such as raw material and product prices. If the slowly varying disturbances occur frequently enough or determining the proper values for the optimization variables is too complex to be achieved from several standard operating conditions calculated off-line, increased plant profit can be achieved via real-time (or on-line) optimization (RTO).

The success of RTO depends on the availability, accuracy and the effective integration of the following parts (De Hennin et al. 1994; Loeblein and Perkins 1998).

A plant model which is essential for the prediction of the plant behavior at the optimal set points and, thus, for the computation of the economic objective. Hence, it must be valid over a sufficient range of operating conditions to guarantee the reliability of the optimization results.
Reliable, i.e. accurate and consistent measurement data.
Robust, flexible, and efficient optimization software.

To meet the above requirements, a modular RTO structure, as illustrated in Figure 1, should be used. Since the optimization is based on a steady-state model of the plant, a prerequisite to use the measurements for optimization is to ensure that, at the considered time, the process is actually at steady-state (Crowe 1996). Once the steady-state has been detected, the data should be analyzed for gross (or systematic) errors. The measured data are then reconciled to ensure their consistency with a process model. Usually, mass and energy balances are employed to enhance the information content of the measurements. Finally, the validated data are used within the optimization module to compute new set points, which are passed to the regulatory control system.

RTO in general has been discussed in De Hennin et al. (1994), Marlin and Hrymak (1997) and Loeblein and Perkins (1998) and many successful applications have been reported (Marlin and Hrymak 1997). For multistage flash (MSF) desalination plants, only a few publications on RTO (Ghiazza et al. 1997; Krause and Hassan 1997) are known. Husain et al. (1992) theoretically discussed the problem of optimizing the operation of an existing MSF plant. Those authors suggested using the objectives minimizing energy cost or minimizing energy consumption and providing inequality constraints which limit the decision variables. They discussed some optimization strategies and the integration problem of optimization and process models. Ghiazza et al. (1997) reported an actual implementation of RTO at the Al Taweelah B plant (United Arab Emirates).

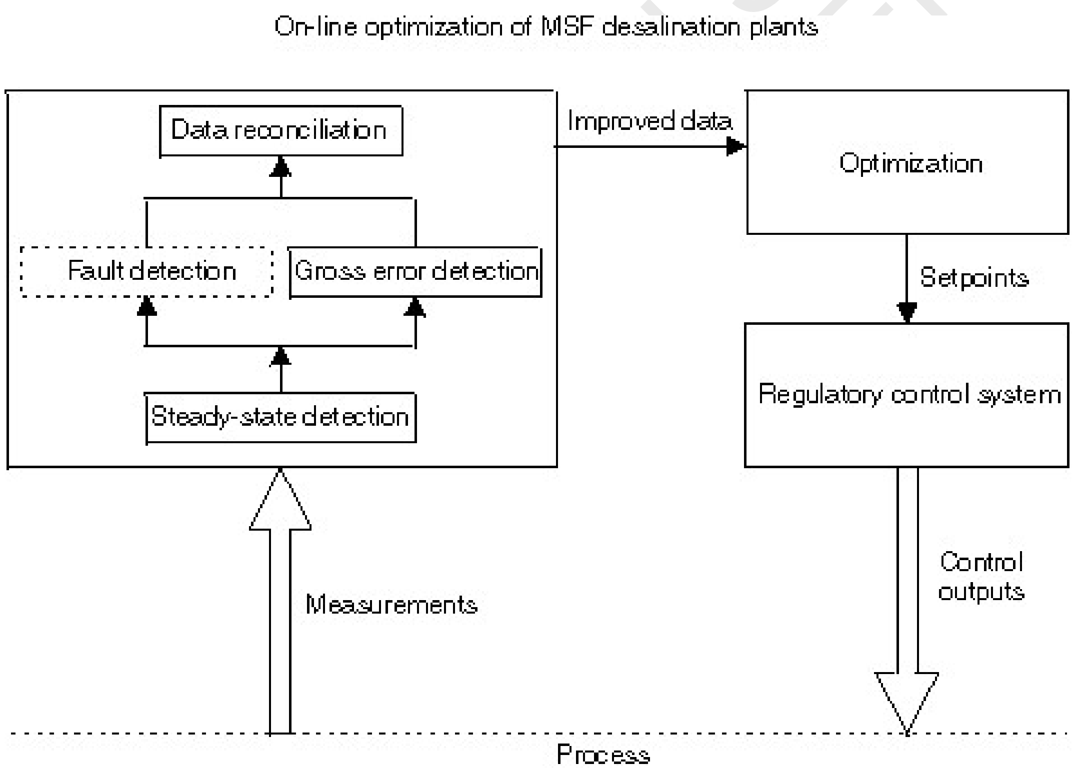

Figure 1. Structure of the steady-state, real-time optimization.

In this work, the modular structure of RTO (Figure 1) has been implemented in a simulation environment for MSF plants using powerful commercial tools, i.e. SPEEDUP (Technology, Aspen 1993) for data reconciliation and optimization and Matlab (MathWorks 1993) for steady-state detection. The coordination and data exchange module between the different tasks of the optimization scheme has been implemented based on the communication mechanism EDI (external data interface) of

SPEEDUP. A distributed client and server architecture have been chosen, to map the partial problems of the full RTO problem to independent and self-sustained software processes. The communication between client and server processes is based on remote procedure calls.

The paper is structured as follows. At first, the different parts of the RTO scheme are briefly described reviewing the existing approaches for each subtask. The chosen algorithms are tested separately. The necessary data for the tests are obtained from simulations using a dynamic model. The final section gives an overview on the interplay of all software modules in a simulated real-time environment. The steady-state model is presented in Section 2. Section 3 deals with steady-state detection based on a novel wavelet strategy. In Section 4 the problem of data reconciliation and gross error detection is studied. Optimization of the MSF plant is dealt with in Section 5. Different objective functions and process parameter constraints are addressed. Off-line results for some optimization scenarios are obtained and discussed. In Section 6, we discuss the on-line implementation of the whole RTO scheme using the client-server coordination module. A case study of a real MSF desalination plant is presented.

2. Steady-state MSF Model

A prerequisite to solving the data reconciliation and optimization tasks is the availability of a steady-state model of the plant considered. The MSF plant (Figure 2) can be structurally decomposed into three sections: a brine heater section, a heat recovery section, and a heat rejection section. The heat recovery and rejection sections are made up of a series of stages, each of which has a flash chamber and a condenser.

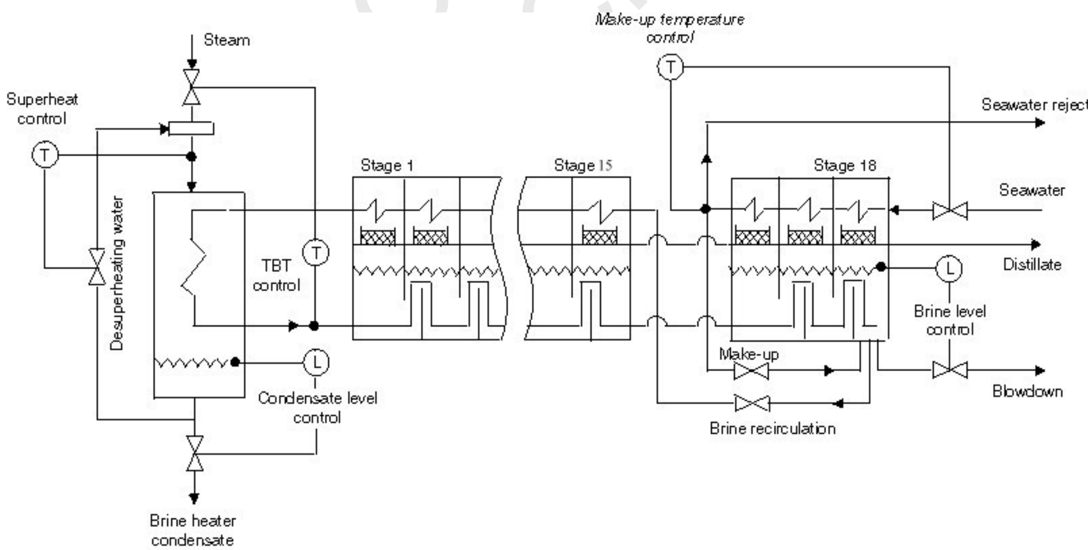

Figure 2. Schematic of the MSF plant with major control loops.

The schema of the steady-state plant model is presented in Figure 3. Since there are principally no differences between the stages of the MSF plant in the rejection and recovery sections, an identical stage model is implemented for all the stages except for the first and last stages. In the brine heater section, models are derived for the injection cooler and the heat exchanger. All submodels comprise global mass and energy balances taking only water into account. A fourth-order polynomial enthalpy-temperature relationship is assumed for liquid streams. The model comprises approximately 300 equations.

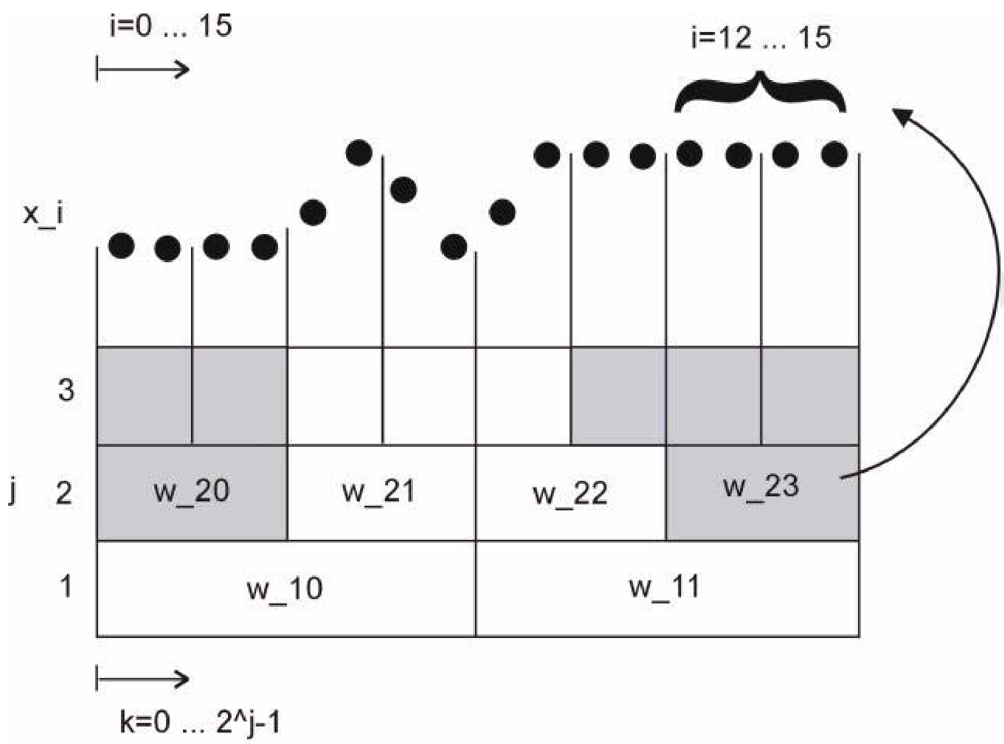

Figure 3. Plant model structure and definition of stream numbers.

3. Steady-state Detection

Steady-state detection is an important task for RTO since it is based on a steady-state model. The existing approaches used in practice include the following.

a) Linear regression over a data window with a subsequent *t*-test on the regression slope; if the slope is significantly different from zero, the process is almost certainly not at steady-state.

b) Use the *t*-test to assert whether the average calculated from recent history is unchanged compared to the value based on earlier history.

c) Standard deviation calculation over a window of recent data and a subsequent comparison of the results with threshold values; if the standard deviation is greater than the threshold, the not-at-steady-state condition is triggered. An alternative approach is to use an *F*-test-type statistic which is the ratio of variances calculated on the same set of data by two different methods. These methods have significant shortcomings (see Cao and Rinehart (1995) for details).

A method aiming to overcome the problems of existing approaches is suggested in Cao and Rinehart (1995). The underlying idea is to use the *F*-test-type statistic, i.e. for the same data set composed of *n* samples of a process variable *x*, the ratio

$$R = \frac{\sigma_1^2}{\sigma_3^2}$$

of two different variance estimations,

$$\sigma_1^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \text{ with } \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \text{ and } \sigma_3^2 = \frac{1}{2(n-1)}\sum_{i=2}^{n}(x_i - x_{i-1})^2.$$

Both estimations are only valid if the data are stationary and uncorrelated. Thus, the variance ratio *R* can only be expected to be near unity if the data are stationary. The method of Cao and Rhinehart (1995) introduces new recursive equations that allow fast calculation of the variances:

$$s_{1,i}^2 = \frac{2-\lambda_1}{2}\lambda_2\left(x_i - \bar{x}_{f_{i-1}}\right)^2 + \left(1-\lambda_2\right)s_{1,i-1}^2;\ \bar{x}_f = \lambda_1 x_i + \left(1-\lambda_1\right)\bar{x}_{f_{i-1}} \qquad (1)$$

$$s_{2,i}^2 = \frac{1}{2}\lambda_3\left(x_i - x_{i-1}\right)^2 + \left(1-\lambda_3\right)s_{2,i-1}^2 \qquad (2)$$

with $0 < \lambda_{1,2,3} < 1$. An estimate of the variance ratio is then

$$R_i = \frac{s_{1,i}^2}{s_{2,i}^2}.$$

These equations require a minimum of data storage and arithmetical operations. If the signal is not stationary due to slow transient process phenomena, then $R_i > 1$. R_i may be smaller than 1 for fast oscillations in *x*. If there is no noise and the signal is stationary, the variance estimations become zero and R_i is not defined. It is thus essential that some degree of noise is present.

The method used in this work is based on wavelets, which are families of basis functions that yield the representation $x(t) = b_{00}\phi(t) + \Sigma_{j,k}\, c_{j,k}\, \Psi_{j,k}(t)$ of a signal *x*. The wavelet basis functions $\{\Psi_{j,k}; \forall_j, k\}$ are obtained by translation, i.e. $\phi(t) \rightarrow \phi(t+1)$ and dilation, i.e. $\phi(t) \rightarrow \phi(2t)$ of the single function $\phi(t)$ called the scaling function. An example is the Haar wavelet, for which the scaling function is unity on the interval [0, 1), i.e. $\phi(t) = 1$, $t\ \varepsilon\ [0, 1)$.

The wavelet method is particularly based on the property which states that the wavelet coefficients of a stationary signal expanded in a wavelet series vanish (Flehmig et al. 1998). As wavelets are compact, this is also valid for a partially stationary signal. In that case, the wavelet coefficients that belong to the stationary interval are zero. Moreover, the Haar wavelet is most appropriate for steady-state detection since it has only a vanishing 0th moment. Stationary intervals can be identified by searching for regions with vanishing wavelet coefficients. Figure 4 shows an example of the wavelet coefficient *c* of a Haar-transformed piecewise constant signal *x*. The originally discrete signal is depicted above the wavelet coefficients. Shaded coefficients are zero.

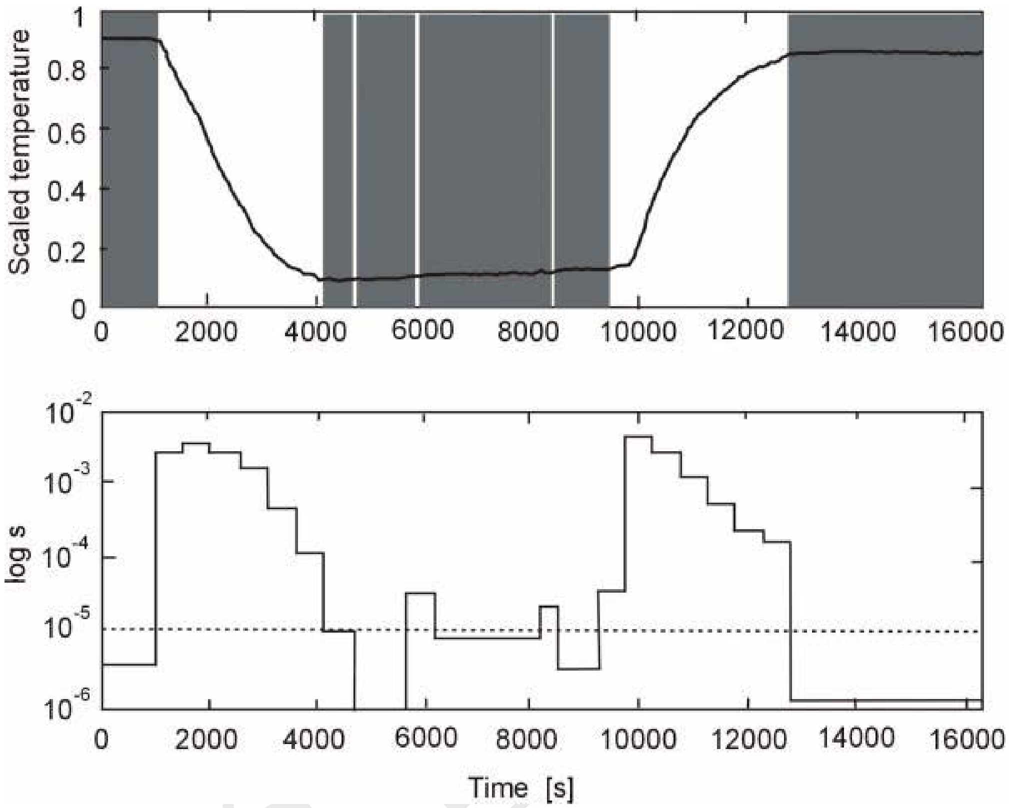

Figure 4. Multiscale representation of a Haar-transformed time series. Grey shaded areas refer to vanishing wavelet coefficients.

The procedure performs the following steps. First, the measurement is transformed in a wavelet series, resulting in a vector of coefficients *c*. A search for coefficients of small magnitudes in *c* follows. The corresponding subintervals which show steady-state are easily determined from the support of the wavelets. Subsequently, the neighborhoods of these intervals are examined more thoroughly. Since the approximation is sensitive to noise, standard wavelet denoising techniques are applied prior to the steady-state detection.

Computational effort could be reduced by using the same wavelet basis for denoising and detection. The suggested wavelet denoising method removes high frequency components with relatively small energy (compared to the noise energy) from the measurement to obtain the reconstructed signal. Depending on the noise level and on the wavelet basis, a part of the signal information will also be removed with the noise.

The user has to provide three parameters: (a) the maximum allowed deviations *Tol* from stationarity, which can be interpreted as a variance limit, (b) j_{end} which defines the minimum length of a stationary interval, and (c) j_{traceend} which defines the accuracy of the detection length. The higher j_{traceend}, the more accurate is the length of the detected stationary interval.

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