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Model based projective monitoring of process unit performances under uncertainties

Flavio Manenti*

Politecnico di Milano
Dipartimento di Chimica, Materiali e Ingegneria Chimica "Giulio Natta"
Piazza Leonardo da Vinci, 32 – 20133 Milano, Italy

The performance monitoring has the fundamental aim to analyze the operative efficiency of single unit operations or overall process sections, especially for lowering costs, increasing profitability and improving the supply chain management in terms of production sites planning and maintenance scheduling. In any case, the industrial state of the art is based on approximated techniques, such as the extrapolation of future behaviour by using plant data historian and/or adopting a (non)linear regression of measurements for predicting the trend of future efficiencies. Instead, as reported in recent literature, a more careful and accurate approach concerns the utilization of detailed first-principles model: the present paper discusses and applies the projective performance monitoring approach, under stochastic disturbances and based on mathematical models. It shows, as preliminary results, comparisons between the expected behaviour obtained by a conventional approximated technique and the prediction of rigorous model based performances.

1. Introduction

After the feedstock supply and the energy consumption, process maintenances represent the largest voice in operative costs for refineries and (petro)chemical plants. Moreover, to further reduce profit margins, failure maintenances due to accidents or malfunctions can occur without notice, by influencing the overall production and the operational planning. In this purpose, the main aim of the present work is to investigate performance monitoring techniques and approaches which are able to predict the future behaviour of unit operations, for reducing number and duration of maintenance shutdowns through a rigorous preventative projection of unit efficiencies. In fact, current techniques adopted in the process industry, such as experience-based analysis or the extrapolation via the process data regression, allow to define no reliable production scheduling, because a lot of units will fail before or after the expected stop. Moreover, White (2003) has recently described how the use of rigorous engineering models were necessary for planning the future production in a more accurate way, even if a lot of them are still conceived as steady state tools, usually incapable to follow the dynamic evolution of the process on the long-term time scale. In literature, several studies try to extend the use of complex mathematical models in the performance monitoring; to

* Phone: (+39)02.2399.3287; e-mail: flavio.manenti@polimi.it

name a few, Jerónimo et al. (1997) and more recently Negrão et al. (2007) have successfully applied the projective performance monitoring on a fouled heat exchanger and on a heat exchange network (HEN), respectively. The present paper will discuss the dynamic modelling and the predictive monitoring based on differential and algebraic equations, in the next section; the adopted case study will be briefly described in the section 3 and the section 4 will show the application of the model based performance monitoring and some preliminary result. At last, conclusions and future developments will be reported.

2. Predictive Techniques in Performance Monitoring

The monitoring of process unit performances is a useful tool in the definition of maintenance scheduling in the process industry, especially if it is able to forecast the equipment efficiency and behaviour. As already discussed by Doymaz et al. (2001) and White (2003), the performance monitoring procedure illustrated in the following picture consists of 5 main steps: the measurement of process variables, the reconciliation of raw data and the gross error analysis, the prediction through preventative techniques, the decision-making about the plant conduction and its implementation, before to restart the performance monitoring cycle.

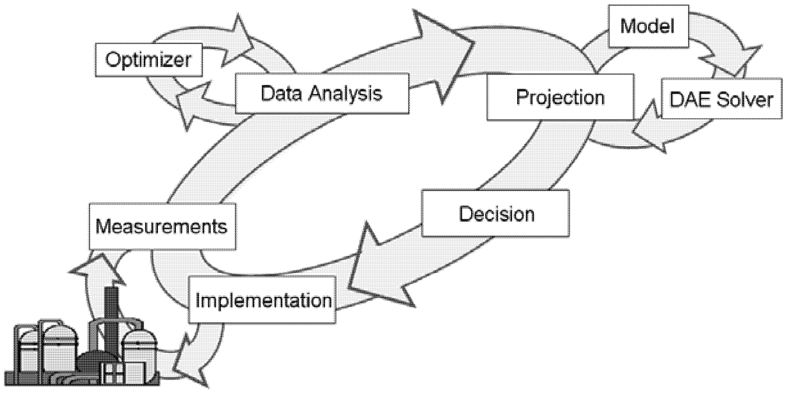

Fig. 1: Model based performance monitoring cycle.

Whereas all the other points seem to be univocally solvable, the projection in the model based performance monitoring can require different numerical techniques or mathematical models and several approaches exist, even if a current widespread method is to wait until a base equipment fail, so to repair, clean or substitute. Unfortunately, in this instance, it is necessary to immediately shutdown the process, without notice, or decide a priori to install redundant units, even if this kind of approach appears expensive in any case: in terms of production losses, when a failure occurs; in terms of design, investment and installation for equipment redundancies. A better way is to predict the malfunction, by using an expected failure time and this has pushed the research toward techniques based on process data and rigorous models.

2.1 Traditional methods based on the data historian

Similar past conditions

The first method is to recognize, inside the historian storages of process data, those operative conditions comparable to the actual plant situation, by purifying the raw set of measures from persistent and stochastic disturbances and from measurements with bad qualities, so to obtain a reliable prediction based on the past experience, for foreseeing future failures and for defining the schedule of programmed maintenances, so to delineate a short- or medium-term operational production planning. If, sometimes, the failure estimation appears correct, this technique predicts incorrect failures on the long-term, making it useless and obsolete, and more accurate techniques are required especially in systems, which are largely affected by uncertainties.

Data regression and extrapolation

Another method concerns the extrapolation of the unit efficiencies by starting from the reconciled process data and by analyzing last measurements through linear or nonlinear regression algorithms. This widespread technique seems to be a good candidate in the esteem of the expected failure time, for the short-term only, because the accuracy of the prediction drastically decreases with persistent disturbances or with the extension of the predictive horizon, by preventing every possibility to define a medium- or long-term planning of the production.

2.2 Model based monitoring

Dynamic modelling

The employment of first-principles models seems to be the only way for obtaining a reliable projection in the forecasting of the behaviour of units and equipment efficiencies, especially when the process operates far from design conditions. Nevertheless, the model based performance monitoring implies to solve all those problems related to a complex dynamic modelling, such as the building a system of differential and algebraic equations, and to overcome difficulties in its numerical integration, such as stiff problems; moreover, the model validation is required, even if it could be carried out by using experimental data or dynamic simulation packages. The accuracy of the prediction can be enhanced by having more detailed models and, above all, by having more information about expected perturbations which can affect operative conditions. In fact, the key-concept in model based techniques is the skill to analytically describe stochastic or persistent disturbances.

Real-time implementation

The next step can be the real time monitoring of the process. It allows to continuously determine if the plant equipment is operating as expected and to continuously re-evaluate the maintenance planning, with a large improvement in prediction accuracy and in plant profitability. The real-time monitoring goes beyond the aim of this paper, especially because it is usually combined with a steady formulation, as recently discussed in the work by Kim and Joo (2005). On the other hand, a dynamic modelling could require too high computational time, above all for the integration of the model equations during the prediction, in disagreement with faster sampling times required by a real-time application.

3. Case Study

The refrigeration and the separation sub-sections, placed immediately downstream the catalytic cracking for the ethylene production of a typical LNG process, are considered as case study. They consist of a compression stage, a heat exchange network and a demethanizer column, as qualitatively schematized in the figure 2. The process flow, coming from the thermal cracking, is fed to compression stages where it is compressed till the operating pressure of the column (40 atm) and, subsequently, the temperature is decreased to 260 K, in the refrigeration section. The performance monitoring has been implemented in every unit of the case study, by introducing typical deteriorations for equipments, even if for space reasons the results of projective performance monitoring of a single unit will be shown only.

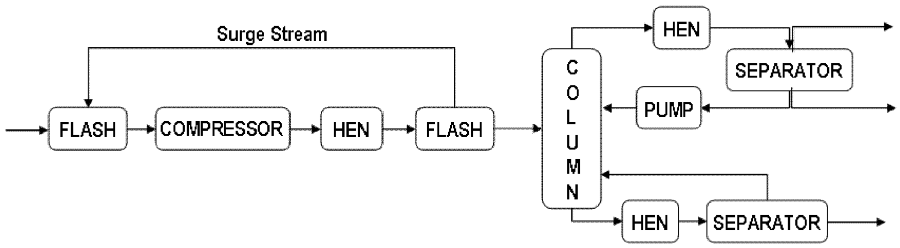

Fig. 2: Compression, refrigeration and separation zones in the case study: process scheme and monitored process units.

Main key performance indicators adopted are:

- in the compressor:
  - the compression efficiency of the single stage and overall equipment;
  - the ratio between the actual compression and design conditions;
- in the distillation column:
  - the overall separation efficiency in terms of distillate/feed ratio;
  - head and bottom losses in key-components;
  - the cleanliness factor for each tray and the relative pressure drop;
- in heat exchangers (including the column condenser and the kettle reboiler):
  - the fouling factor in the tube side;
  - the fouling factor in the shell side.

4. Preliminary Results

4.1 Simulation parameters

During the simulation time, the plant production is characterized by different variations in the molar feed flow, which act as persistent disturbances, and the molar feed flow is affected by a stochastic perturbation in the order of $\pm 5\%$. By roughly supposing a flow variation every 8 days, on a simulation horizon in the order of one month, the table 1 shows the production target considered in each period.

Table 1: Time range with constant production and normalized molar flow rates.

Production Period [#]	Time Range [days]	Used Plant Capacity [%]
1	1 – 8	78
2	9 – 16	92
3	17 – 24	87

Moreover, every key performance indicator is strictly related to the performance degradation, which is modelled and implemented in different way, in accordance with the unit operation and the monitored parameter. The generic formulation can be summarized in the expression $d = f(t, p^n)$ where the degradation d depends on time t and a process variable p which can be a flow, a temperature, a pressure or a complex function, according to literature and standard certifications; n represents the nonlinearity of the formulation. By taking into consideration an heat exchanger and, in particular, the tube side of kettle reboiler, the process variable which mainly increases the fouling factor is the flow rate of non-volatile hydrocarbons, coming from the bottom of the column and vaporized by a medium pressure steam.

4.2 The prediction based on unperturbed process data

By supposing a sampling time in the order of the day, the plant data is continually collected and stored. The picture 3 illustrates different predictions, by adopting two data-based approaches and neglecting uncertainty effects. It can be noted how the date of predicted alarms is continually anticipated and postponed through the increasing of feed flow rate or the adoption of linear or nonlinear extrapolating curves and shorter or larger ranges of process data. Unfortunately, there's no way for knowing a priori which could be a good approach for failure estimations, although in short-term projections and with a reduced production, discrepancies due to the selection of regressive curves decrease (i.e. the 37th day versus the 38th day, in the last extrapolation). For avoiding incorrectness in long-term predictions, due to nonlinear extrapolations, a linear technique can be select for the comparison in the next paragraph.

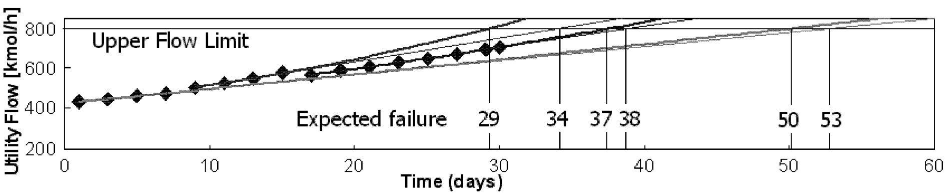

Fig. 3: Linear (thin lines) and nonlinear (thick lines) extrapolation without disturbs. The upper limit represents the maximum, admissible flow of the reboiler heating.

4.3 Model based projective monitoring under uncertainties

The state of the art has been compared with the technique based on dynamic models, by considering a scenario affected by uncertainties in the molar feed flow, besides the workload changes. BzzMath libraries, by Buzzi Ferraris (2006), have been adopted for the process data reconciliation. As shown in figure 4, the perturbation generates large variations in projections obtained with data historian-based approaches, in the order of many days if related to the same linear prediction of figure 3, especially for long-term expected failures. On the other hand, no stochastic noises influence the model based monitoring and its performance projection remains unchanged in a perturbed system. In this particular case, an earlier failure is, generally, estimated. Oscillations, succeeding production changes, are due to closed-loops of the plant-wide control system required for stabilizing the dynamic model. Therefore, whereas linear or nonlinear extrapolation can give different estimation, depending on the perturbation, the projection accuracy of model based performance monitoring can be even improved by a more detailed mathematical modelling.

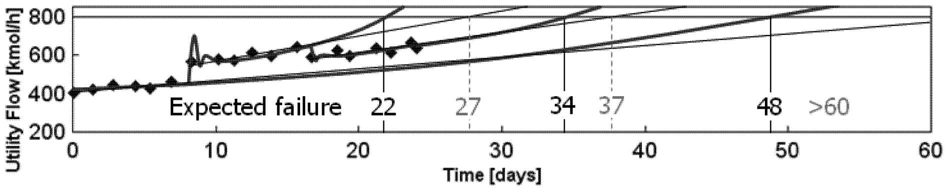

Fig. 4: Comparison between historian-based extrapolation (thin lines) and dynamic model based monitoring (thick lines), starting from reconciled process data (dots).

5. Conclusions

The performance monitoring is a widespread technique useful for improving plant production and unit efficiency though predictive techniques. It has been largely employed in power generation sites and chemical plants, even if it is usually conceived as a steady state tool. The present work has shown, through a simple application, the possibility to ameliorate the projection accuracy, especially in perturbed systems, by using dynamic models and first preliminary results seem to confirm it. Next developments may focus the attention on concrete industrial applications and on the real time solution of the first-principles model based monitoring.

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