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Should I shut down my processing plant? An analysis in the presence of faults☆

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ABSTRACT

An analysis of the economic operability of a processing plant in the presence of faults is presented in this paper. Once a fault has been identified and diagnosed through a suitable fault detection and isolation algorithm, an adaptive hypothesis test is used to determine if the plant can still be operated. Operation may continue through the use a suitable fault tolerant control scheme. Once this analysis is complete, an economic operability analysis is done to determine whether the plant can still operate economically with the faults present, or whether the plant should be shut down to repair the faults. The overall operating profitability of the process may be maximized through this method. The method is illustrated in this article through simulation of a nonlinear grinding mill circuit controlled by a fault tolerant nonlinear model predictive controller in the presence of a variety of actuator faults.

1. Introduction

Once a failure has occurred on a processing plant, be it an actuator failure, a sensor failure, or the failure of a piece of processing equipment, the plant operating performance will likely decrease [1], and this easily develops into production stoppages [2]. FDI (fault detection and isolation) is concerned with detecting that a fault is present, and secondly to isolate the location (and ideally the magnitude) of the fault.

After a fault has entered the system it may be possible to regulate the system through a fault-tolerant control (FTC) strategy. FTC strategies can broadly be classified as either being passive or active [1]. With passive FTC the objective is to design the controller such that it is robust enough to handle a class of presumed faults. Active FTC has the objective of isolating faults and adapting the control strategy such that the stability and control performance of the entire system might be maintained.

Even if an appropriate FTC scheme is in place it may not be possible to regulate the plant for a certain class of faults. A formal analysis would be required to determine whether the plant can be operated after the fault has altered the plant response. A linear controllability analysis [3] will be able to say whether the plant is still input-output controllable. Such a controllability analysis is however not as straightforward in the case of nonlinear systems. The analyses for nonlinear controllability are classified by [4] as being either analytical or optimization based. An example of an analytical test is that of functional controllability through the application of repeated Lie derivatives as shown in [5]. An optimization based approach is presented by [6], where absolute controllability is requested for all possible combinations of uncertainty and disturbances. This analysis is formulated like a min-max optimization problem [7], the solution of which is notoriously conservative [8,9]. In an industrial plant that is perturbed by many disturbances and in which many uncertainties are present the probability that all the worst case disturbances and uncertainties will be present at the same time is very low.

To overcome this conservativeness and the difficulties in solving nonlinear robust control problems some research has gone into probabilistic methods for analysis and controller design of uncertain systems [10,11]. The focus then is to identify the probable control performance through a Monte Carlo based analysis, where the uncertain parameter set is sampled from the allowed set. A Monte Carlo based analysis is performed along these lines in this work to assess the probable controllability of the plant in the presence of the identified fault(s).

To not confuse this method with a functional controllability, state controllability, or input-output controllability analysis (all of which are sometimes simply referred to as controllability

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analyses), the term regulatability analysis will be used in this work, with the following definition:

Definition 1. A system is defined to be regulatable if $\exists \left[u_{t_0}, \ldots, u_{t_f}\right] \in U$ such that $\left[y_{t_0}, \ldots, y_{t_f}\right] \in Y$ as $t_f \to \infty$,

where t_0 is the starting time of evaluation, U contains the input constraints and Y contains the output constraints. The evaluation up to $t_f \to \infty$ is infeasible in practice, and a finite t_f may be selected provided it is sufficiently large to allow the plant to reach steady state.

After it has been established that the system is regulatable, i.e. the plant can still be operated within limits, the question arises whether the plant should still be operated from an economic performance point of view. In other words, is it more economic to continue to operate with the present fault(s) until the next planned opportunity for repair (the next planned shut-down), or should the plant be shut down as soon as possible, the fault(s) repaired, and started up again.

Control performance assessment is an important asset-management technology to maintain efficient operation of automation systems in processing plants [12]. Comparison of the economic operability with a fault present to that without any faults will give an indication of whether efficient operation can be maintained. Optimal economic operability is defined as:

Definition 2. A system is said to operate economically optimal if the economic performance of operating in the current mode is at least as great as operating in any other mode, i.e. $\int_0^{t_f} \psi_i.\mathrm{d}t \geq \int_0^{t_f} \psi_j.\mathrm{d}t$ where ψ is the economic performance as a function of time.

The importance of considering plant economics in the controller design stage was already noted by [13]. It is also noted in [13] that economic assessment is essentially based on the steady-state process operation; [14] however notes that considering steady-state targets may be unnecessary if dynamic reference models can be used to directly optimize a profit objective. The ultimate goal when formulating the control structure however is to achieve the economic objectives [15], and [16] shows how this can be achieved with MPC.

Economic performance assessment of advanced control is well established in the process industry [17]. Comparative economic performance against benchmark control has been presented for example by [18,19]. In this work however the comparative economic performance with and without faults is the focus. As far as the authors are concerned, such a comparative economic performance assessment has not been presented before.

The regulatability and economic operability analyses will be illustrated in this paper through simulation of a nonlinear run-of-mine ore milling circuit model, controlled by a fault tolerant nonlinear model predictive controller. Faults are detected and identified by making use of the nonlinear generalized likelihood ratio method using particle filters, similar to [20]. The control of the milling circuit is similar to that of [21], which makes use of nonlinear MPC to control the slow milling circuit dynamics and a simpler controller to control the fast sump dynamics. In [21] a dynamic inversion controller was used to control the sump, but in this work a PI override controller is used for its simplicity and ubiquity.

The main contributions of this paper are the presentation of the probabilistic controllability analysis through an adaptive hypothesis test, as well as the economic operability analysis of the plant with a fault present compared to that of shutting the plant down, fixing the fault, and starting back up again. The nonlinear generalized likelihood ratio method using particle filters was previously presented by [20], and an expanded illustration with more faults is provided here.

2. Regulatability analysis

If a probabilistic sense of controllability is acceptable in contrast to a guarantee for all combinations of uncertainty in the system, the solution is usually easier to calculate and less conservative [11].

This analysis can be done via simulation and the objective of such a simulation is to find a set of permissible inputs that will be able to regulate the plant outputs within the output limits in the presence of unknown disturbances and/or plant parameters. In order to distinguish this approach from a well-defined, formal controllability analysis, the term regulatability analysis will be used here.

In this section an adaptive hypothesis test is proposed to evaluate the regulatability of a system. The discussion in the rest of this article pertains to the general discrete time state-space representation of a dynamic system

$$x_{k+1} = f\left(x_k, u_k, \theta_k, \nu_k\right) \tag{1}$$

$$y_k = g\left(x_k, \theta_k, d_k, e_k\right) \tag{2}$$

where $x \in \mathbb{R}^n$ is the state vector and $y \in \mathbb{R}^m$ is the output vector, $f(\cdot)$ and $g(\cdot)$ are possibly nonlinear functions describing the state transitions and the outputs respectively, u_k contains the exogenous inputs, θ_k represents the system parameters, $d_k \in D$ represents the modelled disturbances, ν_k is the state noise, and e_k is the measurement noise.

It is assumed that this plant is nominally regulatable. This means that the system conforms to Definition 2 in the absence of faults. In the presence of at least one fault however the regulatability condition may not hold any more. The objective is then to evaluate whether there exists a plant input vector for which the outputs (and states) remain within their respective limits. The future disturbance vector is however not known, and a representative disturbance vector (d^*) is selected such that $d_i^* \in D$. The set, D, depends on the plant in question and is defined according to the physical properties of the disturbances in question. An evaluation is then carried out to find $u \in U$ to keep $y \in Y$. If such a u exists, then the plant is regulatable for d_i^*. The success of this analysis is one result in a binomial test.

Another $d_i^* \in D$ can then be selected and the search for a u to regulate the plant is repeated. The outcome of the search with each independent disturbance vector becomes the result of a binomial test. Choosing successive disturbance vectors in a Monte Carlo manner, and evaluating the regulatability of the faulty system provides the ability to statistically test whether the system is regulatable as the binomial distribution is constructed.

Up to now the only uncertainty referenced in the plant is because of disturbances. Uncertainty in plant parameters, i.e. model-plant mismatch, may be included in the analysis by augmenting the disturbance vector with the uncertain plant parameters as $\left[d^*, \theta^*\right]^T$. The uncertain plant parameters are then included without the loss of generality.

An hypothesis test may be set up for the sequence of binomial samples to complete the regulatability analysis. It is said to be statistically significant to reject the null hypothesis [22], and the null hypothesis should therefore be formulated such that it is likely to be rejected. The other consideration is the amount of samples required to reject the null hypothesis. For a one-sided test on a binomial proportion the sample size required is [22]:

$$n = \left[\frac{z_\alpha\sqrt{p_0(1-p_0)} + z_\beta\sqrt{p(1-p)}}{p - p_0}\right]^2 \tag{3}$$

where p_0 is the null hypothesis probability value, p is the test statistic value, and z_α and z_β are respectively the critical values associated