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Active Perturbations Around Estimated Future Inputs in Modifier Adaptation to Cope with Measurement Delays ⋆

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Abstract: The earlier the plant measurements are available for a given plant input, the quicker iterative real-time optimization by modifier adaptation (MA) can steer the plant to its optimum. In practical applications, in addition to the time required for a plant to reach its steady state and to the time a sensor needs to perform the measurement, further delays can occur. For example, due to the time required for the sample to reach the location of the sensor, caused by a remote positioning of the measurement device. We propose a modifier adaptation strategy where additional plant perturbations are performed around an estimate of the solution to the adapted optimization problem during the waiting period which is caused by the measurement delay. The strategy is tested on the benchmark Otto-Williams reactor case study and its performance is studied.

Keywords: Iterative optimization, Quadratic approximation, Plant-model mismatch, Modifier adaptation, Gradient estimation

1. INTRODUCTION

Improving the economics of processes while fulfilling environmental requirements is nowadays crucial for the process industries worldwide. A central lever to survive the increasing competition is the operation of processing plants at their optima. Provided one has an exact mathematical model of a plant at hand, the optimal operating point can be found by solving an economic optimization problem subject to the model equations and process constraints. However, in practical applications a sufficiently accurate mathematical model is often not available. Models can have uncertainties in the model parameters as well as in the structure of the model equations. This plant-model mismatch can lead to a sub-optimal operation, since the model optimum and plant optimum may not coincide.

Iterative steady state optimization in the past years has evolved as an approach that can identify the plant optimum in the presence of structural and parametric plant-model mismatch. Chen and Joseph (1987) addressed parametric uncertainty in their two-step approach, where the uncertain model parameters are iteratively updated using plant measurements. However, this method does not handle structural plant-model mismatch. The integrated system identification and parameter estimation (ISOPE) approach proposed in Roberts (1979) handles the structural plant-model mismatch by using the plant gradients w.r.t. the process inputs in addition to the plant measurements to converge iteratively to the plant optimum. In ISOPE, the cost function of the optimization problem is reformulated by adding a gradient correction term which is iteratively updated. Redesigned ISOPE was proposed in Tatjewski (2002) where no parameter estimation is performed and only iteratively updated bias and gradient correction terms are used. This scheme was further extended by Gao and Engell (2005) to handle process dependent constraints. Later, Marchetti et al. (2009) analysed this approach and proposed the name modifier adaptation (MA). They provided a proof that indeed the solution at convergence satisfies the Karush-Kuhn-Tucker necessary conditions of optimality of the plant despite the fact that its behaviour deviates from the model that is used in the optimization.

In the iterative optimization methods mentioned above, finite differences are employed to compute the plant gradients w.r.t. the process inputs (Roberts, 2000; Gao and Engell, 2005; Marchetti et al., 2010). The approaches based on finite differences are vulnerable to measurement noise. Recently Gao et al. (2016b) proposed modifier adaptation with quadratic approximation (MAWQA) in which the iterative gradient modification optimization (IGMO) from Gao and Engell (2005) is combined with elements from derivative free optimization (DFO) (Conn et al., 2009). A quadratic approximation (QA) of the behaviour of the plant is built using a selection of the available observed responses and is then used to compute the plant gradients. In the presence of measurement noise this approach outperforms conventional methods based on finite differences.

Stationary optimization using modifier adaptation is built on the assumption that after each change of the manipulated variables the new steady state can be observed

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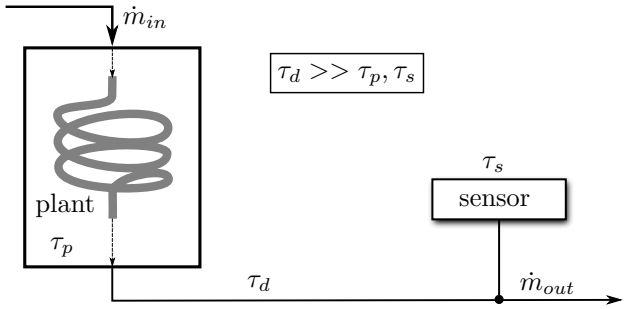


Fig. 1. Illustration of a general plant with a sensor attached in a remote location.

and the next inputs are computed from this information. This may however lead to a slow convergence. Therefore using transient information has been investigated by Gao et al. (2017); Ferreira et al. (2017); Rodríguez-Blanco et al. (2017); Cadavid et al. (2017). Besides the delays caused by the slow convergence of the plant to a new steady state, measurement delays can further slow down the iterative optimization. e.g. due to the remote positioning of measurement devices (Gottu Mukkula et al., 2018). In Fig. 1 this situation is illustrated. The measurement device is located at a significant distance from the plant, which is quite common in the process industries. For example, due to safety regulations, measurement devices like NMRs have to be placed in ATEX certified enclosures located at a distance from the process equipment. The thin, long tubing which carry the sample from the plant to the sensor cause a significant *waiting period*. In this paper, we propose a strategy based on MAWQA that actively performs additional plant perturbations during the waiting period to gain additional plant information instead of remaining idle until the effect of a new operating point has propagated through the plant-measurement device setup. Here we extend the strategy proposed in Gottu Mukkula et al. (2018) by performing additional plant perturbations around an estimate of the future plant inputs.

The paper is organized as follows. First, the formulation of MAWQA is briefly presented. Then an active perturbation strategy is presented to effectively use the waiting period. Finally, the proposed scheme is implemented on the Otto-Williams reactor case study (Williams and Otto, 1960) and its performance is compared with standard MAWQA.

2. MODIFIER ADAPTATION WITH QUADRATIC APPROXIMATION

Given a steady state mathematical model of a plant (1b) with an n_u-dimensional vector of process input variables, an n_y-dimensional vector of measured variables and a cost function $J_m : \mathbb{R}^{n_u} \times \mathbb{R}^{n_y} \to \mathbb{R}$, the model optimum $\boldsymbol{u}_m^*$ is identified by solving the following optimization problem

$$\boldsymbol{u}_m^* = \arg \min_{\boldsymbol{u} \in [\boldsymbol{u}^L, \boldsymbol{u}^U]} J_m(\hat{\boldsymbol{y}}, \boldsymbol{u}) \tag{1a}$$

$$\text{s.t. } \hat{\boldsymbol{y}} = \boldsymbol{F}_m(\boldsymbol{u}), \tag{1b}$$

$$\boldsymbol{G}_m(\hat{\boldsymbol{y}}, \boldsymbol{u}) \leq \boldsymbol{0}, \tag{1c}$$

where $\boldsymbol{F}_m : \mathbb{R}^{n_u} \to \mathbb{R}^{n_y}$ represents the input to output mapping function, which is assumed to be at least twice differentiable w.r.t. the vector of process inputs $\boldsymbol{u}$. The variables $\hat{\boldsymbol{y}}$ and $\boldsymbol{G}_m$ represent the vector of model outputs and the process constraints. The upper and lower bounds of the process inputs are denoted by vectors $\boldsymbol{u}^L, \boldsymbol{u}^U$.

The model optimum $\boldsymbol{u}_m^*$ in (1) may differ from the true plant optimum $\boldsymbol{u}_p^*$ due to plant-model mismatch. Therefore, in order to converge to the true plant optimum, the cost function J_m and the process constraints G_m in the model-based optimization problem (1) are iteratively updated to steer $\boldsymbol{u}_m^*$ towards $\boldsymbol{u}_p^*$. In the MA approach, the following modified optimization problem is considered:

$$J_m^{ad,k} = J_m + (J_p^k - J_m^k) + (\nabla J_p^k - \nabla J_m^k)^T(\boldsymbol{u} - \boldsymbol{u}^k), \tag{2a}$$

$$\boldsymbol{G}_m^{ad,k} = \boldsymbol{G}_m + (\boldsymbol{G}_p^k - \boldsymbol{G}_m^k) + (\nabla \boldsymbol{G}_p^k - \nabla \boldsymbol{G}_m^k)^T(\boldsymbol{u} - \boldsymbol{u}^k), \tag{2b}$$

where $(J_p^k - J_m^k)$ and $(\boldsymbol{G}_p^k - \boldsymbol{G}_m^k)$ are bias correction terms evaluated at the process input for the k^{th} iteration $\boldsymbol{u}^k$. The gradient modifier terms $(\nabla J_p^k - \nabla J_m^k)$ and $(\nabla \boldsymbol{G}_p^k - \nabla \boldsymbol{G}_m^k)$ are the differences between the plant and the model gradients of the cost function and of the process constraints w.r.t. the process inputs $\boldsymbol{u}$ evaluated at $\boldsymbol{u}^k$. For the k^{th} iteration, the modified optimization problem is given by

$$\hat{\boldsymbol{u}}^{k+1} = \arg \min_{\boldsymbol{u} \in [\boldsymbol{u}^L, \boldsymbol{u}^U]} J_m^{ad,k} \tag{3a}$$

$$\text{s.t. } \hat{\boldsymbol{y}} = \boldsymbol{F}_m(\boldsymbol{u}), \tag{3b}$$

$$\boldsymbol{G}_m^{ad,k} \leq \boldsymbol{0}. \tag{3c}$$

In MAWQA, the process input $\hat{\boldsymbol{u}}^{k+1}$ obtained from the optimization problem (3) is restricted to lie inside a confidence ellipsoid the properties of which are defined by the points used for the QA, which will be discussed later in this section. The plant gradients ∇J_p^k and $\nabla \boldsymbol{G}_p^k$ which are required to solve the optimization problem in (3) are estimated using a quadratic approximation of the cost function and of the constraints (Gao et al., 2016b).

The measurements of the cost function and of the constraint functions are locally approximated by fitting the parameters of a quadratic function $\mathcal{Q}$ to the available past measurements. A general quadratic function can be expressed as

$$\mathcal{Q}(\mathcal{P}, \boldsymbol{u}) = \sum_{i=1}^{n_u} \sum_{j=1}^{i} a_{i,j} u_i u_j + \sum_{i=1}^{n_u} b_i u_i + c. \tag{4}$$

To fit the parameters of $\mathcal{Q}$, a set of well distributed data points $\mathcal{U}^k$ around the input point $\boldsymbol{u}^k$ is required. The set $\mathcal{U}^k$ is identified by screening all available data points $\mathbb{U}^k$. In general, $\mathcal{U}^k$ should consist of at least $(n_u + 1)(n_u + 2)/2 - 1$ well distributed distant data points $\mathcal{U}_{dist}^k$ and all neighboring points $\mathcal{U}_{nb}^k$ which lie in the vicinity of $\boldsymbol{u}^k$. The condition number of the matrix $\mathbf{S}^k$, which is formed from the differences of the past distant inputs $\mathcal{U}_{dist}^k$ to the last input $\boldsymbol{u}^k$, is used to assess the quality of the distribution of data points in set $\mathcal{U}_{dist}^k$ (Brdyś and Tatjewski, 1994; Gao and Engell, 2005). If the inverse of the condition number of $\mathbf{S}^k$ is not larger than a lower bound, additional plant perturbations are performed to improve the distribution of the points in $\mathcal{U}^k$. Gao et al. (2016b); Wenzel et al. (2017) have proposed two different selection algorithms to screen $\mathbb{U}^k$ to identify $\mathcal{U}^k$. A comparative study of the screening algorithms was reported in Wenzel et al. (2017). Upon identifying $\mathcal{Q}$, the gradients that are needed to calculate the modifier terms can be approximated by the gradients

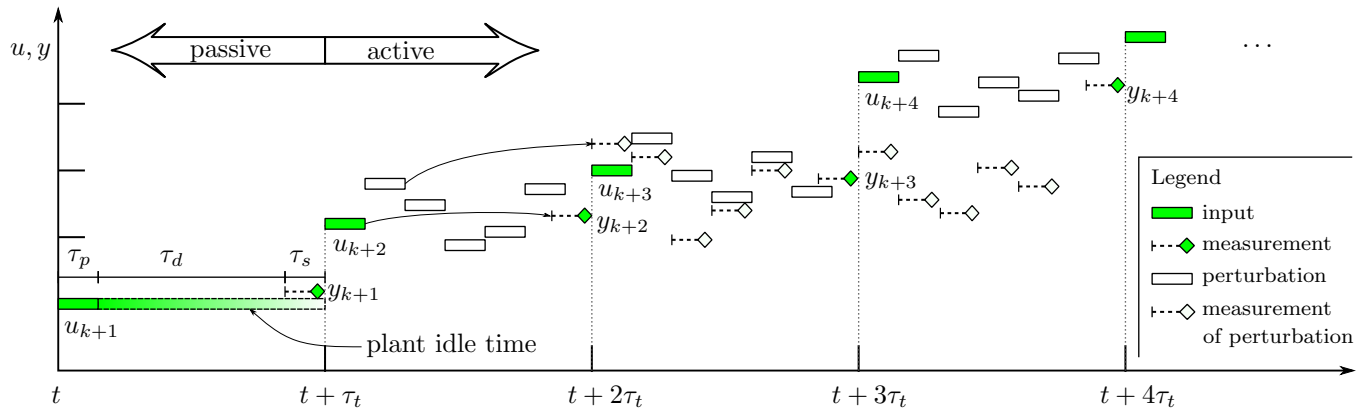


Fig. 2. Illustration of the standard modifier adaptation methods and the proposed active perturbation method.

of $\mathcal{Q}$. Since, there is no guarantee that the fit based on the measurements is perfect, Gao et al. (2016b) proposed an additional constraint for the modified optimization problem (3), which enforces the optimizer to stay within a confidence ellipsoid around the current operating point:

$$(\boldsymbol{u}-\boldsymbol{u}^k)^T \mathrm{cov}(\mathcal{U}^k)(\boldsymbol{u}-\boldsymbol{u}^k) \leq \gamma^2, \tag{5}$$

where γ is a scaling parameter.

3. ACTIVE PERTURBATION STRATEGY

In this section, we propose a strategy to efficiently use the waiting period and thereby reduce the time to converge to the plant optimum. For the topology of the plant-measurement device configuration in Fig. 1, we assume that the time required to transport the steady state sample from the plant outlet, τ_d, is significantly longer than the time to reach the steady state τ_p and the maximal time to measure the sample τ_s. An example is a tubular reactor in which a reaction with fast kinetics takes place. The green symbols in Fig. 2 illustrate the usual MA approaches which remain idle during the waiting period until the steady-state measurements are available. At time t the $(k+1)^{\text{th}}$ modifier adaptation iteration input is applied to the plant. According to the assumptions, at time $t+\tau_p$ the steady state sample leaves the plant. Further assuming a plug flow behavior of the sample through the tube, it takes additional τ_d time units until the sample has reached the sensor at time $t+\tau_p+\tau_d$. The sample is then analyzed and the measurements are available after a total time of $t+\tau_t$, with *iteration time* $\tau_t := \tau_p+\tau_d+\tau_s$. Note that the plant remains at the steady state from $t+\tau_p$ to $t+\tau_t$ and during this *waiting period* no effort is made to acquire additional plant information. We propose to use this time more effectively by performing additional plant perturbations.

The proposed active perturbation strategy is illustrated in Fig. 2 from time $t+\tau_t$ on. The key idea is to perturb the plant during the waiting period. Assume that a new input is given to the plant at time $t+\tau_t$. The steady state sample leaves the plant at $t+\tau_t+\tau_p$, after which the plant waiting period starts. During this period, from $t+\tau_t+\tau_p$ to $t+2\tau_t$ additional perturbations can be made to gain useful information about the plant, the measurements of the responses to these inputs then arrive from $t+2\tau_t$ to $t+3\tau_t-\tau_s$. If an increase of the iteration time should be avoided, the maximum number of perturbations is limited to P_{max}, where P_{max} is given by

$$P_{max} := \left\lfloor \min\left\{ \frac{\tau_d+\tau_s}{\tau_p}, \frac{\tau_d+\tau_p}{\tau_s} \right\} \right\rfloor. \tag{6}$$

In Gottu Mukkula et al. (2018), we proposed an active perturbation strategy where additional perturbations are made around the current input $\boldsymbol{u}^k$. In the following subsection, we propose a scheme to estimate the future input and to perturb the plant around this value during the waiting period. The scheme is illustrated using a case with two inputs and with $P_{max}=4$. We assume the points in the regression set to be well distributed for simplicity of the exposition.

3.1 Active perturbation around the estimated future input

The strategy is illustrated in Fig. 3. The plant is perturbed around an estimated future input point $\hat{\boldsymbol{u}}_e^{k+1}$, marked by "$*$". As the measurement and thus the plant gradient at the current input point $\boldsymbol{u}^k$ are not yet available, the next input $\boldsymbol{u}^{k+1}$ cannot be calculated precisely. To estimate the future input we make the following assumption.

Assumption 1. If the current input $\boldsymbol{u}^k$ is close to the previous input $\boldsymbol{u}^{k-1}$, the difference between the plant and the model gradients at the current input is approximately equal to the gradient difference at the previous input point, i.e., $(\nabla J_p^k - \nabla J_m^k) \approx (\nabla J_p^{k-1} - \nabla J_m^{k-1})$ and $(\nabla \boldsymbol{G}_p^k - \nabla \boldsymbol{G}_m^k) \approx (\nabla \boldsymbol{G}_p^{k-1} - \nabla \boldsymbol{G}_m^{k-1})$.

The same assumption is made for the bias correction terms $(J_p - J_m), (\boldsymbol{G}_p - \boldsymbol{G}_m)$. With these assumptions the future input is estimated by solving the following modified optimization problem

$$\hat{\boldsymbol{u}}_e^{k+1} = \arg \min_{\boldsymbol{u}\in[\boldsymbol{u}^L,\boldsymbol{u}^U]} J_{m,e}^{ad,k} \tag{7a}$$

$$\text{s.t. } \hat{\boldsymbol{y}} = \boldsymbol{F}_m(\boldsymbol{u}), \tag{7b}$$

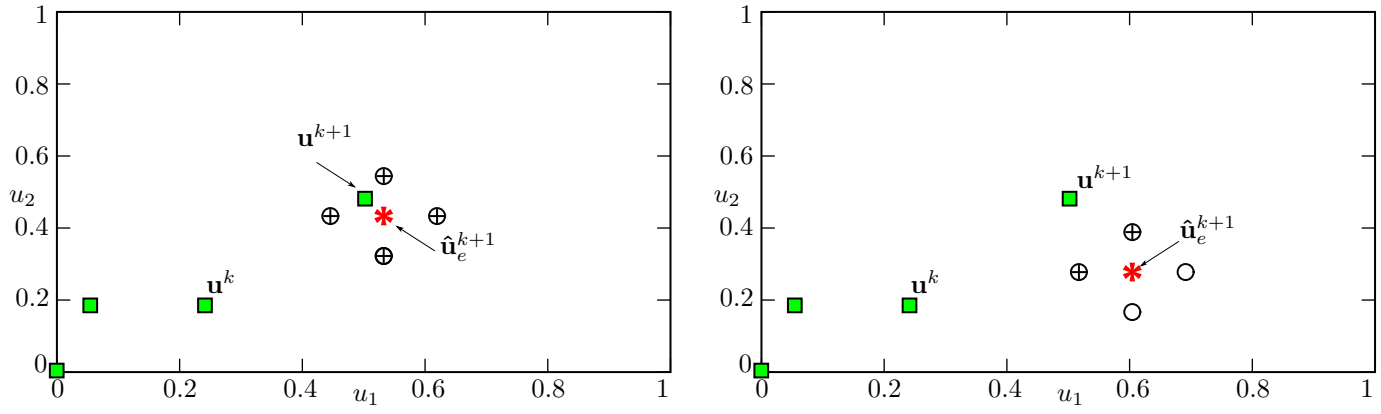
$$\boldsymbol{G}_{m,e}^{ad,k-1} \leq \boldsymbol{0}, \tag{7c}$$

where

$$J_{m,e}^{ad,k} = J_m + (J_p^{k-1} - J_m^{k-1}) + (\nabla J_p^{k-1} - \nabla J_m^{k-1})^T(\boldsymbol{u}-\boldsymbol{u}^k), \tag{8a}$$

$$\boldsymbol{G}_{m,e}^{ad,k} = \boldsymbol{G}_m + (\boldsymbol{G}_p^{k-1} - \boldsymbol{G}_m^{k-1}) + (\nabla \boldsymbol{G}_p^{k-1} - \nabla \boldsymbol{G}_m^{k-1})^T(\boldsymbol{u}-\boldsymbol{u}^{k-1}). \tag{8b}$$

The optimization problem in (7) for the $(k+1)^{\text{th}}$ iteration is similar to the optimization problem in (3) for the k^{th} iteration, except that the confidence ellipsoid in (5) for $(k+1)^{\text{th}}$ iteration is centered around the input point



(a) Ideal scenario

(b) Usual scenario

Fig. 3. Illustration of the active perturbation strategy with perturbation around the estimated future input point $\hat{\boldsymbol{u}}_e^{k+1}$.

resulting from the optimization problem (3) for the k^{th} iteration.

In Fig. 3, "■" represent the inputs to the plant for each iteration. For the k^{th} iteration, the input $\boldsymbol{u}^k$ is applied to the plant. Once the plant reaches the steady state, it can be perturbed by new inputs represented by "○". The perturbation points should be chosen such that they are well distributed around $\hat{\boldsymbol{u}}_e^{k+1}$. To avoid frequent revisiting of almost the same input point, perturbing around already existing data points is suppressed (Gottu Mukkula et al., 2018). In Fig. 3, all the four circles represent the planned perturbations around $\hat{\boldsymbol{u}}_e^{k+1}$. In Fig. 3a, an ideal scenario for active perturbations is illustrated, i.e., when $\boldsymbol{u}^{k+1} \approx \hat{\boldsymbol{u}}_e^{k+1}$. In the ideal scenario, all the additional perturbations made will be selected by the screening algorithm for QA (Gao et al., 2016b). If the assumption upon the plant gradients does not hold, i.e., when $\boldsymbol{u}^{k+1} \neq \hat{\boldsymbol{u}}_e^{k+1}$, as shown in Fig. 3b, the estimate may deviate from the next input point. However, even if the estimated future input $\hat{\boldsymbol{u}}_e^{k+1}$ is at a distance from the next input point $\boldsymbol{u}^{k+1}$, the performed perturbations are useful as explorative moves (Gao et al., 2016a). In this case, among the additional perturbations made not all of them may be selected by the screening algorithm for QA. For example, in Fig. 3b, only the points marked by "⊕" are selected by the screening algorithm.

The modifier adaptation approach in Gao et al. (2016b) considers the iteration inputs that do not improve the plant objective as unsuccessful iterations. To estimate the future input $\hat{\boldsymbol{u}}_e^{k+1}$ by solving the optimization problem in (7), the input $\boldsymbol{u}^k$ is required, which depends on whether or not the earlier iteration was successful (Gao et al., 2016b). It does not make sense to wait until the plant measurements for input $\boldsymbol{u}^k$ are obtained to determine whether the iteration was successful or not since reaching the plant optimum fast is a priority. Therefore, we propose the following steps to implement the proposed scheme:

(1) Probe the plant with the iteration input $\boldsymbol{u}^k$.
(2) Assume that $\boldsymbol{u}^k$ is a successful iteration input and solve (7) for $\hat{\boldsymbol{u}}_e^{k+1}$.
(3) Identify the additional perturbation points around $\hat{\boldsymbol{u}}_e^{k+1}$ and probe.
(4) For the remaining part of the waiting period (if any), operate the plant at the last known successful iteration input.
(5) Upon availability of plant measurements for $\boldsymbol{u}^k$, evaluate if the iteration is successful.
(6) Solve the MA problem for $(k+1)^{\text{th}}$ iteration.

Additionally, in order to avoid frequent probing of the plant with unsuccessful inputs and thus deteriorating the plant performance, we propose the following rule: A set containing the list of unsuccessful moves is maintained. An iteration input is applied to the plant iff the number of points in the set that are close ($\leq \bar{\phi}_{max}$) to the iteration input $\boldsymbol{u}^k$ is less than a predefined number ($\leq \phi_{count}$). $\phi_{count}, \bar{\phi}_{max}$ are defined depending on the expected level of measurement noise and the sensitivity of the plant profit function w.r.t. the inputs.

4. CASE STUDY

4.1 The Otto-Williams reactor

The benchmark Otto-Williams reactor (Williams and Otto, 1960) case study is used to investigate the performance of the proposed scheme. Both parametric and structural plant-model mismatch are considered. The plant (simulated reality) consists of a CSTR in which the reactants A and B react to produce products E and P in a three step reaction scheme. The model only accounts for two reactions, which leads to a structural mismatch.

Plant:	Model:
$\mathrm{A} + \mathrm{B} \xrightarrow{k_1} \mathrm{C},$	$\mathrm{A} + 2\mathrm{B} \xrightarrow{\tilde{k}_1} \mathrm{P} + \mathrm{E},$
$\mathrm{C} + \mathrm{B} \xrightarrow{k_2} \mathrm{P} + \mathrm{E},$	$\mathrm{C} + \mathrm{B} + \mathrm{P} \xrightarrow{\tilde{k}_2} \mathrm{G} + \mathrm{E}.$
$\mathrm{P} + \mathrm{C} \xrightarrow{k_3} \mathrm{G}.$	

The reaction schemes of the plant and the model are listed above. The manipulated variables are the flow rate of reactant B (F_B) and the reactor temperature (T_R) with bounds $[3, 6]$ kg/s and $[70, 100]$°C. The objective is to maximize J, defined as

$$J(\boldsymbol{y}, \boldsymbol{u}) = 1143.38X_pF + 25.92X_EF - 76.23F_A - 114.34F_B,$$

where $F := F_A + F_B$ and X_P and X_E are the measured variables of the process at steady state. For the purpose of illustration, we assume that the values of τ_p, τ_d and

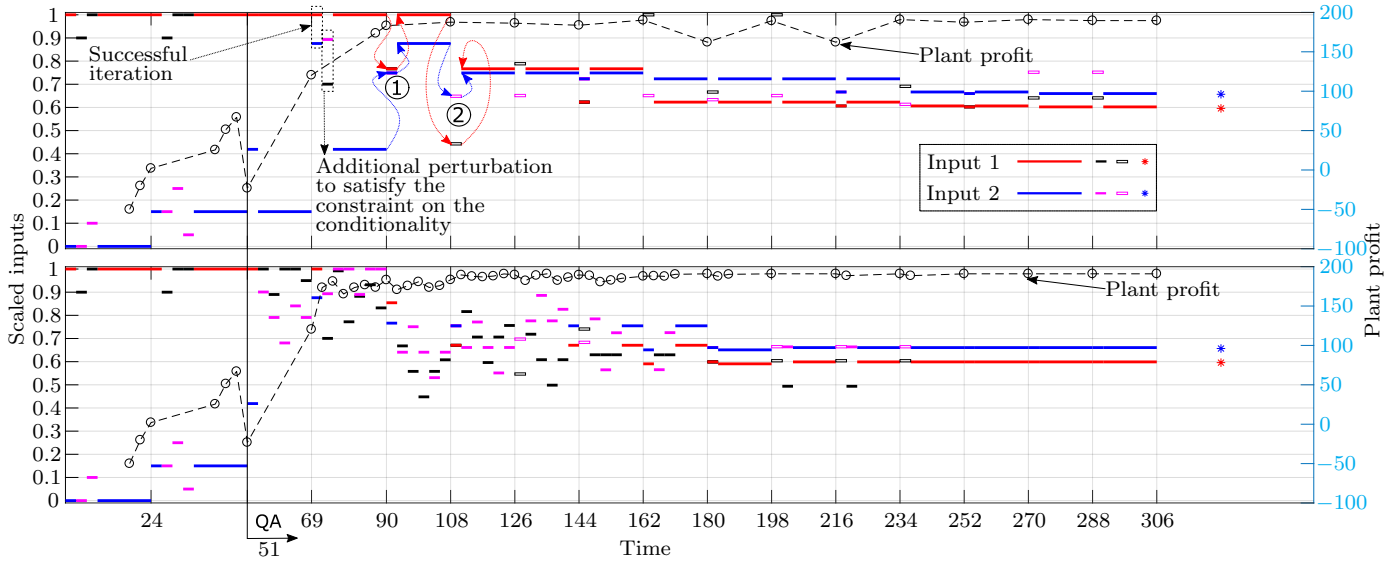


Fig. 4. Evolution of the input variables F_B (Input 1) and T_R (Input 2). Standard MAWQA scheme in the top figure and the proposed active perturbation scheme in the bottom. The values of the plant objective are indicated by circles at the times when the measurement information is available.

τ_s are 3, 12 and 3 minutes, i.e., $\tau_t = 18$. The remaining parameters can be found e. g. in Marchetti et al. (2010).

4.2 Settings of the parameters of the algorithm

Standard MAWQA and MAWQA with the active perturbation approach are applied with the following settings:

- The inputs are scaled to $[0, 1]$
- The screening algorithm from Gao et al. (2016b) is used
- $\mathcal{U}_{nb}^k = \{\boldsymbol{u} : ||\boldsymbol{u} - \boldsymbol{u}^k||_2 \leq 0.1; \boldsymbol{u} \in \mathbb{U}^k\}$
- Perturbation factor for finite differences $= 0.1$
- Lower bound on the inverse of the condition number of $\mathbf{S}^k = 0.1$.

The following additional settings are used in the proposed scheme:

(1) $\phi_{count} = 3, \bar{\phi}_{max} = 0.005$
(2) Perturbation points around $\hat{\boldsymbol{u}}_e^{k+1} = \hat{\boldsymbol{u}}_e^{k+1} + \{0.11[\mathbb{I}_{n_u \times n_u}, -\mathbb{I}_{n_u \times n_u}], 0.055[\mathbb{I}_{n_u \times n_u}, -\mathbb{I}_{n_u \times n_u}]\}$
(3) Suppress additional plant perturbation if the minimum distance between $\mathbb{U}^k$ and the input choice for perturbing the system is less than the threshold 0.05,

where $\mathbb{I}$ is the identity matrix. Step (4) and the rule proposed in section 3.1 are active for both schemes.

4.3 Simulation results

The evolution of the input variables over time for 15 iterations of both schemes without measurement noise are illustrated in Fig. 4. Both schemes are initialized at time $t = 0$ at the scaled input $[F_B, T_R] = [0, 1]$. ("*,*") represent the true plant optimum. The input of a successful iteration is marked by "▬, ▬" and of an unsuccessful iteration the inputs are marked by ("▭, ▭"). In the 0^{th} and 1^{st} iteration of both schemes, i. e., for $t = [0, 24]$ and $t = [24, 51]$, two and three plant perturbations ("▬, ▬") are made to estimate the plant gradients. From the 2^{nd} iteration on wards, i. e., from $t = 51$, QA is used for the gradient estimation. Step (4) in section 3.1 can be observed, e. g. at points ①, ② for standard MAWQA. The input obtained by solving the MA problem is given to the plant as a perturbation, after which the plant is driven to its previous successful iteration. If there are additional perturbations needed due to the constraint on the condition number of $\mathcal{U}_{dist}$, they are made after the input perturbation. For the proposed scheme (bottom figure in Fig. 4), it can be seen that a maximum of five (P_{max}) additional perturbations ("▬, ▬") are made around the estimated future input in each iteration. In the interval from $t = [69, 90]$, the proposed scheme makes six additional perturbations of which one is made to satisfy the constraint on the condition number. The additional perturbations that are made around the future estimate help to reach the plant optimum earlier. Upon convergence, all additional plant perturbations and input moves which do not improve the plant profit are suppressed due to the setting (3) in section 4.2 and the rule proposed in section 3.1.

The values of the plant objective for each input for standard MAWQA and the proposed schemes are also shown in Fig. 4. The plant profit for all inputs, computed by the MA iterations and by the perturbations are marked by "○" and displayed at the point in time when they become available, i. e., with a delay of τ_t minutes.

The performance of the schemes are compared based on the cumulative cost, i.e., the summation of the plant profit over the plant run time, and by their ability to steer the plant to an acceptable region $\mathbb{O} = \{\boldsymbol{u} : ||\boldsymbol{u} - \boldsymbol{u}_p^*||_2 \leq \epsilon\}$ and to remain within it. The standard MAWQA and the proposed schemes were initialized at 49 different initial points (scenarios) identified at the intersection points of a 7×7 uniform grid of the operating region. The average cumulative profits per scenario for 50 iterations without noise for the standard MAWQA and the proposed scheme is 1.7432×10^5 and 1.7648×10^5. For the case with a measurement noise of 0.5 standard deviations the results are 1.5486×10^5 and 1.5519×10^5. The average profit of the proposed scheme has a higher value for the objective function for both noisy and noise free measurements. This shows that the performance loss due to the perturbations is recovered by reaching the plant optimum earlier. Figures

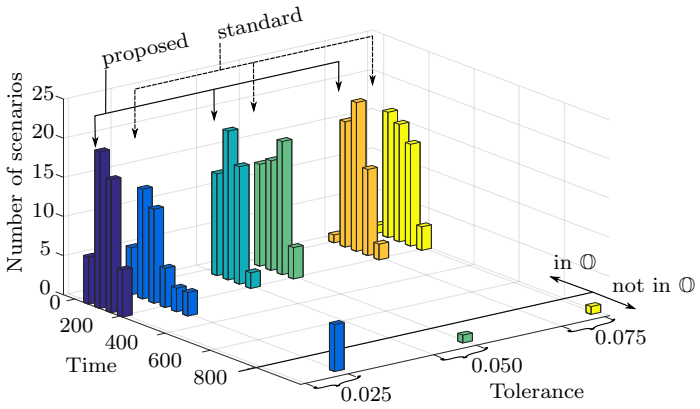


Fig. 5. Histogram plot comparing the time for the proposed and the standard MAWQA schemes to reach and stay inside the acceptable region $\mathbb{O}$ for noise free measurements

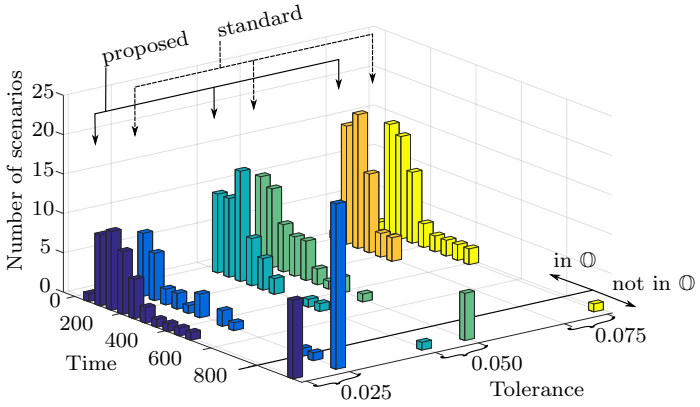


Fig. 6. Histogram plot comparing the time for the proposed and the standard MAWQA schemes to reach and stay inside the acceptable region $\mathbb{O}$ for measurements with noise

5 and 6 show histograms comparing the time at which the plant is driven into the acceptable region ($\mathbb{O}$) for $\epsilon = \{0.025, 0.05, 0.075\}$ for both standard MAWQA and the proposed scheme with and without measurement noise. In both cases the proposed scheme drives the plant to the acceptable region faster due to the additional information gained by perturbing the plant.

5. CONCLUSION

An active perturbation strategy where additional plant perturbations are made around an estimated future input point is proposed to efficiently use the waiting period which occurs due to measurement delays. A method to estimate the future input of MAWQA is presented. The proposed scheme was simulated for the Otto-Williams reactor case study. It was shown that the proposed scheme has a better performance than the standard MAWQA scheme without perturbations.

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