Dynamic Time to Surge Computation for Electric Driven Gas Compressors during Voltage Dips

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Abstract: This paper investigates the influence of voltage dips on large electric driven gas compressors (EDC) considering a typical application in the oil and gas industry. Voltage or power dips are electric disturbances encountered in EDC which are mainly caused by faults in the electrical grid and might last for durations up to 150ms. For gas compression applications, the loss of driver torque often puts the gas compression process at risk of surge conditions, which is a safety critical constraint. The critical nature of the present problem and the fast dynamics involved, pose challenging requirements for the control and safety systems of the gas compressor and the variable-speed drive system. The main focus of the present paper is the dynamic computation of the time to surge using online information of the estimated motor torque and a process model to predict the future behavior of the compression system. The time to surge can then be used for ride-through or shut-down decisions of the complete system, as well as for manipulating safety valves, e.g. the anti-surge valve. The fulfillment of strict real-time requirements and their direct implications on the complexity of the chosen prediction model and the implementation of the algorithm on an embedded system are also addressed in this article. As an industrial case study, the algorithm is applied to a voltage dip situation using high fidelity simulation data of a compression station.

Keywords: Gas compressor modeling; Electric driven gas compressors; Surge Protection; Voltage dip ride-through

1. INTRODUCTION

Centrifugal gas compressors are widely used in industrial applications such as gas lifting, gas processing and pipeline transport. These large rotating machines are almost always mission critical, where down-times automatically lead to large economic losses. As a consequence high availability and dedicated control and safety systems are strict requirements for gas compression systems (Niesenfeld (1982)).

There are several operational limits in centrifugal gas compressors such as minimum speed, maximum speed, maximum power limit, choke limit and surge limit. Most of these limits can be handled without difficulties, however the surge limit is the most challenging constraint to be enforced due to unexpected exogenous disturbances (Cortinovis et al. (2014)). Compressor surge occurs when the network resistance becomes larger than the pressure gradient generated by the compressor and it leads to unstable operating conditions. These periodic unstable conditions result in fluctuations of pressure and flow up to the point of flow reversal. Typically observed adverse effects include higher vibrations levels, overheating and mechanical damage to the system components but also to the compressor blades and the surrounding piping system. Anti-surge control systems rely on dedicated valves that can recycle or blow-off the compressed gas to reduce the system resistance and to ensure forward compressor flow (Dukle et al. (2003)).

A persistent technology trend in the oil and gas industry is the employment of variable-speed drivers and the replacement of gas turbine driven machines by EDCs. These systems are expected to gain more market share in the future, mainly because of higher efficiencies and a reduced need for maintenance. Moreover, new legislations in various countries on CO₂ emissions will further encourage the utilization of electrical drives or ban the installation of new gas turbine driven gas compressors in certain areas. Finally, for sub-sea applications, electrical driven machines are the only viable option.

One problem encountered in EDC systems is the temporary or permanent loss of driver power (Wymann et al. (2014)). Loss of fuel injection in gas turbines affects the driving torque only in the range of seconds, whereas the loss of electric power in EDC leads to a reduced torque within tens of milliseconds. This sudden torque loss almost always results in surge conditions for the gas compression process and is much more pronounced if the driving torque vanishes fast. The physical explanation for the loss of driver torque causing surge conditions is straightforward. The compressor torque reduces the speed of the shaft in
absence of driver torque, when the impeller of the compressor is still in pressurized conditions. At some point, the impeller cannot maintain the pressure gradient across the machine anymore and local back-flow will occur causing the onset of surge. If the speed continues to fall, the compression system will be pushed into surge conditions and a shutdown needs to be initiated. Power losses typically occur in remote places where grid conditions are already weak and are mainly caused by grid faults, e.g. due to lightning strikes or iced overhead power lines touching each other in winter (Naidoo et al. (2007)). Since most compressor stations are located in remote places, these electrical disturbances have a direct influence on their operation.

The present paper focuses on how to dynamically compute the time to surge value. The time to surge is defined as the time elapsed starting from the actual operating point to the crossing of the surge line given the process boundary conditions and some assumptions on the driver torque. The proposed method uses numerical integration of a process model over a predefined prediction horizon in order to estimate the process trajectories. From these trajectories, the time to surge is computed using additional information on the surge line. The specific case treated in this article is a gas compressor driven by an electrical motor fed by a load commuted inverter (LCI). It is assumed that the LCI drive system is able to ride-through voltage dips larger than 20% for example by using the advanced control method described in Besselmann et al. (2016). Using the time to surge information, it is possible to assess if the drive and compressor system can ride-through the under-voltage conditions or if a trip sequence has to be initiated. Moreover, the information can be used to directly manipulate safety valves, such as the hot recycle or the cold recycle valve.

As an example, more details of a typical industrial application are shown in Fig. 1. The electrical system consists of input transformer, line and machine converters, synchronous motor and excitation system. The electrical system is connected to the gas compressor through a gear box. The gas compression process consists of centrifugal gas compressor, control and safety valves, inlet scrubber, hot and cold recycle paths and cooler. The most significant challenges encountered in computing the time to surge are: (i) the safety-critical nature of the problem and its implications on the accuracy of computations, (ii) the strict real-time requirements because of the fast dynamics involved, (iii) the access to process and electrical signals on the same control hardware with fast sampling resolution and (iv) finally the handling of multi-rate signals. Moreover, there is no clear state of the art solution for the present problem. One possible solution is to compute a static time to surge in an off-line fashion, reducing the problem to a look-up table in the real-time setting. However, this approach does not incorporate varying operating conditions, e.g. boundary conditions or changes in system resistance and is typically designed to be over-conservative.

The remaining parts of this article are structured as follows: Sec. 2 gives the details of the time to surge function by presenting the compressor model and the integration scheme. The industrial case study is introduced in Sec. 3, where the considered under-voltage event is explained and the results of the time to surge algorithm are discussed. Finally a conclusion is given in Sec. 4.

2. TIME TO SURGE FUNCTION

The overview of the time to surge algorithm is depicted in Fig. 2. As shown in the figure, measurements are acquired at different sampling rates. Electrical signals comprising motor speed, motor torque and possibly also grid voltages and DC current are sampled every 1 ms, whereas the process measurements are collected at a much slower sampling rate of 50 ms. The reason for the slower sampling rate is the slower dynamics of the process sensors, which are mainly a consequence of internal time constants resulting from specific measurement techniques. Process signals might consist of suction pressure, discharge pressure, suction temperature, discharge temperature, compressor flow, inlet and outlet boundary pressures. As explained later in Sec. 2.3, the time to surge function should be executed at a sampling rate of 1 to 10 ms. The process signals are used to determine the initial conditions for the numerical integration, whereas the electrical signals are used as inputs to the model. The initial conditions for the numerical integration are computed in the initialization block. The compressor model is then numerically integrated over a predefined prediction horizon $T_{\text{pred}}$. Finally, the stored system trajectories are used to
Fig. 2. Schematic overview of the dynamic time to surge computation blocks executed at every sampling instant

compute the time to surge given a parametrized surge line. In the following more details are given for the compressor model, the numerical integration and for the implementation and tuning of the time to surge function.

2.1 Gas Compressor Model

The model of the gas compression process is based on the well-known Gravdahl and Greitzer model for centrifugal gas compressors (Gravdahl et al. (2008), Gravdahl et al. (2002), Gravdahl et al. (1999), Greitzer (1976) and Cortinovis et al. (2012)). The dynamic equations can be summarized as:

\[
\frac{dp_s}{dt} = \frac{a^2}{V_s} \cdot (q_s - q_c) \\
\frac{dp_d}{dt} = \frac{a^2}{V_d} \cdot (q_c - q_d) \\
\frac{dq_c}{dt} = \frac{A_c}{L_c} \cdot (\Pi_c(q_c, \omega) \cdot p_s - p_d) \\
\frac{d\omega}{dt} = \frac{1}{J} \left( T_m - T_c - k_1 \omega^2 \right)
\]

where \( p_s \) and \( p_d \) are the suction and discharge pressures before and after the compressor, \( a \) is the speed of sound, \( V_s \) and \( V_d \) are the suction and discharge tank volumes and \( q_s, q_c \) and \( q_d \) are the suction flow, the compressor flow and the discharge flow respectively. Moreover, \( A_c \) is the cross section of the piping, \( L_c \) the duct length after the compressor, \( J \) the inertial of the mechanical system, \( T_m \) the motor or driver torque, \( T_c \) the compressor torque, \( \omega \) the speed of the compressor and \( k_1 \) a factor accounting for rotating losses. Note that the recycle paths can also be included in the model, but due to the specifics of the case study considered in this article, they are not taken into consideration mainly because of the fact that their actuation dynamics were significantly slower compared to the relevant system behavior. Suction and discharge flows are approximated using the following functions derived from simplified Bernoulli throttle equations:

\[
q_s = k_s \cdot u_{in} \cdot \sqrt{p_{in} - p_s} \\
q_d = k_d \cdot u_{out} \cdot \sqrt{p_d - p_{out}}
\]

where \( p_{in} \) and \( p_{out} \) are the boundary inlet header and outlet header conditions, \( u_{in} \) and \( u_{out} \) are the inlet and outlet valve openings. The state equation for the compressor flow \( q_c \) is equivalent to the model of Gravdahl, where \( \Pi_c(q_c, \omega) \) is a fitted polynomial map for the steady-state pressure ratio. The compressor torque \( T_c \) resulting from the gas compression is defined as:

\[
P = \frac{q_c \cdot H_c(q_c, \omega)}{\eta(q_c, \omega)} \\
T_c = \frac{P}{\omega}
\]

where \( P \) is the power consumed by the compressor, \( \eta(q_c, \omega) \) is the efficiency map of the compressor and \( H_c(q_c, \omega) \) is the compressor head map. Efficiency and head maps are also fitted with polynomials for steady-state conditions.

This model has been identified and validated using high fidelity simulation data similar to the data shown in the next section. Interested readers are referred to Cortinovis et al. (2015) for more details about the identification and validation of a similar model using measurement data.

2.2 Integration Algorithm

The nonlinear system of ordinary differential equations (ODEs) presented in Sec. 2.1 can be written in the general form:

\[
\dot{x} = f(x, u) \\
y = g(x, u)
\]

where the input vector is defined as \( u = T_m \) and the output equation:

\[
y = SD = q_c - \left( \frac{H_c}{a_2} - a_1 \right) q_{ss} \left( \frac{H_c}{a_2} - q_{ss} \right)
\]

The surge distance \( SD \) is the key parameter for computing the time to surge value. The surge line parameters \( a_1, a_2 \) define the surge line in the \( H_c, q_c \)-coordinate space as:

\[
H_{SL} = a_1 + q_c \cdot a_2
\]

where \( \Pi \) corresponds to the horizon length and \( N_{pred} \) to the number of prediction steps. The initial conditions \( x_0 \) and the input vector \( u_k \) at the sampling instant \( k \) are updated as follows: if new process signals are available, the initial conditions \( x_0 \) and \( u_k \) are updated using the new sensor readings, otherwise the state prediction of the previous integration is used, e.g. the one step ahead estimate \( x_{k-1} | k-1 \) at time \( k-1 \) is stored and used for initial conditions \( x_0 | k \). The input \( u_k = T_m \) corresponding to the estimated motor torque is updated at every sampling instant and assumed to be constant over the prediction horizon \( T_{pred} \). During zero torque conditions caused by a voltage dip, this is the worst case assumption due to the fact that the torque is likely to recover back at some point but the algorithm is assuming zero torque for the whole prediction horizon \( T_{pred} \). Nevertheless, this is the safest option for a torque trajectory assumption, as it might be the case that the torque is never recovering. At the same time, the receding horizon implementation of the algorithm will ensure that an updated estimate of the motor torque is used in the predictions at the next sampling instant.

For an efficient computation of the time to surge only the \( SD \) vector containing all surge distances over the prediction horizon \( T_{pred} \) is stored. The time to surge value is then computed comparing the \( SD \) vector with a given condition, e.g. finding
The compression system described in the introduction is running at some operating point in steady-state conditions when a voltage dip hits the system at \( t = 0 \text{ms} \). The type of voltage dip is a symmetric dip and its duration is approximately 150\( \text{ms} \). As shown in Fig. 3, the motor torque is dropping to zero almost instantaneously within a very short time period. The plotted grid lines in x-direction represent 50\( \text{ms} \) steps for motor torque and compressor speed. After some 50\( \text{ms} \) at zero torque conditions, the torque recovers back to the previous level with a small overshoot. Note that this motor torque trajectory was measured at an industrial compression station. To compare the impact on the compressor speed, it can be observed in the lower plot that the speed drops slower and reaches its minimum when the torque starts to increase again. The recovery of the speed to the pre-disturbance conditions takes much longer, e.g. 10\( \text{sec} \) and is not shown in the plot.

The impact of this disturbance on the gas compression process is shown in Fig. 4. As it can be seen from the time ranges, these variables need much more time to settle back to steady-state conditions. The settling time amounts to approximately 10\( \text{sec} \). The process variables of interest comprise compressor flow, inlet pressures, outlet pressures and temperatures. In general, it can be observed that only the compressor flow is affected significantly by the torque loss. The compressor flow response is directly coupled to the compressor speed response. These two variables seem to have comparable dynamics. The suction and discharge pressures are also affected instantaneously, but with

### 2.3 Implementation and Tuning

In order to fulfill real-time requirements and produce useful results for the anti-surge protection systems, the execution rate of the time to surge function has to be in the range of 1 to 10\( \text{ms} \). As a consequence the discretization and prediction horizon need to be chosen, such that a real-time execution is possible. For the specific case treated in this paper the following parameters were used: discretization step size \( h = 12\text{ms} \), integration steps \( N_{\text{pred}} = 85 \), prediction window \( T_{\text{pred}} = 1020\text{ms} \). This choice made it possible to execute the algorithm at a rate of 5\( \text{ms} \). As presented in Sec.3.2, a prediction duration smaller than 1\( \text{sec} \) does not make much sense, due to the fact that the function would not be able to predict far enough into the future to produce valuable information. Some code optimization was necessary at the embedded system level to make the implementation more efficient, e.g. factorization of polynomial expressions, avoiding m-power functions and inlining of sub-functions to name a few.

### 3. INDUSTRIAL CASE STUDY

This section describes a specific voltage dip occurrence in an industrial compression station and uses this data to obtain the time to surge results. The electrical and process data for the voltage dip were obtained using a high fidelity dynamic simulation in UNISIM Design (2010). The simulation was fed using as input a torque profile measured at an industrial compression station.

![Fig. 3. Recorded motor torque and compressor speed in under-voltage conditions lasting 150\( \text{ms} \). Grid steps correspond to 50\( \text{ms} \) starting at the instant of voltage loss](image)

![Fig. 4. Process signals during a voltage dip. Data was generated by high fidelity dynamic UNISIM simulation using an actual recorded torque trajectory](image)
reduced intensity. While the discharge pressure tends to decrease, the suction pressure is increased during the voltage dip occurrence. In contrast, there is no noticeable impact on inlet and outlet boundary pressures as well as on the temperatures.

3.2 Time to Surge Results

The data presented in the previous section was sampled at different rates according to Fig. 2 and fed to the time to surge function in a receding horizon fashion. It is important to point out that the process simulation in Fig. 4 is obtained by UNISIM, whereas the time to surge value is computed using the simplified model introduced in Sec. 2.1. In the following, a detailed analysis of the results is presented by looking at the trajectories within the prediction horizon at different time instants of the voltage dip. Due to space restrictions only a limited number of snapshots can be shown. Before investigating the snapshots, an overview is given in Fig. 5 showing motor torque, surge distance and the dynamic time to surge. The plot in the middle shows the surge distance $SD$ and the minimum surge distance $SD_{min}$ within the prediction horizon $T_{pred}$ as defined in (8) and (11) respectively, both as percentages from the initial operating point. $SD = 0$ corresponds to a surge line crossing, while for negative values the system is in surge conditions. In the present example the $SD$ never crosses the surge line meaning that a safe operation is always ensured. As the torque reduces, it can be observed that the minimum surge distance $SD_{min}$ decreases and as soon as $SD_{min}$ crosses zero, a corresponding time to surge value, as defined in (13), is computed in the lower plot. For conditions where $SD_{min} > 0$ the time to surge is set to a maximum value corresponding to the prediction window $T_{pred} = 1020 ms$.

Under zero torque conditions, the time to surge value constantly decreases as the speed of the compressor decreases. When finally the torque comes back, the time to surge quickly raises again. The minimum time to surge is found to be $T_{25} = 444 ms$ and it occurs at $t = 145 ms$ shortly before torque recovery. Five time instances comprising 0ms, 50ms, 100ms, 150ms and 180ms have been selected and depicted in Fig. 5 as different markers. At every one of these time instances, the corresponding snapshots of prediction horizons can be found for the surge distance in Fig. 6 and for the model states in Fig. 7. As expected at 0ms when the voltage drops, all variables remain relatively constant in the prediction horizon. The surge distance is predicted to remain at the initial value, similarly for all other predicted model states (see solid lines). At 50ms the surge distance already dropped to approximately 50% at the end of the prediction horizon, while the motor torque dropped to 64% of its initial value. As expected the discharge pressure, the compressor flow and the compressor speed are dropping significantly within the prediction horizon (see dashed lines). After 100ms zero torque conditions are encountered for the first time. It can be seen in the surge distance plot that the corresponding prediction crosses the surge line. In this specific case, the time to surge can be observed in the figure by looking at when the surge line crossing takes place in the prediction horizon. The crossing takes place at $T_{pred} = 456 ms$, which matches the time to surge value at 100ms in the lower plot of Fig. 5. The trajectory trends of the process variables within the prediction horizon become more extreme, as the situation is getting worse. At the time instant 150ms the torque recovered partially back to 51% of its initial value. This has a major positive impact on the surge distance predictions, which now come close to the surge line only at the very end of the prediction horizon. It can be seen that the system recovers quite quickly, even if only partial torque is available. The last snapshot shows fully recovered torque conditions with torque overshoot. This torque availability results in quick movement away from the surge line into the safe operating regime.

The influence of the prediction horizon length on the time to surge computation can be observed in Fig. 8. For the selected cases of $T_{pred}$ equal to 504ms, 1020ms, 2040ms and 3060ms the same industrial case study was carried out as described previously. Whenever the surge line was not crossed, the time to surge was set to the maximum prediction time of the corresponding case. The most obvious observation is that
all algorithms can only see time to surge values smaller than $T_{pred}$ as expected. By increasing the prediction horizon, it is possible to see the time to surge values much earlier even for the small torque reduction in the first phase of the voltage dip (at $t = 50\, ms$). As the torque reduces to zero at around $t = 100\, ms$, all time to surge values are superposed, meaning that all algorithms predict the same time to surge as expected. However, the case with 504\, ms prediction horizon is able to see only time to surge values smaller than 504\, ms and therefore it detects the decrease in time to surge quite late compared to the other cases. The two cases 2040\, ms and 3060\, ms provide more accurate time to surge information, but they are not possible to be executed in real-time. Only by decreasing the integration steps $N_{pred}$ within the horizon, it might be possible to meet real-time requirements, however with an unacceptable loss in prediction accuracy. Therefore, the preferred choice of $T_{pred} = 1020\, ms$ was used for the case study finding a good trade-off between accuracy and execution rate.

4. CONCLUSIONS

This paper presents a novel model-based method to compute in real-time the dynamic time to surge for EDCs during voltage dips. The time to surge is defined as the time difference from the actual operating point up to reaching the surge line. The described method uses a dynamic compressor model to predict the future behavior of the compression system within a predefined prediction horizon and uses the state trajectories to estimate the time to surge at each sampling interval. In order to demonstrate the advantages of the algorithm, an industrial case study is carried out illustrating the implementation for a voltage dip at a compression station. The results show that an accurate time to surge computation is possible in real-time, which enables the utilization of this information in safety systems or to manipulate safety valves, e.g. the hot recycle valve.

REFERENCES