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Model predictive control strategy of energy cost management for a compressed natural gas fuelling station

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Abstract: Optimized scheduling of compressor operation in compressed natural gas stations can achieve significant reduction in the cost of electricity in time-of-use electricity tariff environments. A model predictive control strategy for the scheduling of compressor activity is presented in this paper. The strategy ensures a robust responsiveness to meeting potential changes in gas demand patterns while at the same time minimizing electricity cost by a margin of up to 53.87%.

Keywords: Model predictive control, compressed natural gas, demand response, disturbances.

1. INTRODUCTION

In order to slow down the effects of climate change, reduce energy dependency and improve air quality, the use of vehicles powered by alternatives to fossil fuels has been identified as an important strategy that will contribute significantly to the aforementioned targets (Yeh (2007)). However, global transportation is still largely dominated by the internal combustion engine (ICE) given the versatility that it offers in comparison with competing technologies (Lave and MacLean (2002)). In transitioning away from fossil fuels, lower emission options such as compressed natural gas (CNG) and liquid petroleum gas (LPG) have been demonstrated as viable lower-emission replacements for petrol and diesel for ICEs (Weaver (1989)). CNG has been shown to provide the lowest green house gas emissions as well as provide vehicle owners with the lowest total cost of ownership among hydrocarbon fuels (Hesterberg et al. (2008)). CNG has therefore been growing in its use globally along with the CNG delivery infrastructure to end users (Frick et al. (2007)).

The CNG fast-fill station is especially popular for roadside CNG filling stations because it allows consumers to refuel their vehicles within four to five minutes which is comparable to filling times at diesel and petrol pumps (Khadem et al. (2015)). CNG compression that has to be done for vehicle fuelling incurs electricity costs which contribute to the cost of delivery of gas to consumers. CNG fuelling stations can benefit from considering energy efficiency strategies from performance, operation, equipment and technology standpoints (Xia and Zhang (2010); Xia et al. (2012); Xia and Zhang (2015)). Higher energy efficiency at the CNG station can help lower the cost of gas delivery which translates to lower price of gas and therefore increased attractiveness of CNG as a transportation fuel.

The study of the CNG fast-fill station has been significant in literature starting with the initial modelling based on the first law of thermodynamics by Kountz (1994). Subsequently, researchers improved on this model by considering different components of the fast-fill station that interact with the gas to give mathematical description of the CNG station (Farzaneh-Gord (2008); Deymi-Dashtebayaz et al. (2012); Khadem et al. (2015)). There are few studies dealing with the interaction between CNG refuelling infrastructure and the electricity grid networks from which they draw power to run the compressors (Bang et al. (2014)). The current work presents an operation optimization strategy for CNG fast-fill stations to achieve minimized cost of electricity where electricity is purchased based on a time-of-use (TOU) tariff. The TOU tariff is a demand response (DR) strategy implemented by power utility providers in order to influence consumer behaviour in their pattern of electricity use, in response to differential pricing based on time (Albadi and El-Saadany (2008); Nwulu and Xia (2015); Wanjiru and Xia (2015)). DR programs achieve financial benefits for the participants in the short term while lowering aggregate system capacity requirements in the long term as well as increasing grid reliability by minimizing likelihood of forced outages (Setlhaolo et al. (2014)). The model predictive control (MPC) strategy of a CNG fast-fill station operation with an objective of lowering station electricity cost is the novel contribution of this paper. MPC approaches have been used for various process optimization problems because of the ability to cope with hard constraints and states as well as deal with possible disturbances (Mayne et al. (2000); Wanjiru et al. (2016); Mei and Xia (2017); Xia et al. (2011)). Economic MPC work has been particularly popular in recent literature due to demonstrable versatility in various process optimization applications (Rawlings et al. (2017); Van Staden et al. (2011)). This has been the case for applications involving demand side energy management problems such as in the current study (Wu et al. (2015); Zhang and Xia (2016)). The present problem requires the prediction of future fast-fill station behaviour optimized for minimum electricity

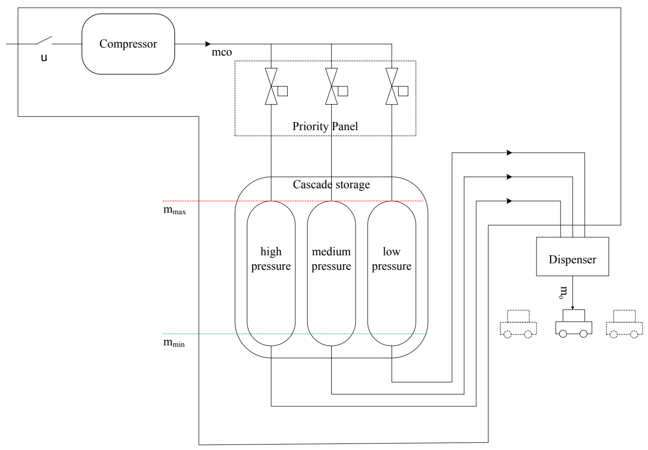

Fig. 1. Schematic layout for the fast-fill CNG station

cost while dealing with possible disturbances in the gas demand profile at the station.

2. STRATEGY FORMULATION

The schematic diagram for the CNG fueling station is shown in Figure 1. In the baseline operation, gas from the utility is compressed at the station compressor, turned on at switch u. The gas is filled into the three tanks of the cascade storage to raise pressure from the minimum values corresponding to a mass minimum m_{min}. The gas passes through the priority panel valves which transfer the filling between the three levels of the cascade storage until the maximum pressure is reached corresponding to a maximum mass of gas m_{max}, when the compressor is switched off. Vehicles fuelling at the station via the dispenser receive gas in kilogram from the cascade storage with the dispenser algorithm compensating for temperature variations and switching between the three levels of the cascade storage to ensure the flow rate of gas is maintained above a minimum value. When the gas levels in the cascade storage reach m_{min}, the compressor is turned on to replenish the storage. The cost of electricity incurred by the running of the station compressor is dependent on the time of day because the compressor is operating in the TOU regime. The objective of the present study is to optimally schedule compressor-on time such that gas demand at the station is met, and at the same time, minimum electricity costs are incurred. The system is considered as a mass flow system where mass exiting the cascade storage to vehicles must be adequately replenished by the compressor to enable adequate filling of subsequent vehicles. The pressure limits of each of the three reservoirs of the cascade storage are normally such that the mass of gas held in storage is able to fill any vehicle visiting the CNG station and has a corresponding mass limit when the system is considered as a mass flow system (Kagiri et al. (2017, 2018)). A robust MPC approach is proposed in order to determine system performance in the control horizon while also maintaining the ability to deal with disturbances in gas demand. The control action at the current instant is obtained by solving a finite open loop optimization problem using the system's current state of mass of gas in cascade storage as the initial state (Bemporad et al. (2002)). The compressor switch u, is the control variable for the current problem so that

$$u(k|k) \in \{0, 1\} \tag{1}$$

which is the predicted status of the switch at the k_{th} sampling interval based on information available at time t and N is the control horizon and

$$N = \frac{T}{t_s} - k + 1 \tag{2}$$

where T is the total simulation time and t_s is the sampling time. The objective function is to minimize electricity cost from the compressor-on time such that

$$J = \sum_{j=k}^{k+N-1} P_{comp} P_e(j) u(j|k) \tag{3}$$

where P_{comp} is the power rating of the compressor, $P_e(k)$ is the price of electricity per kWh. It is also important to limit the frequency of on/off actions that the compressor switch undergoes because high frequencies of start/stop instances increases the wear and tear on the compressor's mechanical parts (Nguyen et al. (2008)). We minimize the difference between the value of the first control step solution in the current control instant and the first control step solution in the previous iteration

$$J = (\xi) \sum_{j=k}^{k+N-1} P_{comp} P_e(j) u(j|k) + (1-\xi)(u(j+1/k) - u(j|k))^2 \tag{4}$$

where ξ is a weighting factor chosen so that a minimum number of switching times is achieved with no increase in cost of electricity from the global minimum. The objective function is subject to the constraints of storage capacity such that

$$m_{min} \leq m(j|k) \leq m_{max} \tag{5}$$

where

$$m(j|k) = m(k) + ts \sum_{i=k}^{j} \dot{m}_{cmp} u(i|k) - \sum_{i=k}^{j} m_o(i) \quad k \leq j \leq k+N-1 \tag{6}$$

where $\dot{m}_{cmp}$ is the mass flow rate of gas from the compressor and $m_o(i)$ is the gas dispensed in the i^{th} sampling instant, whose values are the gas demand profile over the control horizon. In the algorithm, the linear inequality is transformed to

$$A^{mpc} X^{mpc} \leq b_1^{mpc} \tag{7}$$

$$-A^{mpc} X^{mpc} \leq b_2^{mpc} \tag{8}$$

where

$$A^{mpc} = \begin{bmatrix} -t_s\dot{m}_{cmp} & 0 & \cdots & 0 \\ -t_s\dot{m}_{cmp} & -t_s\dot{m}_{cmp} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -t_s\dot{m}_{cmp} & -t_s\dot{m}_{cmp} & \cdots & -t_s\dot{m}_{cmp} \end{bmatrix}_{N \times N} \tag{9}$$

$$b_1 = \begin{bmatrix} m(k) - m_{min} - m_o(k) \\ m(k) - m_{min} - \Big(m_o(k) + m_o(k+1)\Big) \\ \vdots \\ m(k) - m_{min} - \Big(m_o(k) + m_o(k+1) + \cdots + m_o(k+N-1)\Big) \end{bmatrix}_{N \times 1} \tag{10}$$

$$b_2 = \begin{bmatrix} m_{max} - m(k) + m_o(t) \\ m_{max} - m(k) + \Big(m_o(k) + m_o(k+1)\Big) \\ \vdots \\ m_{max} - m(k) + \Big(m_o(k) + m_o(k+1) + \cdots + m_o(k+N-1)\Big) \end{bmatrix}_{N\times 1} \quad (11)$$

The linear inequality constraints in the form of $AX \leq b$ becomes

$$A = \begin{bmatrix} A^{mpc} \\ -A^{mpc} \end{bmatrix}_{2N\times N} \quad b = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}_{2N\times 1} \quad (12)$$

Additionally, the objective function is subject to the terminal constraint

$$m(N) = m(0) + t_s \sum_{i=k}^{k+N-1} \dot{m}_{cmp} u(i|k) - \sum_{i=k}^{k+N-1} m_o(i) = m(0) \quad (13)$$

which in the algorithm can be written as

$$A_{eq}^{mpc} X^{mpc} \leq b_{eq}^{mpc} \quad (14)$$

where

$$A_{eq}^{mpc} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ t_s \dot{m}_{cmp} & \cdots & t_s \dot{m}_{cmp} \end{bmatrix}_{N\times N} \quad (15)$$

$$b_{eq}^{mpc} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ m(0) - m(k) + \Big(m_o(k) + \cdots + m_o(k+N-1)\Big) \end{bmatrix}_{N\times 1} \quad (16)$$

The control vector for the problem, X^{mpc} can be written in the standard form

$$X^{mpc} = [u(k|k), u(k+1|t) \cdots u(k+N-1|k)]^T_{N\times 1} \quad (17)$$

and in the general OPTI toolbox solver algorithm the objective function is formulated as

$$min_x\ f^T x \ subject\ to = \begin{cases} A \cdot x \leq b \\ A_{eq} \cdot x \leq b_{eq} \\ x \in \{0, 1\} \end{cases} \quad (18)$$

At a sampling instant t, the controller solves an open loop optimization problem for the horizon N. The first element of the control variable $u(k|k)$ in the solution is the only one that implemented on the plant. The state $m(j|k)$ is then measured and the measured quantity is fed back to the controller for use as the initial mass of the system for the subsequent sampling instant, $k+1$. All input variables are also updated and the optimization cycle repeated up to the end of the total simulation time.

The workflow of the MPC controller is,

(1) For the instant t, find the control horizon $N(t)$ using Equation (2)
(2) Find the optimal solution for the control variable $u \in \{0, 1\}$ in the control horizon, by minimizing objective function (4)with $m(k)$ subject to the constraints (5) and (13)
(3) Implement only $u(k|k)$ to the plant from the solution
(4) Measure the state $m(k+1)$ for feed back
(5) set $k = k + 1$ and update system states, inputs and outputs
(6) Repeat steps 1-5 until k reaches predefined value

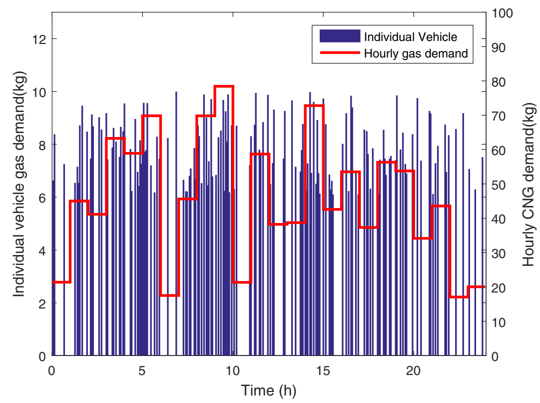

Fig. 2. CNG demand at the fast-fill station unit

3. CASE STUDY

A CNG fuelling station in Johannesburg, South Africa is the case study for the present work. The station is supplied with natural gas from the municipal pipeline via a $132kW$ reciprocating compressor with a capacity of $900Nm^3/hr$ which has a three line priority panel feeding a $6000L$ cascade storage. The cascade storage tanks have a minimum operating pressure of 210,150 and 75 $bars$ respectively for the high pressure, medium pressure and low pressure levels respectively while all the three levels of the cascade storage are filled to a maximum pressure of $250bar$.

The gas demand profile at the station dispenser for a 24 hour control horizon is shown in Figure 2. Peak gas demand is experienced in the morning hours between 05:00 and 10:00, which is a time of day where people begin journeys to various destinations for the day. A substantial demand peak is also observed late afternoon at 15:00 as motorists fill up their vehicles in preparation for the evening people movement rush hour. Gas demand in the night is lower than during the day, although some motorists fuel in preparation for the next day's travel. The station purchases electricity from the South African national utility provider Eskom, under the Miniflex TOU tariff where the price of electricity $P_e(t)$ in South African Rands per kilowatt hour (R/kWh) is

$$P_e(t) = \begin{cases} p_{offpeak} & = 0.5157 & \text{if } t \in [0, 6] \cup [22, 24] \\ p_{standard} & = 0.9446 & \text{if } t \in [9, 17] \cup [19, 22] \\ p_{peak} & = 3.1047 & \text{if } t \in [6, 9] \cup [17, 19] \end{cases}$$

with $p_{offpeak}$, $p_{standard}$ and p_{peak} being the prices for the offpeak, standard and peak times as determined by the utility respectively. Beginning with maximum mass of gas held in the cascade storage m_{max} and the compressor off, the vehicles are fuelled in the baseline operation until the mass of gas in storage falls to the minimum m_{min}. The compressor switch u is turned on to fill up the cascade storage until maximum mass of gas in storage m_{max} is reached when the compressor is switched off and the cycle

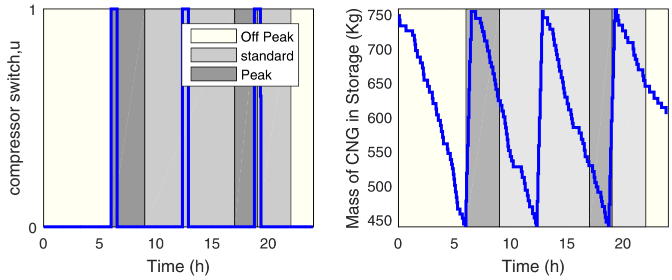

Fig. 3. Compressor operation and level of gas in the cascade storage under baseline operation

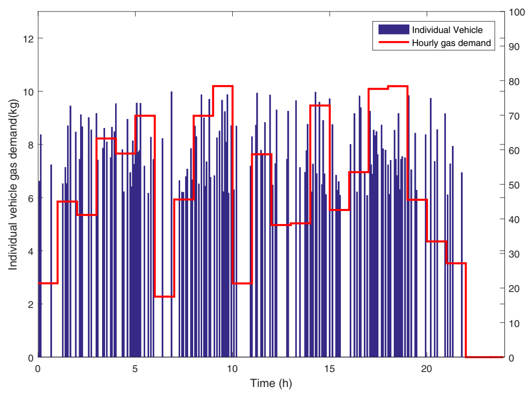

Fig. 4. CNG demand at the fast-fill station unit with a demand profile disturbance

is repeated. Figure 3 shows the compressor switch action in the baseline operation and the change in the mass of gas in the cascade storage. The compressor operation in the morning peak electricity pricing time, standard electricity pricing time as well as partial on-state in the evening peak electricity pricing times incur R432.59 in electricity cost for the day. The current study optimizes the compressor operation so that compressor on-state is minimized in the higher electricity pricing times while also minimizing switching frequency and having the ability to respond to disturbances.

3.1 Gas demand disturbance

A sudden change in gas demand caused by some vehicles shifting fuelling time from between 20:00 and 23:59 to between 17:00 to 19:00 is considered as a plausible source of disturbance in the CNG fast-fill station, so that the gas demand changes from that shown in Figure 2 to that in Figure 4. The disturbance is characterized by there having zero vehicles fuelling in the last two hours of the 24 hour period under the study.

4. RESULTS AND DISCUSSION

The solution to the optimization problem is obtained using the SCIP solver in Matlab's OPTI toolbox interface over a control horizon of 24 hours with a sampling time of 4 minutes and a weighting factor ξ of 0.2. The compressor switch action and the state of mass in the cascade storage are shown in Figure 5. The compressor is turned on just before the morning peak to replenish the cascade storage so that gas in storage can sustain the morning demand

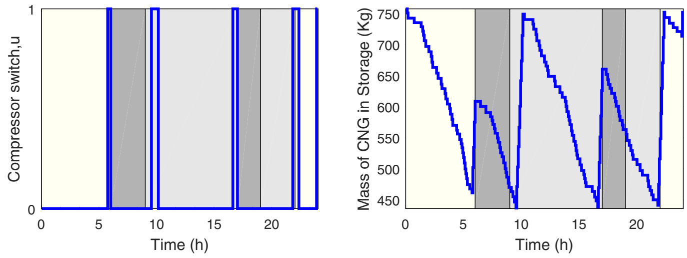

Fig. 5. Compressor operation and level of gas in the cascade storage under optimized operation

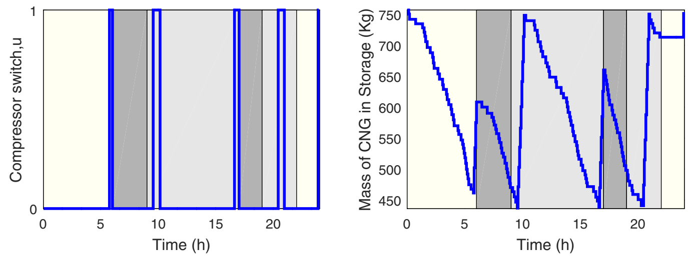

Fig. 6. Compressor operation and level of gas in the cascade storage under optimized operation with a demand profile disturbance

over the peak electricity pricing period between 06:00 and 09:00. The compressor stays off during the morning peak and is turned on after the end of the morning peak to fill up the cascade storage in order to meet late morning and early afternoon gas demand. The compressor is further turned on briefly just before the onset of the evening peak electricity pricing time at 17:00 ensuring the compressor stays off in that peak pricing period and is tuner on in the late night off-peak electricity pricing period to satisfy the terminal conditions. The cost of electricity incurred under the MPC optimized operation is R199.54 which is a significant 53.87% reduction in electricity cost from the baseline.

When the disturbance is considered, the controller under the MPC strategy adjusts the system response accordingly resulting in a shift in the compressor switch profile and level of gas in storage to the new one shown in Figure 6. The system meets the new gas demand profile by shifting compressor on-state from between 21:48 and 22:16 without the disturbance to between 20:28 and 20:52 when the disturbance occurs. The robustness of the MPC strategy is demonstrated in responding to shifts in the demand profile although at a higher electricity cost of R218.42, but still achieves 49.5% in electricity cost savings.

5. CONCLUSION

CNG fuelling stations can benefit from operation optimization in order to take advantage of TOU tariff differential pricing of electricity and save on energy costs. The MPC approach proposed in this study allows for the achievement of these advantages while remaining responsive to changes in gas demand profile that are bound to occur in a public CNG fuelling station. Participation of CNG stations in DR programs enable savings that may be passed on to consumers as incentives. By shifting operations to lower priced electricity usage time of the day using the proposed strategy, the CNG station also contributes to the achievement of the power utility provider's goal of affecting customer behavior in order to reduce the strain on grid resources at certain times of the day. The CNG stations by participating in these DR programs therefore aid in achievement of the wider goal of increasing grid reliability and efficiency.

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