A0820

Reliable Dynamic Operation of SOFC Systems with Anode Off-Gas Recirculation using Multi-linear and Neural Network Model Predictive Control

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Abstract

SOFC systems with anode off-gas recirculation (AOGR) and pre-reforming using hydrocarbon fuels such as methane or methanol as electrochemical energy converters are considered a major lever to reduce CO_2 and pollutant emissions of sea-going vessels [1]. However, due to their non-linear and highly coupled multiple input multiple output (MIMO) nature, these systems are considered complex to control. In addition, the operating range is typically limited due to various constraints: e.g. maximum fuel utilization on stack level, minimum oxygen to carbon ratio, maximum pressure levels, minimum cell voltages as well as maximal thermal gradients along the cell flow direction. Operation close to these limitations is typically desired to achieve highest efficiency. Exceeding these operating ranges, however, leads to significant degradation of the SOFC itself or the catalyst in the pre-reformer [2].
Apart from the targeted steady-state operation close to these limits, a certain load change capability is required in order to be economically used together with battery storage systems. Two dynamic system processes need to be considered in particular: gas residence times (in order of seconds) in the off-gas loop, and thermal processes (in order of minutes or hours). Conventional control strategies with multiple single PID control loops are prone to failure under off-design conditions and are not capable to handle the above-mentioned constraints directly. As a promising alternative, model predictive controllers (MPC) are able to control a multivariable system over the entire operating range while respecting its constraints by using a mathematical dynamic prediction model.
In this submission, several MPC designs are presented that were deducted from a non-linear plant model and tested in a Software in the Loop environment. The MPCs differ by either using (I) a set of linearized plant models or (II) a trained Neural Network as the prediction model. The reliability of the controllers is evaluated by investigating the load-following capability and constraint compliance while delivering highest possible load changes (i) along realistic vessel load profiles and (ii) for significant prediction model – plant model mismatches such as severe cell degradation.
The results of this submission will be published elsewhere in a journal article currently under revision.

Introduction

In the scope of the SchIBZ and MultiSchIBZ projects funded by the German Ministry of Transport and Digital Infrastructure, a modular LNG-fueled SOFC system was designed to be used in an intermodal container on board seagoing ships. The overall plant layout is depicted in Figure 1 and consists of a spatially separated fuel processing module (FPM) and one or multiple fuel cell modules (FCM). The FPM integrates anode off-gas recirculation (AOGR), pre-reforming, catalytic combustion of the depleted AOG and heat integration. In contrast to many system designs, the cathode air and oxidation unit air supplies are installed separately. The AOGR side channel blower with a maximum permissible temperature of 300°C is actuated by a variable-frequency electric drive system. If necessary, the recirculated AOG is cooled down upstream of the blower by means of an external coolant flow. A laboratory system consisting only of one FCM and a respective FPM with a rated power of 15 kW net output was designed and built in the project, which serves as the basis for the plant model used in this submission.
While the steady-state characteristics of such systems are already understood well [3,4], the dynamic behavior and controllability of a spatially separated SOFC system with AOGR is of particular interest, as the application on seagoing vessels requires a high load change capability to minimize the required installation capacity of electrical energy storage. With regard to SOFC systems, model predictive control (MPC) is considered a powerful approach in literature, as it can handle multi-variable control problems with a high level of complexity, non-linearity and operating constraints [5]. It does so by using a mathematically reduced internal model to predict the near-future consequences of its actuations along with a state estimator and a cost function which is minimized numerically at each sampling time step.

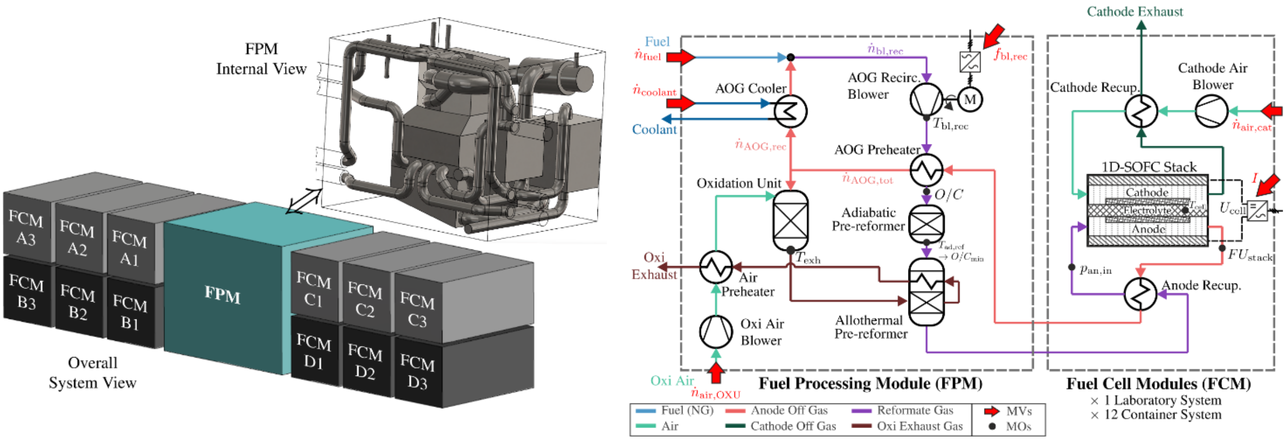

Figure 1: Investigated system layout consisting of one or multiple fuel cell modules (FCM) and a centrally located fuel processing module (FPM).

1. Scientific Approach and Control Objective

The overall research aim of this submission is the development and qualification of a high-level real-time capable MPC architecture. In a first step, this is realized by means of a Software in the loop environment in Matlab Simulink shown in Figure 2 using a sophisticated dynamic non-linear state-space plant model described in detail in [2] and the Model Predictive Control Toolbox. The plant model is simulated with a sampling time of 10 ms and contains a spatially discretized SOFC model in flow direction using 36 control volumes to accurately depict the distribution of electrical current density, electrochemical losses and the associated heat flows and temperature profiles. Due to the separated design of FPM and

FCM, the gas transport delays in the anode loop in the range of 5 to 20 s total must not be neglected and are implemented as a function of mass flow and fluid temperature at component level. Instead of a constant recirculation ratio often assumed in literature, this plant model utilizes the recirculation blower characteristics as well as the mass-flow dependent pressure drops of the anode off-gas loop components, resulting in the imposed pressure difference on the blower to determine the amount of recirculated gas at each time step. This results in a highly interlinked and delayed plant behavior considered complex to control.
According to Figure 1 on the right, the plant model comprises six manipulated variables (MV), given as red arrows, namely the electric stack current, the molar fuel flow, the electrical rotation frequency of the recirculation blower assigned to the corresponding inverter as well as the air flow of stack and oxidation unit as well as the coolant flow. The measured outputs (MO) are selected in order to cover all variables with a specific set point or constraint, resulting in nine variables depicted in Figure 2 on the right.

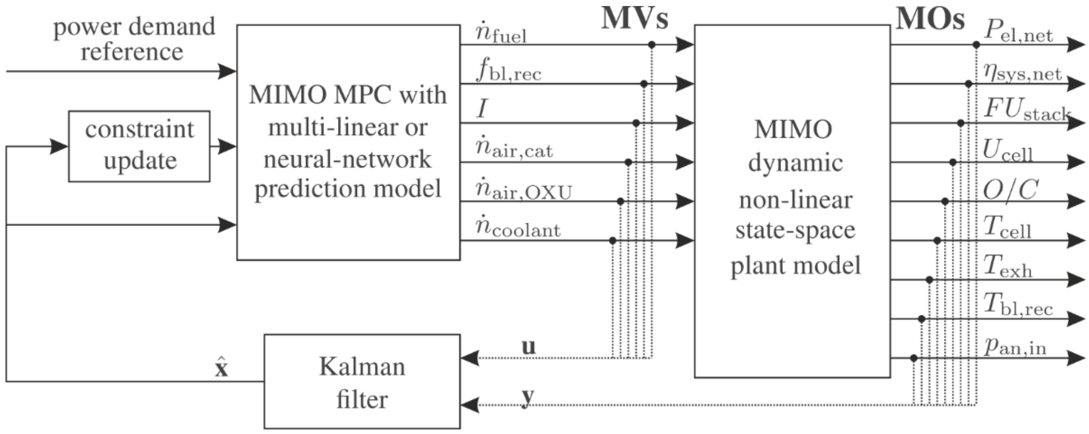

Figure 2: Software in the loop Control structure for controller performance analysis.

The MPC architectures in this submission will be tuned to satisfy the following control objectives, with descending priority:

1. **Reliable operation:** the SOFC system must continuously be operated within the constrained operating range, limited by: minimum cell voltage, minimum oxygen-to-carbon ratio, maximum stack fuel utilization, maximum anode overpressure, as well as maximum temperatures and temperature gradients in the stack, oxidation unit and blower. The control performance with regard to these targets is quantified by measuring the overall time during which a violation of the respective constraint occurs.
2. **Load-following operation**: the system must closely follow a given power demand provided externally, which cannot be predicted. The control performance with regard to this target is quantified by the mean absolute error between power demand and provided demand by the plant model.
3. **Efficient operation**: if the upper two criteria are met, the system net efficiency shall be maximized. This is typically achieved by operating the system at maximum stack fuel utilization and minimum oxygen-to-carbon ratio, the latter one being determined as a function of the catalyst temperature of the adiabatic pre-reformer. The control performance with regard to this target is quantified by the integral efficiency over the mission, given as the ratio of electrical work output and provided amount of fuel.

Due to the multi time scale nature of the SOFC system, a compromise between prediction model sampling time and the prediction horizon has to be made to maintain real-time capability. While the mass transport and gas delay phenomena in the anode loop comprise time constants in the range of seconds, the settling times associated with thermal inertia of the components are significantly higher in the range of minutes to hours. In order to correctly predict the AOG loop behavior and to achieve a stable closed-loop performance, especially when operated in the most efficient mode close to the above-mentioned two constraints, it could be demonstrated that a prediction model sampling time of less than 1 s is required. With a chosen sampling time of 0.5 s, solving the MPC optimization problem using a linear prediction model and a prediction horizon of 300 steps, thus allowing a prediction of 150 s, could be achieved well within the real-time capable regime (0.23 s on average for each sampling step of 0.5 s) on an Intel Xeon Silver 4216 CPU with 2.1 GHz. This however prevents the MPC from assessing the long-term thermal effects of its action, which has to be mitigated during the tuning of the cost function, e.g. by setting guidance reference temperatures for stack, exhaust and blower temperature. However, this countermeasure does not exclude unforeseen actions by the MPC during specific conditions, which will be shown for minimum cell voltage operation in the section 3.

The tuning parameters of the investigated MPC architectures, namely the weights and soft constraint ECR values of the cost function, were obtained from a profound parameter study and are documented in detail in the submission currently under revision.

2. Prediction Model Generation

Apart from proper cost function parameterization, the choice of prediction model type and properties is decisive for a stable closed-loop control performance, especially if operation close to constraints is desired. Reliable actuation predictions can only be made for moderate prediction model – plant model mismatches. Figure 3 shows the range of prediction model methodologies chosen in the project to be analyzed. Starting from the simplest architecture, a single linearized prediction model derived from the plant model at a chosen steady-state operating point, several multi-linear MPC architectures were investigated. A completely different approach is the utilization of a neural network as a prediction model.

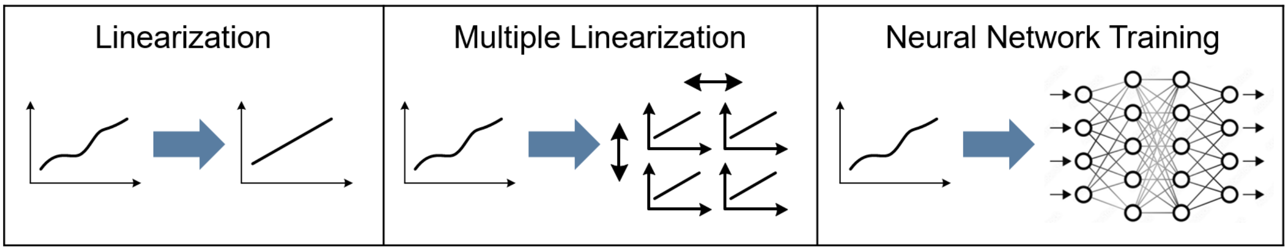

Figure 3: Investigated methodologies for prediction model generation from the dynamic non-linear state-space model

Linear and multi-linear architectures can be obtained comparatively fast from non-linear plant models. If a strong non-linear nature can be observed, as is the case for the SOFC system due to exponential or logarithmic plant model equations, such as ASR temperature dependency, Nernst equation, chemical equilibria and the blower operating map, multiple linearization at different operating conditions has been proven successful in literature. However, suitable switching conditions have to be defined and excessive switching has to be avoided to prevent instability. Apart from linearization error minimization, multi-linear MPC can additionally be used to alter cost function parameters during specific operating conditions. It has to be noted that the linearized prediction models had to be deducted from a reduced system model with a 0D SOFC model due to numerical and real-time capability reasons, so that spatial and time thermal gradients along the cell cannot be predicted. To compensate for this, a rate constraint of 15 A/min was put on the electrical current to cap the gradients, which roughly corresponds to 6 kW/min or 40% per minute related on rated power. In contrast, the neural network prediction model is trained with the plant model including the 1D SOFC model, thus allowing for specifying constraints for the spatial or time gradients themselves. However, time-consuming training of the neural network is required and non-physical results may occur if training data did not cover the entire operating range.

3. Closed-loop performance of single linear and multi-linear MPC

The functionality as well as the limitations of the proposed control architectures are exemplarily demonstrated in a closed-loop operation of a single linear and a multi-linear MPC in combination with the non-linear plant model. A synthetic set of power ramps is used as a power demand reference, depicted in Figure 4a as a black dotted line with two upward and downward ramp rates of 3 kW/min and 6 kW/min, corresponding to a medium and highest possible load change as mentioned above. The prediction models are linearized at reference conditions in the center of the operating range (P_{net} = 10.8 kW, I = 22 A, O/C = O/C_{min}, $FU_{stack} = FU_{stack,max}$), from which the performance test is started.

A single linear MPC in blue, and a multi-linear MPC in red are depicted in the five diagrams and are identical for the first 11 min along the ramps. For both architectures, it can be concluded that the power demand is followed closely and that no constraints are hurt. As the system always returns to the most efficient operating point close to the O/C and FU_{stack} constraints, it can be demonstrated that with this parameterization all of the three control objectives formulated above are met.
However, it can be observed that at the end of the last ramp, which was deliberately extended slightly higher to 15 kW, the single liner MPC fails to work properly and does not return to a stable operating mode. This is due to reaching the cell voltage minimum at comparatively low cell temperature and a misleading actuation caused by the short-sightedness of the MPC during its intent to raise the cell voltage. The controller sharply increases the cathode molar flow in order to quickly lift the Nernst potential by means of the oxygen partial pressure. As can be seen however, this worsens the situation in the long term, as the cell temperature begins to drop, in turn resulting in higher voltage losses and lower cell voltage superimposing the effect of the increasing Nernst potential. A more suitable approach would be to remain at minimum cell voltage and to keep the cathode air flow to a minimum in order to heat the stack up as fast as possible, which in turn lowers the voltage losses. However, as stated above, the need for a small sampling time does not allow for a prediction horizon far enough to grasp these effects.
To compensate for this, Architecture B is proposed, which consists of an additional state with the same linearized prediction model, but altered cost function parameters, mainly aiming to guide the MPC away from this misjudged condition by increasing the stack temperature, and to put a strong penalty for voltage minimum violation and a lower penalty for load-following deviation. This new state becomes active as soon as the cell voltage falls below a threshold of 0.66 V. As can be seen in red in Figure 4, using this architecture results in a stable condition and the required high power demand can be held in long-term.
Apart from the two presented architectures, more complex multi-linear concepts were investigated to further decrease linearization errors. Figure 5 exemplarily shows Architecture C consisting of four states and different linearization operating points at partial and full load

conditions. It was found suitable to select the cell temperature as switching condition instead of the electrical current or net power, as the temperature does not change rapidly.

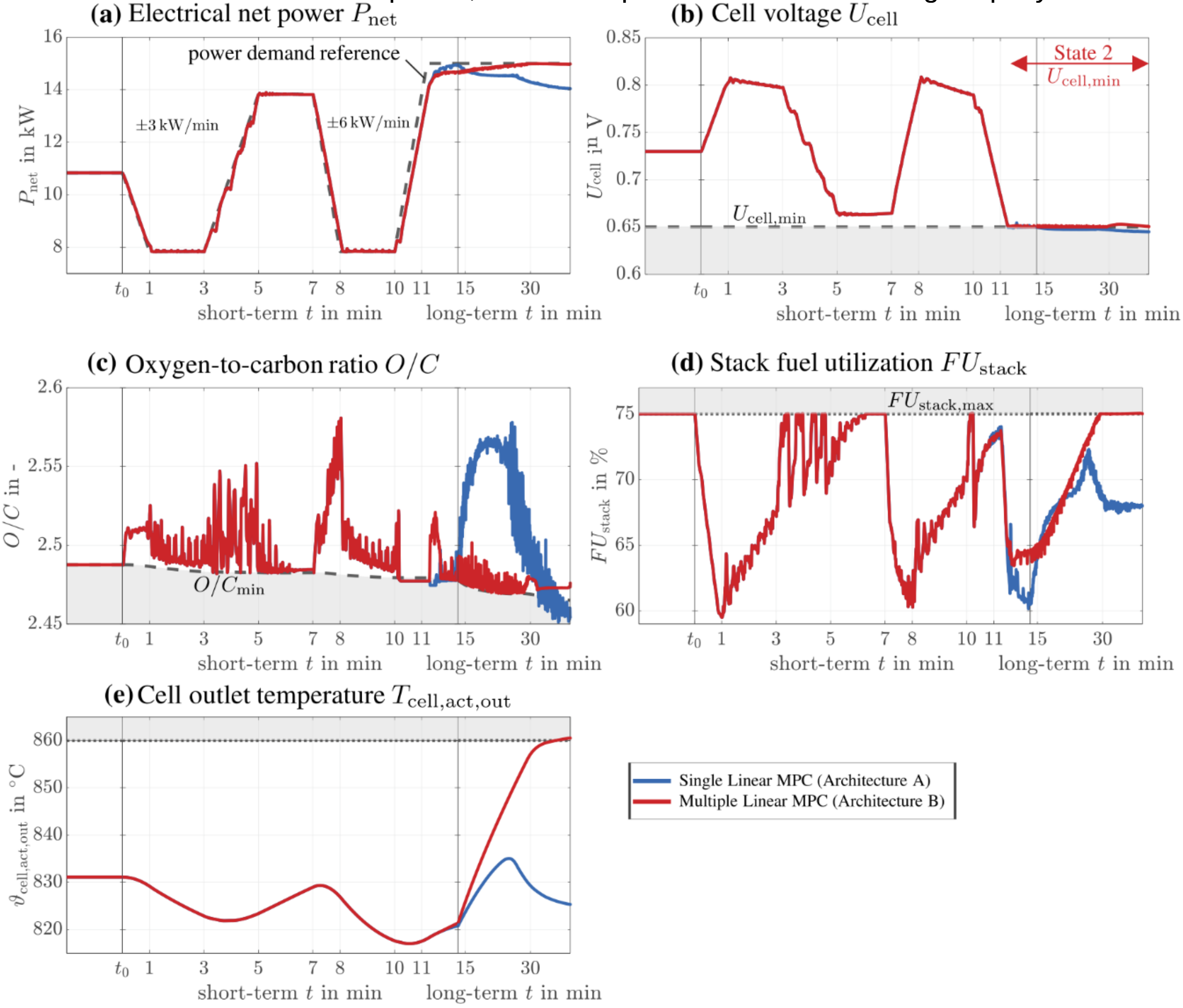

Figure 4: Closed-loop performance of Architectures A and B with a synthetic ramp profile

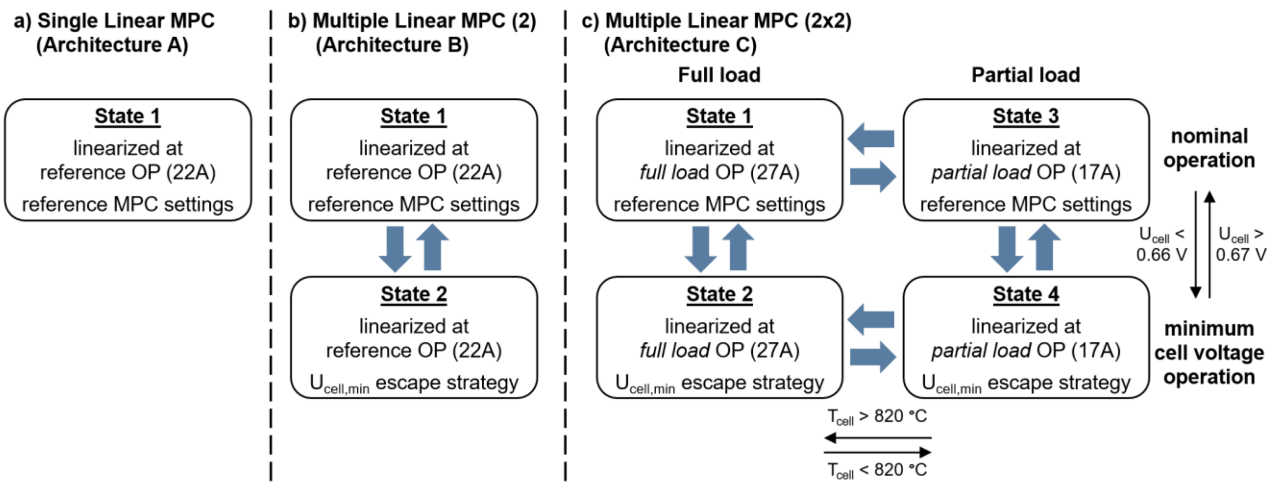

Figure 5: Investigated Architectures of Single and Linear MPC with switching conditions

Acknowledgments

The authors gratefully acknowledge the financial support by the Federal Ministry of Transport and Digital Infrastructure, Germany (BMVI, funding code 03B10605H) and the coordination of the MultiSchIBZ project by the National Organization Hydrogen and Fuel Cell Technology (NOW GmbH), Germany.

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Keywords: SOFC System, Control, Model Predictive Control (MPC), Anode Off-gas recirculation (AOGR)