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A New Switching Method for Multiple Model Predictive Control Based on Dempster-Shafer Theory of Evidence

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ABSTRACT
Nowadays, multiple model predictive control is widely used in constrained nonlinear control. A well known problem in multiple model predictive control is the frequent switching between different controllers which leads to poor transient response. Generally, the active controller is selected according to operating conditions, or output prediction error. In this study, the Dempster-Shafer theory of evidence is used to combine two independent sources of information (operating point and output estimation error), to make decision about the active controller of multiple model predictive control. A novel method is accordingly proposed for Basic Probability Assignment. The proposed controller is utilized to control the inlet air flow of a PEM fuel cell. Simulation results show that the proposed switching method reduces the undesired switching and improves transient response of the multiple model predictive control compared to conventional methods.

Key words: Evidence theory, basic probability assignment, multiple model predictive control, PEM fuel cell

INTRODUCTION
Model Predictive Control (MPC) has gained a lot of attention in control of industrial processes. MPC is one of few methods which is capable of controlling multivariable systems while handling input-output and state constrains (Mayne *et al.*, 2000). MPC utilizes linear model of the process to predict future performance and calculate an optimal control signal to lead the output to a desired target (Camacho and Bordons, 2004). Multiple MPC has been widely adopted in industry as an effective means to deal with nonlinear constrained control problems (Yu *et al.*, 1992; Narendra and Balakrishnan, 1994, 1997; Anderson *et al.*, 2000; Stojanovski *et al.*, 2010; Dougherty and Cooper, 2003; Giovanini *et al.*, 2006; Chen *et al.*, 2009; Abu-Rmileh and Garcia-Gabin, 2010; Guolian *et al.*, 2010). A Multiple MPC is composed of several MPCs, each of which is designed based on linear model of the process at a specific operating point. Models cover the entire operating space whilst a switching signal is designed by which the multiple MPC switches from one MPC to another. The switching criterion plays a crucial role in the design of multiple MPC. Generally two different approaches are used as the switching criterion: The switch is determined according to the operating point of the system (Dougherty and Cooper, 2003; Abu-Rmileh and Garcia-Gabin, 2010) or output prediction error of multiple models (Giovanini *et al.*, 2006; Chen *et al.*, 2009; Guolian *et al.*, 2010). A well known problem in multiple

MPC is the frequent switching between different controllers which leads to poor transient response. In this study, a new switching method is proposed for multiple MPC to reduce the undesired switching between different controllers. The proposed method combines the information of operating conditions and output prediction error by means of Dempster-Shafer theory of evidence, to make decision about the switch of the multiple MPC. Dempster-Shafer (D-S) theory of evidence is a method to infer from incomplete and uncertain knowledge, provided by different independent sources of knowledge. An advantage of the Dempster-Shafer theory is its ability to deal with ignorance and missing information. In particular, it provides explicit estimation of imprecision and conflict between information from different sources and can deal with any unions of hypotheses (Dempster, 1967; Shafer, 1976). Dempster-Shafer theory is widely used in engineering problems, including imprecisely specified distributions, poorly known and unknown correlation between different variables, modeling uncertainty and measurement uncertainty (Yager, 1999; Bendjebbour *et al*., 2001; Zhu *et al*., 2002; Salzenstein and Boudraa, 2004; Ghasemi *et al*., 2012, 2013; Jiang *et al*., 2012). The fundamental and important object of this theory is a primitive function called Basic Probability Assignment (BPA) which should be defined based on some sufficient knowledge about the problem.

PEM fuel cell is a good candidate to generate clean electricity in both stationary and automotive applications. One of the main challenges in managing a PEM fuel cell is to control the inlet air flow, according to the demanded current (Gruber *et al*., 2009; Arce *et al*., 2010; Minagar *et al*., 2011).

In this study, a multiple MPC controller is designed to control the inlet air flow of a PEM fuel cell. The switch signal is assigned according to operating point and output prediction error, based on the Dempster-Shafer theory of evidence. A novel method is accordingly proposed for Basic Probability Assignment.

MATERIALS AND METHODS

General idea of MPC: A general idea behind MPC is indeed structural. Reliable model of the system predicts near future of the system, based on measurement of the process states/outputs. At k^{th} sampling time instance, control inputs are calculated to minimize the difference between the predicted controlled outputs and foreseen set points, over a prediction horizon, according to input-output and state constraints. Then only first element of the calculated control inputs is applied to the process. At next sample time i.e., $(k+1)^{st}$, a new set of measurement is available and whole procedure is repeated again.

Idea of multiple MPC: MPC utilizes a linear model of the process to predict future performance. Most industrial processes are almost strongly nonlinear. One MPC is able to control such processes about an operating point but the performance is degraded when the operating point changes drastically. A nonlinear process is approximated by multiple linear (affine) models and multiple model predictive controller is composed of the corresponding MPC controllers. At each sample time, one MPC is assigned to get activated by a switching algorithm. The switching algorithm plays a crucial role in the design of multiple MPC.

Dempster-shafer theory of evidence: The Evidence theory is an effective technique to make decision under uncertainty. It provides convenient and comprehensive way to handle engineering problems including modeling and measurement uncertainty. A frame of discernment denoted as

Θ is a set of mutually exclusive and exhaustive propositional hypotheses, one and only one of which is true. A function m: $2^{\Theta}\rightarrow[0, 1]$ is called basic probability assignment on the set Θ if it satisfies two following conditions:

$$m(\varnothing) = 0,\ \sum_i m(A_i) = 1 \tag{1}$$

where, $\varnothing$ is an empty set and A_i is any subset of Θ. An A_i subset of frame Θ is called a focal element, if $m(A_i)>0$. A Dempster-Shafer belief structure **m** is composed of a set of focal elements $\{A_1, A_2,..., A_n\}$ and related basic probability assignment $m(A_i)$ which is called the mass function. A main step in application of the evidence theory is obtaining the basic probability assignment which should be assigned based on some sufficient knowledge about the application. Mass functions which are obtained from different information sources, are combined with Dempster's orthogonal rule in Eq. 2-3. The resultant is a new mass function which incorporates the joint information provided by the corresponding sources:

$$m(A_k) = (1-K)^{-1}\times \sum_{A_1\cap A_2 = A_k} (m_1(A_1)\times m_2(A_2)) \tag{2}$$

$$K = \sum_{A_1\cap A_2 = \varnothing} (m_1(A_1)\times m_2(A_2)) \tag{3}$$

where, K is a measure of conflict between information sources. For any A_i subset of Θ the belief and plausibility measures are defined as:

$$Bel(A_i) = \sum_{A_j\subseteq A_i} m(A_j) \tag{4}$$

$$Pls(A_i) = \sum_{A_j\cap A_i \neq \varnothing} m(A_j) \tag{5}$$

The belief measures a least or necessary support whereas plausibility reflects a maximum or potential support for A_i. The less the difference between belief and plausibility, the less the uncertainty.

PEM fuel cell: A PEM fuel cell is composed of two electrodes: anode and cathode and a polymer electrolyte membrane. It generates electricity from the chemical reaction between hydrogen and oxygen. In the anode, the hydrogen is dissociated in protons and electrons. The protons flow through the membrane and arrive to the cathode and the electrons flow to the cathode through an external electric circuit connected between the electrodes, thus generating electric current. The protons and electrons react with the oxygen in the cathode and water and heat is generated. Hydrogen is available in a tank, with a control valve to regulate the flow. The oxygen supply system includes a compressor and the supply manifolds. The inlet air flow to the cathode is controlled by regulating the compressor voltage. To prevent stress on membrane, anode-cathode pressure ratio is regulated in a safe relation by modifying the hydrogen control valve. This regulates the anode pressure to follow the cathode pressure. This implies that hydrogen and oxygen flows are correlated. Consequently the oxygen flow is treated as a main variable during the control objectives.

Ratio of the input oxygen flow to the reacted oxygen inside the stack is stated as excess oxygen ratio (λ_{O2}). When current is drawn from a fuel cell, the air supply system should replace the reacted oxygen; otherwise the cathode will suffer from oxygen starvation which damages the stack and limits the power response of the fuel cell. In order to prevent the starvation, λ_{O2} has to be controlled. A critical value for λ_{O2} is set to 2. Positive deviations of λ_{O2} above the reference imply lower efficiency, whilst negative deviations increase the probability of the starvation phenomena. The main contribution of this study is development of a multiple MPC to control the compressor voltage of a PEM fuel cell, to prevent oxygen starvation when stack current varies according to load demands.

In this study, data are collected from nonlinear dynamical model of the PEM fuel cell power system developed and validated by Arce *et al.* (2010) and Del Real *et al.* (2007). The non-linear model includes not only the stack itself but also the auxiliary devices such as air pumps, fuel valves and cooling fans.

Control system description: The proposed control system is shown schematically in Fig. 1 by means of Simulink™ language. It consists of the nonlinear model of PEM fuel cell, multiple MPC and fuzzy Dempster-Shafer inference system. The compressor voltage (V_{cmp}) and the stack current (I_{st}) are inputs to the fuel cell. V_{cmp} is the control signal which is computed by the Multiple MPC and I_{st} is a measured disturbance. The excess oxygen ratio (Lambda) and the stack voltage (V_{st}) are measured outputs of the fuel cell.

The multiple MPC is composed of three MPCs which each is designed based on linearized model of the PEM fuel cell around one of the Operating Points; op1: (I_{st} = 5, V_{st} = 40.86), op2: (I_{st} = 10, V_{st} = 36.80) and op3: (I_{st} = 22, V_{st} = 33.54). Each MPC receives the measured output (mo), the

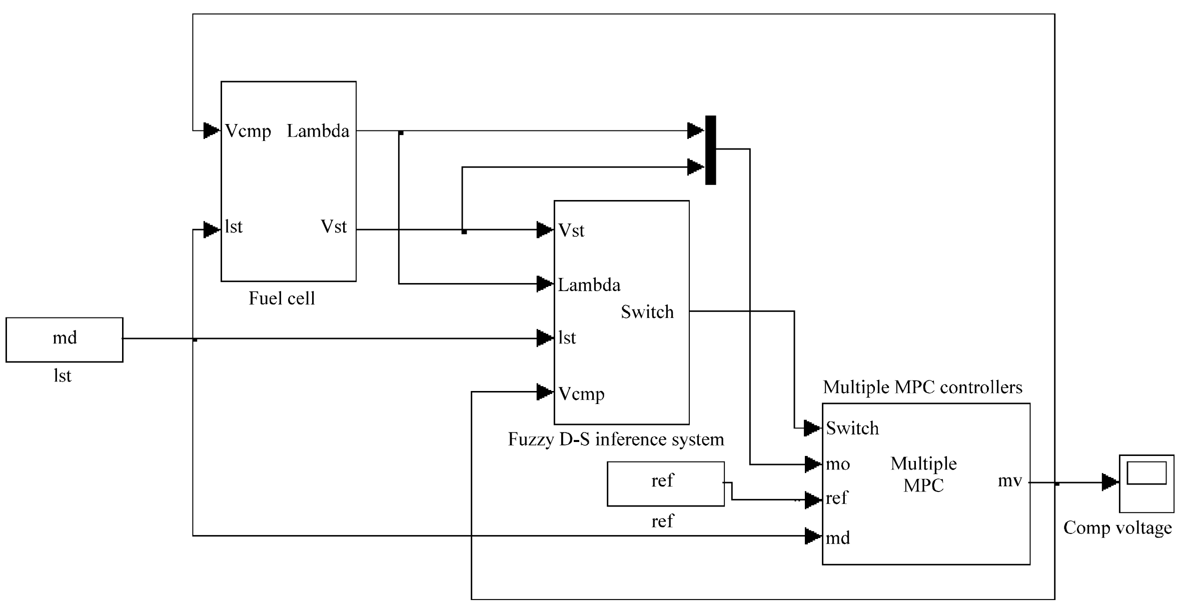

Fig. 1: Simulink block diagram of the proposed control system

measured disturbance (md) and the reference signal (ref) as inputs and computes the compressor voltage as output. The multiple MPC switches from one MPC to another as the switch signal (switch) changes. The switch signal is determined by the Fuzzy D-S inference system which receives the measurements of I_{st}, V_{st}, Lambda and V_{cmp}. The Fuzzy D-S inference system is fully detailed as follows.

Proposed switching method: The fuzzy D-S inference system determines the switch signal of the multiple MPC. As mentioned before, two different approaches are available as the switching criterion:

- **Operating point approach:** Let us consider three predetermined center points op1: (I_1,V_1), op2: (I_2,V_2) and op3: (I_3,V_3). The stack operating point is measured through instrumentation of the stack current (I_{st}) and the stack voltage (V_{st}). An auxiliary aim is to select the closest center point to the measured operating point
- **Output estimation error approach:** Let's consider three linear models model 1, 2 and 3, corresponding to the center points op1, 2 and 3 (Each model is a linear approximation of the process around the corresponding center point). The process output (Lambda, Vst) is available by means of some instrumentation. The output is estimated by the three linear models, as well. The aim is to select the linear model with the least output estimation error
- **Problem definition:** There is a problem with each of the mentioned approaches: When the measured operating point is rather equidistant from two predefined center points, or output prediction error of two linear models are rather equivalent, there is some ambiguity to determine which MPC is the best candidate to be selected by the switching algorithm. This problem has been resolved by our proposed method as follows: Two Dempster-Shafer belief structures **m1** and **m2** are composed based on operating point and output estimation error information, respectively, as is detailed in the next paragraph. The relating mass functions are combined by the Dempster rule 2-3 and then the belief of each MPC is computed. The MPC with the greatest belief is selected by the switch. The switching subsystem is schematically shown in Fig. 2 by means of Simulink™ language

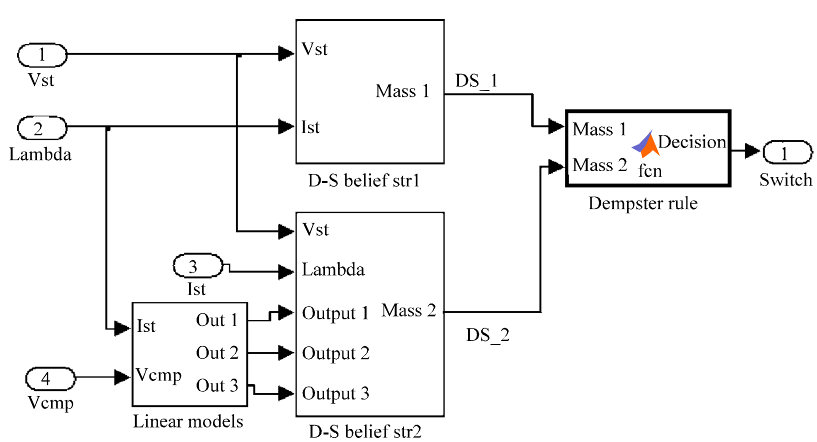

Fig. 2: Simulink block diagram of the switching subsystem (fuzzy D-S inference system)

Organizing the dempster-shafer belief structure: The set of MPC numbers {1,2,3} is considered as the frame of discernment Θ. So, the focal elements are {1}, {2}, {3}, {1, 2}, {1, 3}, {2, 3}, {1, 2, 3} and the mass functions are represented as m({1}), m({2}), m({3}), m({1, 2}), m({2, 3}), m({1, 3}), m({1, 2, 3}).

The set {1} means "The switch is 1" and the set {1,2} means "The switch is 1 or 2", i.e., the information source cannot distinguish between 1 and 2. The set {1,2,3} means "The switch is 1 or 2 or 3", i.e., the information source cannot distinguish between 1, 2 and 3.

The mass functions related to belief structure **m1** are assigned according to the measured values of I_{st} and V_{st} as follows. The normalized distance of the operating point (I_{st},V_{st}) from the center points op1: (I_1,V_1),op2: (I_2,V_2) and op3: (I_3,V_3) is calculated by Eq. 6-8:

$$R1 = \sqrt{((I_{st} - I_1)/w_I)^2 + ((V_{st} - V_1)/w_v)^2} \tag{6}$$

$$R2 = \sqrt{((I_{st} - I_2)/w_I)^2 + ((V_{st} - V_2)/w_v)^2} \tag{7}$$

$$R3 = \sqrt{((I_{st} - I_3)/w_I)^2 + ((V_{st} - V_3)/w_v)^2} \tag{8}$$

where, w_I and w_v are the normalization coefficients. Now the mass functions of **m1** are calculated as follows:

Basic probability assignment: The constant c>1 is chosen as threshold (c = 2 at current configuration). The workspace is partitioned to 7 regions and the related mass functions are assigned as follows:

- **Region 1 (close to point 1):** If R1/R2<1/c and R1/R3<1/c, then m({1}) = 1 and the other mass functions equal to 0
- **Region 2 (close to point 2):** If R2/R1<1/c and R2/R3<1/c, then m({2}) = 1 and the other mass functions equal to 0
- **Region 3 (close to point 3):** If R3/R1<1/c and R3/R2<1/c, then m({3}) = 1 and the other mass functions equal to 0
- **Region 4 (rather equidistant from 1 and 2 and far from 3):** If 1/c<R1/R2<c and R3/R1>c and R3/R2>c, then m({1}) = $P_{12}(1)$, m({2}) = $P_{12}(2)$, m({1, 2}) = P(1 or 2) and the other mass functions equal to 0, where P(1or2),$P_{12}(1)$ and $P_{12}(2)$ are defined in Fig. 3
- **Region 5 (rather equidistant from 2 and 3 and far from 1):** If 1/c<R2/R3<c and R1/R2>c and R1/R3>c, then m({2}) = $P_{23}(2)$, m({3}) = $P_{23}(3)$, m({2, 3}) = P(2 or 3) and the other mass functions equal to 0, where P(2or3), $P_{23}(2)$ and $P_{23}(3)$ are defined in Fig. 4
- **Region 6 (rather equidistant from 1 and 3 and far from 2):** If 1/c<R1/R3<c and R2/R1>c and R2/R3>c, then m({1}) = $P_{13}(1)$, m({3}) = $P_{13}(3)$, m({1, 3}) = P(1 or 3) and the other mass functions equal to 0, where P(1or3),$P_{13}(1)$ and $P_{13}(3)$ are defined in Fig. 5
- **Region 7 (rather equidistant from 1, 2 and 3):** Elsewhere at least two of fuzzy sets P(1or2), P(2or3) and P(1or3) are nonzero. Then:

$$m(\{1\}) = P_{12}(1) \cap P_{13}(1) \tag{9}$$

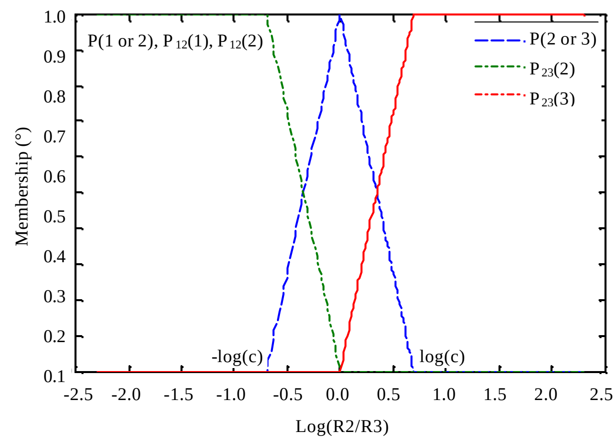

Fig. 3: Fuzzy sets P(1or2), $P_{12}(1)$ and $P_{12}(2)$

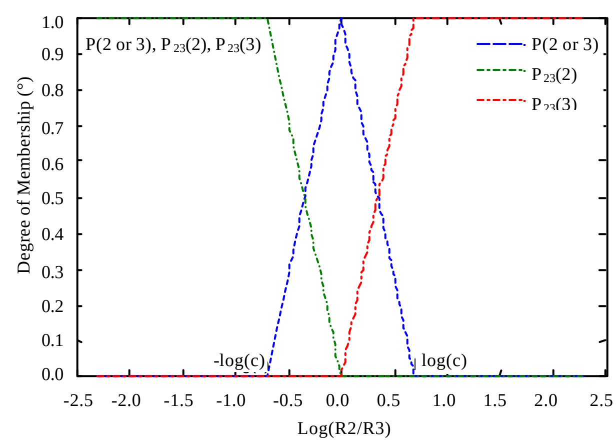

Fig. 4: Fuzzy sets P(2or3), $P_{23}(2)$ and $P_{23}(3)$

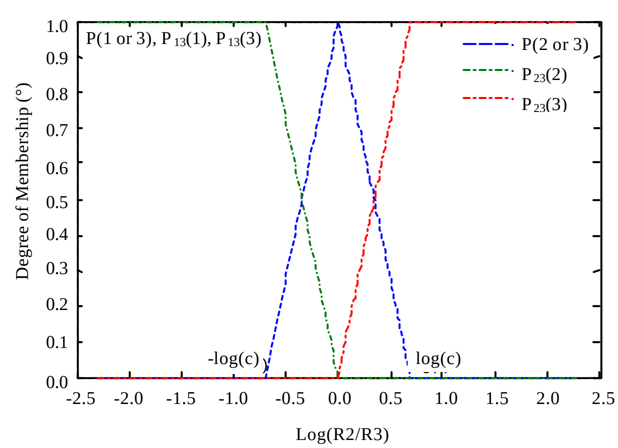

Fig. 5: Fuzzy sets P(1or3), $P_{13}(1)$ and $P_{13}(3)$

$$m(\{2\}) = P_{12}(2) \cap P_{23}(2) \quad (10)$$

$$m(\{3\}) = P_{13}(3) \cap P_{23}(3) \quad (11)$$

$$m(\{1, 2, 3\}) = (P(1 \text{ or } 2) \cap P(1 \text{ or } 3)) \cup (P(1 \text{ or } 2) \cap P(2 \text{ or } 3)) \cup (P(1 \text{ or } 3) \cap P(2 \text{ or } 3) \quad (12)$$

$$m(\{1, 2\}) = P(1 \text{ or } 2) - m(\{3\}) - (P(1 \text{ or } 2) \cap P(1 \text{ or } 3)) \cup (P(1 \text{ or } 2) \cap P(2 \text{ or } 3)) \quad (13)$$

$$m(\{1, 3\}) = P(1 \text{ or } 3) - m(\{2\}) - (P(1 \text{ or } 2) \cap P(1 \text{ or } 3)) \cup (P(1 \text{ or } 3) \cap P(2 \text{ or } 3)) \quad (14)$$

$$m(\{2, 3\}) = P(2 \text{ or } 3) - m(\{1\}) - (P(1 \text{ or } 2) \cap P(2 \text{ or } 3)) \cup (P(1 \text{ or } 3) \cap P(2 \text{ or } 3)) \quad (15)$$

The $\cup$ and $\cap$ operators are implemented by functions max and min, respectively.

The mass functions of the belief structure **m2** are assigned according to the output estimation errors. Let (λ_{est1}, V_{est1}), (λ_{est2}, V_{est2}) and (λ_{est3}, V_{est3}) be the estimated outputs of model1, model2 and model3, respectively. The normalized distance of the measured output (λ, V_{st}), from the estimated outputs is calculated by Eq. 16-18:

$$R1 = \sqrt{((\lambda - \lambda_{est1})/w_\lambda)^2 + ((V_{st} - V_{est1})/w_v)^2} \quad (16)$$

$$R2 = \sqrt{((\lambda - \lambda_{est2})/w_\lambda)^2 + ((V_{st} - V_{est2})/w_v)^2} \quad (17)$$

$$R3 = \sqrt{((\lambda - \lambda_{est3})/w_\lambda)^2 + ((V_{st} - V_{est3})/w_v)^2} \quad (18)$$

where, w_λ and w_v are the normalization coefficients. Finally the mass functions of **m2** are calculated as similar as the mass functions of **m1**.

Advantages of the proposed basic probability assignment:

- The mass functions sum up to 1 and there is no need to normalize them
- Let's consider two operating points a and b for which the ratio of R1/R2 is equal to c and 1/c, respectively. It is obvious that the mass function m({1, 2}) should be equal for a and b, i.e., there is the same ambiguity between 1 and 2 for the mentioned operating points. This aim is achieved by considering log scale for the horizontal axis and symmetrical fuzzy membership functions in Fig. 3-5
- The threshold value of c can be tuned according to process specifications

RESULTS AND DISCUSSION

Here, simulation results of using the proposed decision system are presented. The results are compared to two conventional switching algorithms: Operating point and output estimation error approaches. The stack current and voltage together with the center points are shown in Fig. 6 and 7. The switch signal of Fig. 8 is determined by the proposed fuzzy D-S inference system. The switch signal determined based on operating point conditions (stack current and voltage) is

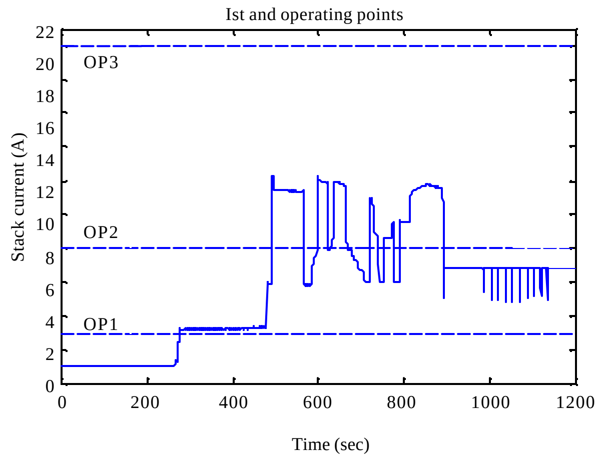

Fig. 6: Stack curent and center points

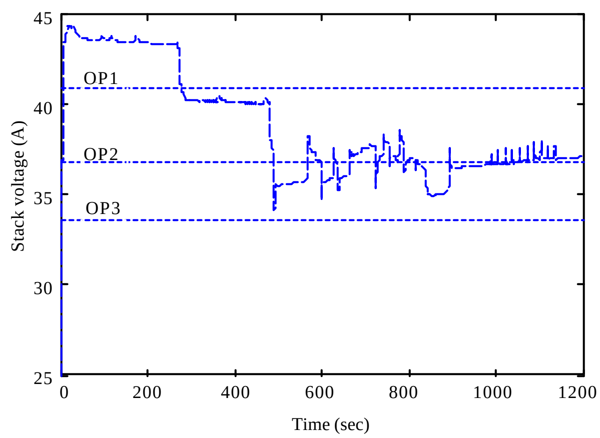

Fig. 7: Stack voltage and center points

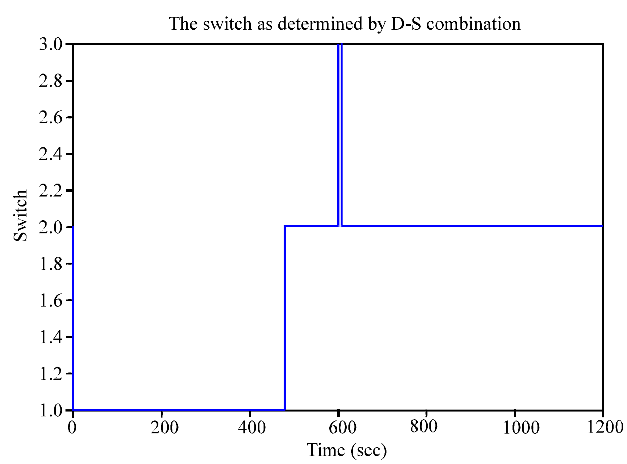

Fig. 8: Switch signal as determined by the proposed fuzzy D-S decision system

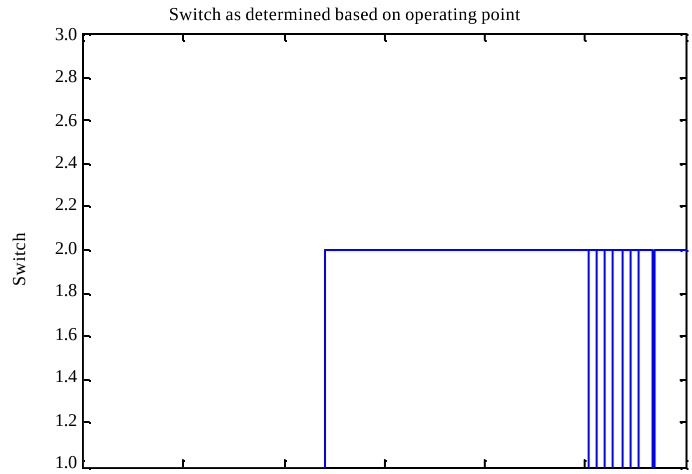

Fig. 9: Switch signal as determined based on operating point conditions

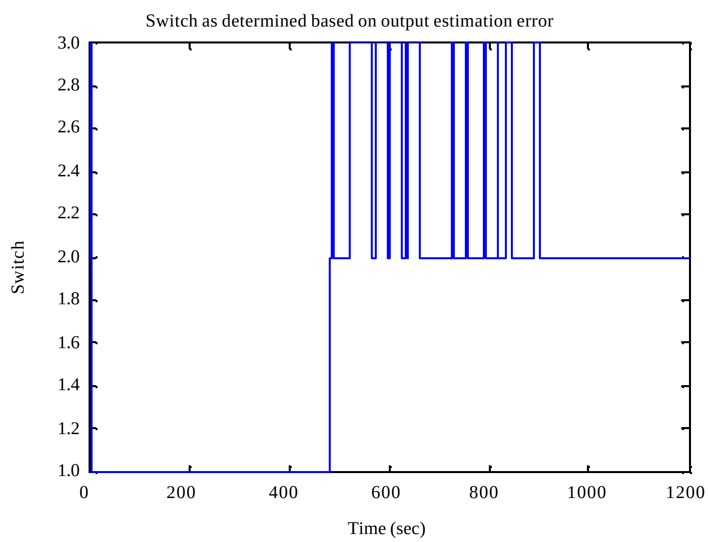

Fig. 10: Switch signal as determined based on output estimation errors

shown in Fig. 9. The switch signal of Fig. 10 is a result of output estimation error approach. The switch is changed 18 times when determined based on operating conditions, it is changed 74 times if determined according to output estimation error while it is changed only 4 times when the proposed fuzzy D-S decision system is used. As a result, the proposed fuzzy D-S decision system has led to 78 and 95% reduction in undesired switching in comparison with operating conditions and output estimation error approaches, respectively.

To show how undesired switching degrades the performance of the control system, let's focus on time between 720 and 800 sec. Figure 11 shows two switch signals determined by the proposed method and the output estimation error approach, respectively. It can be seen that there are 3 undesired pulses in the second switch signal. The control signal (compressor voltage) and the

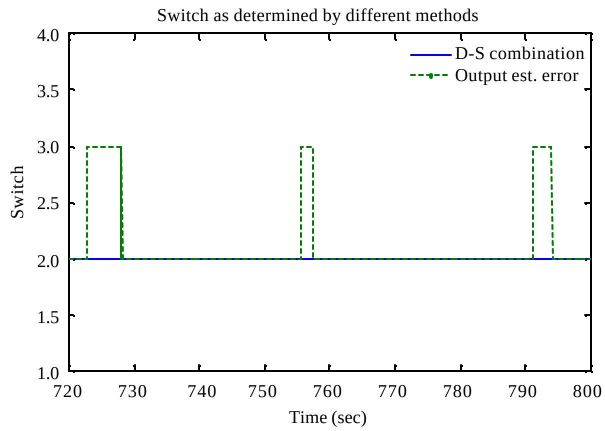

Fig. 11: Switch signal as determined by two methods (zooming the time scale)

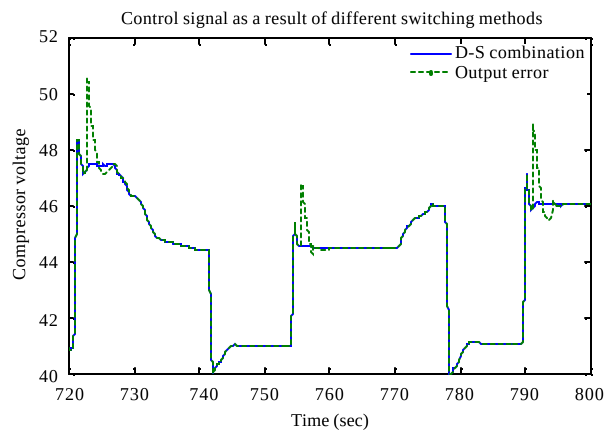

Fig. 12: Control signal

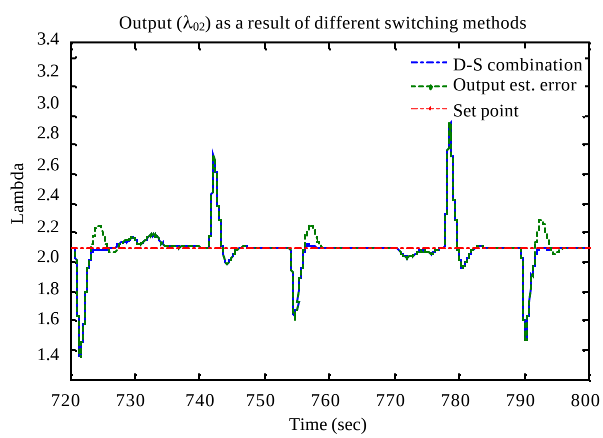

Fig. 13: Output (Lambda)

regulated output (λ_{O2}) using the mentioned switching schemes are compared in Fig. 12 and 13, respectively. As it is shown, the control signal and the output have some overshoot and oscillations at the transient response when the undesired pulses occur in the switch signal.

CONCLUSION

In this study, a multiple MPC is designed to control the inlet air flow of a PEM fuel cell. The corresponding switch signal is determined by a fuzzy Dempster-Shafer decision system, based on information about operating point and output estimation errors. A novel method is proposed for basic probability assignment. Simulations indicate that the undesired switching is reduced considerably compared to the conventional switching methods, leading to an improved transient response.

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