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Turbojet Engine Industrial Min–Max Controller Performance Improvement Using Fuzzy Norms

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Abstract: The Min–Max control strategy is the most widely used control algorithm for gas turbine engines. This strategy uses minimum and maximum mathematical functions to select the winner of different transient engine control loops at any instantaneous time. This paper examines the potential of using fuzzy T and S norms in Min–Max selection strategy to improve the performance of the controller and the gas turbine engine dynamic behavior. For this purpose, different union and intersection fuzzy norms are used in control strategy instead of using minimum and maximum functions to investigate the impact of this idea in gas turbine engines controller design and optimization. A turbojet engine with an industrial Min–Max control strategy including steady-state and transient control loops is selected as the case study. Different T and S norms including standard, bounded, Einstein, algebraic, and Hamacher norms are considered to be used in control strategy to select the best transient control loop for the engine. Performance indices are defined as pilot command tracking as well as the engine response time. The simulation results confirm that using Einstein and Hamacher norms in the Min–Max selection strategy could enhance the tracking capability and the response time to the pilot command respectively. The limitations of the proposed method are also discussed and potential solutions for dealing with these challenges are proposed. The methodological approach presented in this research could be considered for enhancement of control systems in different types of gas turbine engines from practical point of view.

Keywords: Min–Max control strategy; gas turbine engine; fuzzy norms; control engineering; T-norm; S-norm

1. Introduction

The control system in Gas Turbine Engines (GTEs) is to provide the stable and safe operation of the engine components at the operability and performance level for which it is designed. The control system should be able to satisfy all engine control modes simultaneously. These control modes are steady state control mode, transient control mode, and physical limitation control modes [1]. The steady state control mode is to track the pilot lever angle (PLA) command precisely and with the minimum error. The transient control mode is to satisfy the thrust requirement with the minimum possible response time. The physical limitation control mode is to protect the engine from malfunctions or exceeding limits like over-speed, over-temperature, surge and stall. These control modes should be satisfied simultaneously to guarantee the safe and precise operation for the engine [2].

There are several control strategies proposed to deal with the above-mentioned requirements dating back to 1952. Each of these algorithms has its advantages and disadvantages [3,4]. Some of them are not capable to satisfy all engine control modes simultaneously and some of them are weak in some modes and strong in some other modes. A comprehensive review and analysis on the history of GTEs control strategies could be found in [5,6].

The Min–Max control strategy is known as a practical algorithm to satisfy all engine control modes simultaneously without any error and malfunction [7]. Results of design and implementation of Min–Max controller were presented within the Basic Research in Industrial Technologies for Europe-Europe/America (BRITE-EURAM) project OBIDICOTE (On Board Identification, Diagnosis and Control of gas Turbine Engines) and confirmed by all OBIDICOTE partners (SNECMA, Rolls-Royce plc, MTU Aero Engines, Volvo Aero Corporation, Fiat Avio, Techspace Aero S.A., Lufthansa Technik AG, Aerospatiale, Chalmers University of Technology AB, National Technical University of Athens, Technische Universität München, Universität Stuttgart, Université Catholique de Louvain). Thus, this strategy is the most practical control method for gas turbine engines [8–10].

A Min–Max controller contains different control loops:

- Steady-state control loop to calculate the steady state fuel flow according to the engine operating condition,
- Transient control loop to control the engine acceleration and deceleration in response to the power lever angle (PLA),
- Physical limitation control loops to satisfy the engine constraints including the engine stall, flameout, over speed, and over temperature limitations.

The main idea of a Min–Max control structure for a single spool turbojet engine is shown in Figure 1. As shown in this figure, the fuel flow to the engine could be divided into two parts: steady-state fuel flow calculated by the steady state control loop, and transient fuel flow calculated by one of the transient (PLA loop) or physical limitation control loops. The transient fuel flow will then be added to the steady state fuel flow to calculate the total fuel flow for the engine combustion chamber at any instantaneous time.
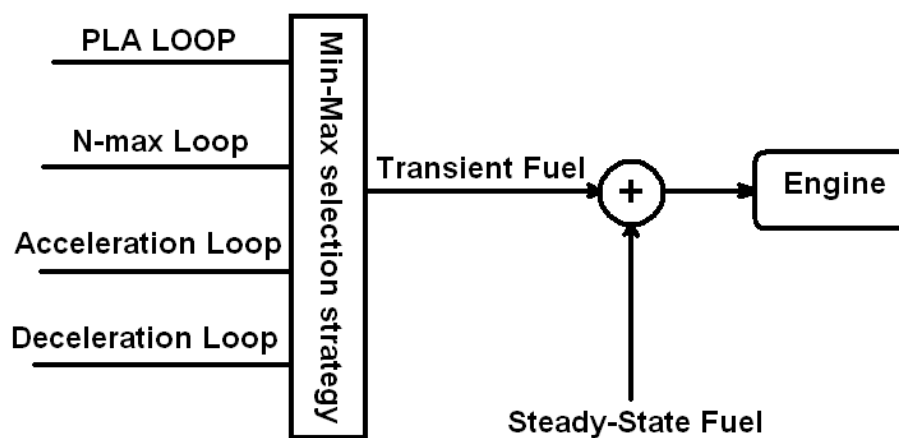

Figure 1. Min–max control structure for jet engines.

In order to select the appropriate control loop for transient fuel flow calculation, a selection strategy should be defined in the controller structure. The Min–Max control strategy is proposed and confirmed by well-known industry and engine manufacturers during last decades [7]. The min–max control loop selection strategy uses the following logical algorithm:

$$W_{f,transient} = min\left(min\left(max\left(W_{f,dec}, W_{f,PLA}\right), W_{f,acc}\right), W_{f,Nmax}\right) \tag{1}$$

where $W_{f,PLA}$, $W_{f,dec}$, $W_{f,acc}$ and $W_{f,Nmax}$ are the transient fuel flow rates calculated by the PLA, maximum deceleration, maximum acceleration and maximum speed loops, respectively. All details about design, development, and implementation of Min–Max control strategies could be found in [2,11,12]. The schematic of Min–Max selection strategy in the controller structure is shown in Figure 2.
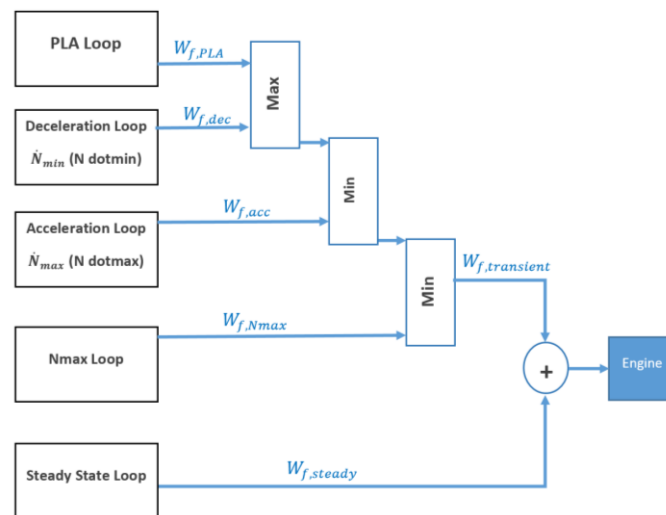
Figure 2. Schematic of engine fuel controller with min–max selection strategy.

After formation of the Min–Max control algorithm, many studies have done for performance improvement of this strategy. Control loops gain tuning in single objective [1,13] and multi-objective feature [14,15], additional control modes definition for engine constraints [2,16], emission level reduction [17,18], adding start-up phase modelling and optimization [19,20], multi criteria decision making strategy [21], integrated flight/propulsion control strategy [22,23], real-time simulation test [24,25], and performance optimization of engine and controller from different points of view [15,17] are some of these milestones in Min–Max control strategy improvements. However, in all these studies the final selection strategy between the transient control loops are kept fixed.

On the other hand, advanced control algorithms like fuzzy logic [26–28], model predictive control [29,30], and sliding mode control [31,32], are investigated theoretically in recent years. Although these studies present successful approaches in designing controller for GTEs, they are usually focused on a specific jet engine and do not use a methodological approach like Min–Max control system as well. Moreover, these approaches are relying more on computer simulations rather than real-world applications respect to stability and/or reliability issues.

The main contribution of this paper is to use advanced mathematical concepts in the practical Min–Max control algorithm to start filling the existing gap between the two above-mentioned approaches. For this purpose, section two will focus on problem formulation with a turbojet engine as a case study where the main idea is to change the Min–Max selection strategy (Equation (1)) by using different fuzzy T-norms and S-norms to optimize a pre-defined performance index for the engine. Section three presents the simulation results by applying different norms in the selection strategy. Section four is to discuss and analyze the simulation results, to raise the limitations and challenges of the proposed approach, and to propose potential solutions for dealing with future challenges. Finally, conclusion remarks are presented in section five.

2. Problem Formulation

The main idea of the paper is to use fuzzy norms in the Min–Max selection strategy of Equation (1). From mathematical point of view, for union and intersection operators it could be written that:

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \tag{2}$$

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \tag{3}$$

It means that the set defined by Equation (2) is the smallest set containing both A and B and the set defined by Equation (3) is the largest set contained by both A and B [32]. In the literature, only the

above type of operation is used in the GTEs control strategy. However, other possibilities exist in fuzzy sets definition. In other words, we could define $A \cup B$ as any fuzzy set containing both A and B and not necessarily the smallest set. The aim of this paper is to study other types of operators for union and intersection of fuzzy sets in the Min–Max control strategy and to investigate the performance of this contribution. The main reason is that the operators in (2) and (3) may not be satisfactory in some situations. For instance, an operator that calculates larger fuzzy sets for intersection may have a positive impact on the final performance of the controller and the GTE simulation results. Moreover, it is interesting from theoretical point of view to explore the possibility of using fuzzy sets in industrial control strategies as it may result in higher and/or more flexible performance for the controller and the engine. For non-fuzzy sets only one type of operation is possible for union and intersection. However, fuzzy sets give us the flexibility of defining different operator in the context of industrial Min–Max control structure. Thus, the main advantage is to keep the ability of satisfying all control loops simultaneously (having the Min–Max structure) while trying to improve the performance without using huge computational efforts of meta-heuristic optimization algorithms. The T and S norms are functions mapping T/S: $[0, 1] \times [0, 1] \to [0, 1]$ which satisfies the mathematical commutativity, monotonicity, and associativity conditions. The fuzzy S-Norms and T-Norms that could be used for union and intersection values calculation are listed in Table 1 [33,34].

Table 1. Different fuzzy sets for T and S norms.

Norms	Title	Formulation
t1	Bounded difference	t1(A,B) = max (0, A + B − 1)
s1	Bounded sum	s1(A,B) = min (1, A + B)
t2	Einstein product	t2(A,B) = (AB/(2 − [A + B − AB])
s2	Einstein sum	s2(A,B) = (A + B)/(1 + AB)
t3	Algebraic product	t3(A,B) = AB
s3	Probabilistic sum	s3(A,B) = A + B − AB
t4	Hamacher product	t4(A,B) = (AB)/(A + B − AB)
s4	Hamacher sum	s4(A,B) = (A + B − 2AB)/(1 − AB)
t5	Minimum	t5(A,B) = min (A,B)
s5	Maximum	s5(A,B) = max (A,B)

Thus, the Equation (1) could be re-written in the following form:

$$W_{f,transient} = t_i(t_i \; (s_i \left(W_{f,dec}, W_{f,PLA} \right), W_{f,acc}), W_{f,Nmax} \right) \tag{4}$$

where i could be selected from Table 1 (1 to 5). It means that any T-norm and S-norm from Table 1 could be used to select the winner between different transient control loops in the Min–Max control system structure. In other words, the transient control loops structure for the GTE could be plotted as Figure 3.
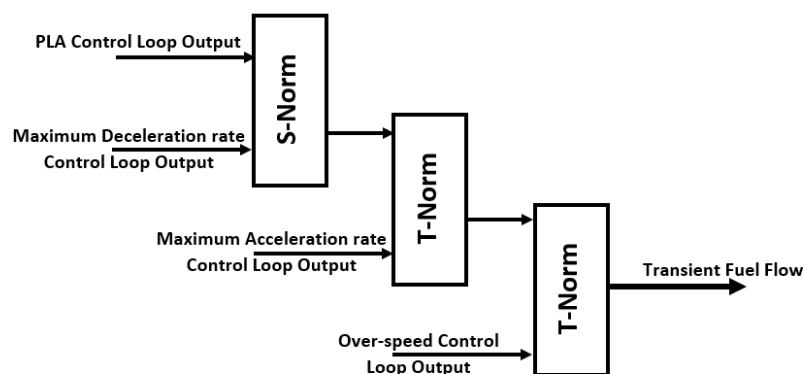

Figure 3. Transient control loops for a turbojet engine with fuzzy sets.

Since there are 5 different possibilities defined for each norm in this paper, all different possibilities for Min–Max selection strategy in the Equation (4) would be: $5 \times 5 \times 5 = 125$. The idea is to simulate these 125 scenarios to investigate the effectiveness of using fuzzy norms in gas turbine engines Min–Max controllers.

3. Simulation Results

In order to investigate the effects of fuzzy sets for union and intersection in gas turbine engine performance, a Matlab/Simulink program is generated including an engine and an industrial Min–Max controller. A single spool turbojet engine is selected as a case study. The engine characteristics are listed in Table 2. A reduced order Wiener model based on experimental results is generated to predict the dynamic behavior of the engine [35]. The engine is modelled and analyzed with details by the authors in [12], and [22]. The results of the modelling are also validated against experimental data. The Min–Max control strategy is also designed for the engine in [1,2] and the gains of the controller are optimized using genetic algorithm in [1], using particle swarm optimization in [12], and using invasive weed optimization in [15,21]. The schematic of the engine and Min–Max control strategy is shown in Figure 1. The developed Matlab/Simulink program block diagram is shown in Figure 4.

Table 2. Turbojet engine characteristics [36,37].

Characteristics	Value
Type	Single Spool Turbojet
Length	851 mm (33.5 in)
Diameter	348 mm (13.7 in)
Dry weight	61.2 kg (135 lb)
Compressor	4 stage axial
Combustors	Annular
Turbine	Single Stage
Maximum thrust	5.33 kN (1200 lbf)
Overall Pressure Ratio	6.3:1
Air mass flow	8.14 kg/s (17.94 lb/s)
Specific fuel consumption:	1.1 kg/(daN h) (1.03 lb/(lbf h))
Maximum rotational Speed	29,700 rpm
Thrust-to-weight ratio	8.9:1

A brief description about the operating procedure of the model and controller is as follow:

- Firstly, a predefined PLA profile is defined for the model. This command is a percentage of the available thrust that the pilot requires at any instantaneous time. Since the thrust is not measurable directly, other parameters (engine rotational speed or engine pressure ratio [38–40]) are used to translate the required thrust to a measurable parameter in Min–Max algorithm. In this study, the engine pressure ratio is used for this purpose.
- The Min–Max controller gets the PLA command as well as engine situation (acceleration, deceleration, rotational speed) and using the strategy described earlier calculates the appropriate fuel flow for the engine. The control law in each loop could be Proportional (P), Proportional-Integral (PI), or Proportional-Integral-Derivative (PID) algorithm [2].
- The calculated fuel flow will satisfy all engine control modes simultaneously and protect the engine from malfunctions and physical limitations. More details and simulations of the engine and Min–Max control system could be found in [1,2].

Since a reduced order Wiener model is used for the engine, it is fast and enough to use the direct search approach for engine and controller simulation to get the results. Therefore, the model is run 125 times with different T and S norms (from Table 1) to generate the results.
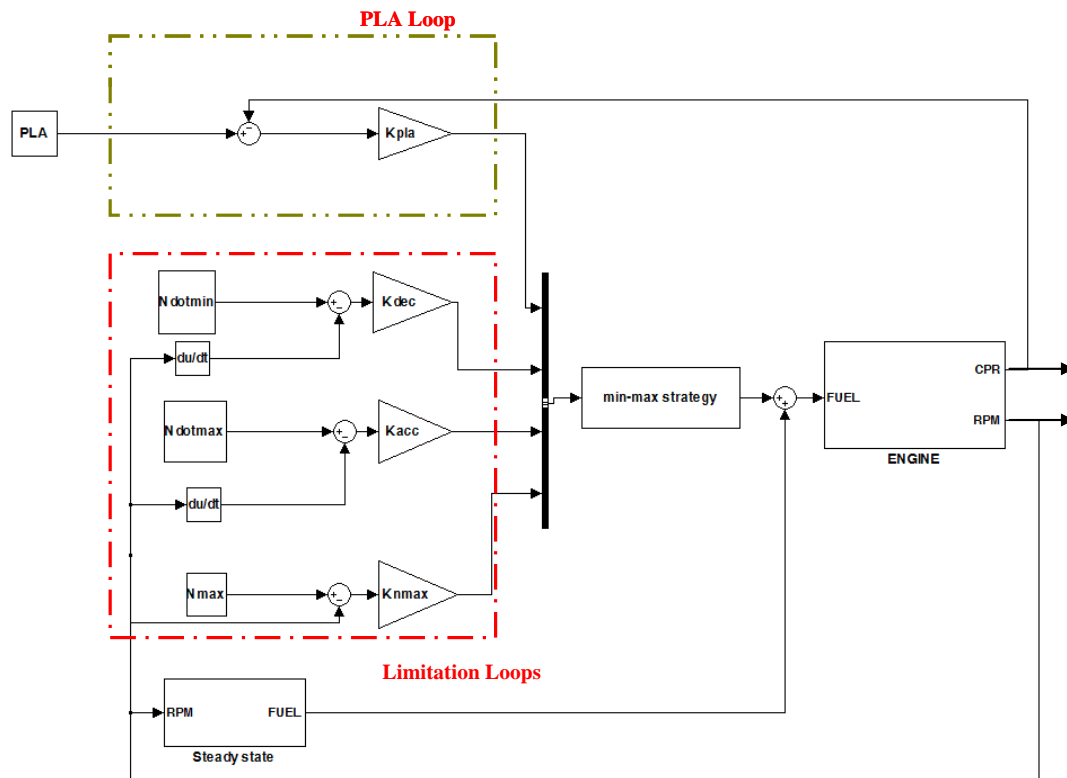
Figure 4. Engine and controller program block diagram developed in Matlab/Simulink.

The pre-defined PLA profile that should be tracked by the engine is shown in Figure 5. As can be seen from this figure, for $t \leq 15$ s, the PLA value is constant at 0.6. It means that the pilot requires the 60 percent of the available thrust from the engine; it then increases to the value of 1 at $t = 15$ s, and remains at this level for a further 15 s; it is associated with a sudden change in the pilot command to test the ability of transient and physical limitation control modes simultaneously; and then will return to the value of 0.7 at $t = 30$ s and remains constant until the end of the simulation. It will also test the deceleration control loop, transient behavior of the engine and controller in deceleration procedure and the capability of the controller in tracking the pilot command. The predefined PLA profile is the worst case scenario containing the sudden change (acceleration and deceleration) in pilot command with a very large amplitude (from idle to maximum power). Therefore, the different control modes satisfaction capability of the controller will be tested using this scenario.

Moreover, to investigate the effects of different norms quantitatively, a performance index should be defined. The indices defined in this paper are error of PLA tracking and the response time. The former satisfies the steady state control mode and the latter satisfies the transient control mode. These indices are formulated as follow:

$$J_1 = \int_0^{sim\_time} \left| PLA - \frac{EPR}{EPR_{max}} \right| dt \tag{5}$$

$$J_2 = \left\{ \frac{t_{acc} + t_{dec}}{sim\_time} \right\} \tag{6}$$

$$J_3 = \frac{1}{\beta_1 + \beta_2} \{ \beta_1 J_1 + \beta_2 J_2 \} \tag{7}$$

where the EPR is the instantaneous engine pressure ratio, EPR_{max} is the maximum engine pressure ratio during the simulation, *sim_time* is the simulation time, and t is the time index. The t_{acc}, t_{dec} are the acceleration and deceleration times which the engine requires to follow the PLA command (settling times with $\pm 2\%$ error). The performance criteria are normalized. The index J_1 is focused on

the tracking ability of the controller to follow the pilot requirements. J_2 will consider the controller response time and J_3 is a weighted combination of J_1 and J_2 in which criteria are weighted according to their importance by the coefficients of β_i. In this paper, the weight factors $\beta_1 = 0.5$, $\beta_2 = 0.5$ are selected for J_3. It means that the importance of the two objectives is equal in the optimization process.
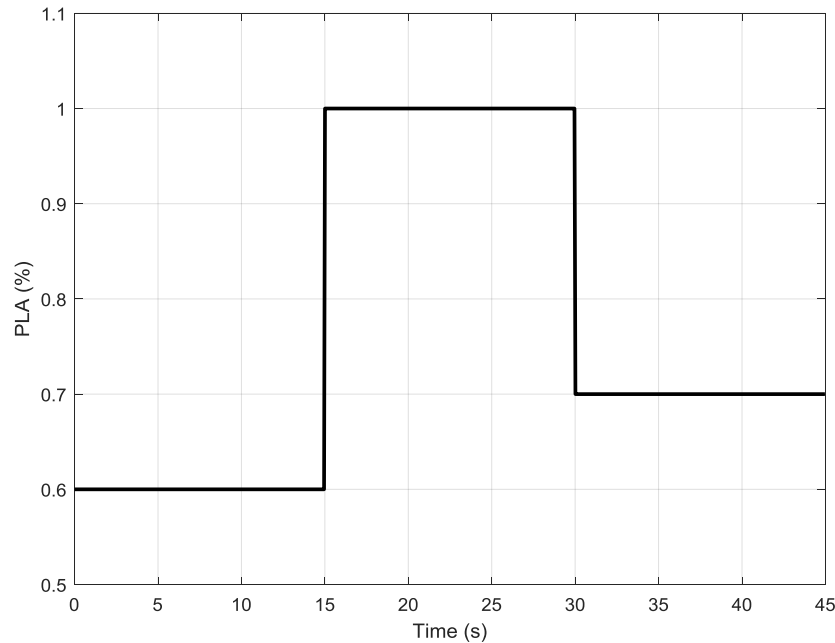

Figure 5. Variation of PLA value for the simulation.

The maximum steady state error of 10 percent and the maximum acceleration/deceleration time of 60 s are set to define the boundary of solution space for acceptable combinations. The values of J_1, J_2 and J_3 are normalized against these predefined values to make the comparison fair.

Figure 6a–c show the normalized value of the performance indices (J_1, J_2 and J_3) for all 125 possibilities. It can be seen that there are three cases with high potential for using in Min–Max algorithm: number 24 and 76 and 125. These cases are discussed here.

Case I: This case has the minimum value of the tracking error in all combinations (number 24 in Figure 6a). In other words, the best PLA tracking ability is achieved with this Min–Max selection strategy:

$$W_{f,transient} = t_5(t_2 \ (s_5 \left(W_{f,dec}, W_{f,PLA} \right), W_{f,acc}), \ W_{f,Nmax}) \tag{8}$$

Thus, by using Einstein T-norm (t_2 in Table 1) in the second step of the Min–Max control strategy, the tracking ability of the controller will be enhanced in comparison with the conventional Min–Max controller.

Case II: This case has the minimum response time in all combinations (number 76 in Figure 6b). In other words, the best maneuverability will be achieved with this Min–Max selection strategy:
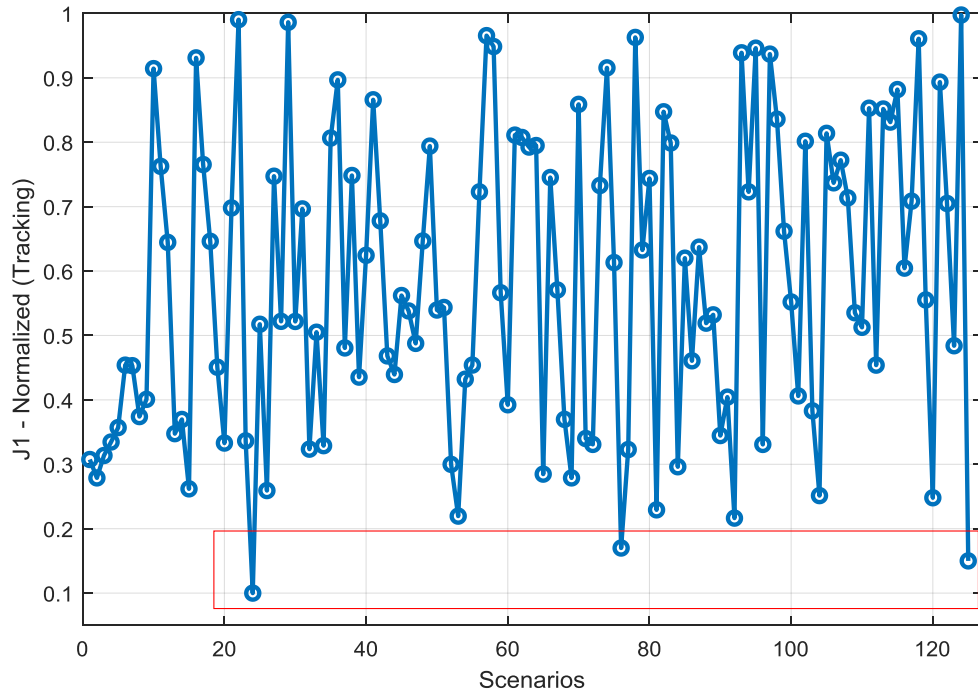
$$W_{f,transient} = t_5(t_4 \ (s_5 \left(W_{f,dec}, W_{f,PLA} \right), W_{f,acc}), \ W_{f,Nmax}) \tag{9}$$

Equations (9) states that using Hamacher T-norm (t_4 in Table 1) will enhance the maneuverability of the Min–Max control strategy.
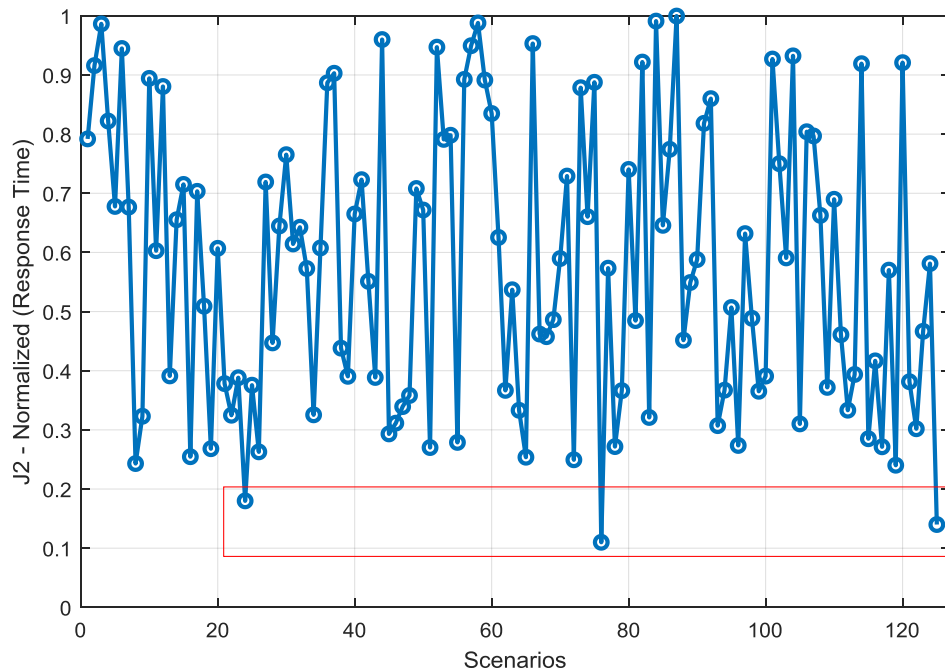
Case III: This case has the minimum weighted indices in all combinations (number 125 in Figure 6c). In other words, both track-ability and maneuverability will be considered with the same importance with this Min–Max strategy:

$$W_{f,transient} = t_5(t_5 \ (s_5 \left(W_{f,dec}, W_{f,PLA} \right), W_{f,acc}), \ W_{f,Nmax}) \tag{10}$$

The above combination is the standard Min–Max control algorithm. It means that if we want to consider a weighted combination of tracking and maneuverability into account (with equal importance), the conventional Min–Max algorithm with standard minimum and maximum mathematical functions will perform well.

(**a**)

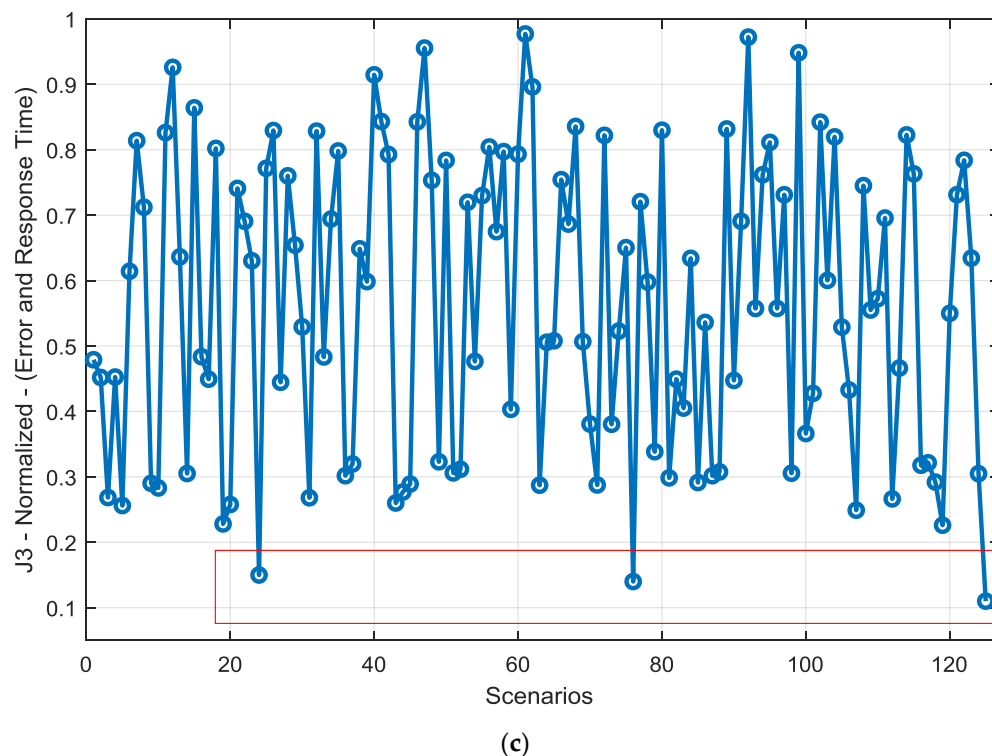(**b**)

Figure 6. *Cont.*

(**c**)

Figure 6. Performance indices values for engine and controller simulations with different T and N norms. Normalized values for J_1 (**a**), J_2 (**b**), and J_3 (**c**).

To confirm the abovementioned conclusions, the results of engine and controller simulations with the above achieved three cases are shown in Figures 7–9. Figure 7 shows the PLA tracking with the three different optimal cases. As it can be seen in this figure, case I (using Einstein T-norm in the selection strategy) has the best tracking ability (minimum steady state error). Thus, it could be concluded that if the winner between the maximum acceleration rate control loop and the maximum of PLA control loop and maximum deceleration rate control loop will be selected using Einstein t-norm formulation, the controller would perform better than the standard Min–Max controller from tracking PLA command point of view. Moreover, it could also be seen that case II has the minimum response time between the three simulated cases. It means that using Hamacher t-norm in the selection strategy will enhance the maneuverability of the engine.
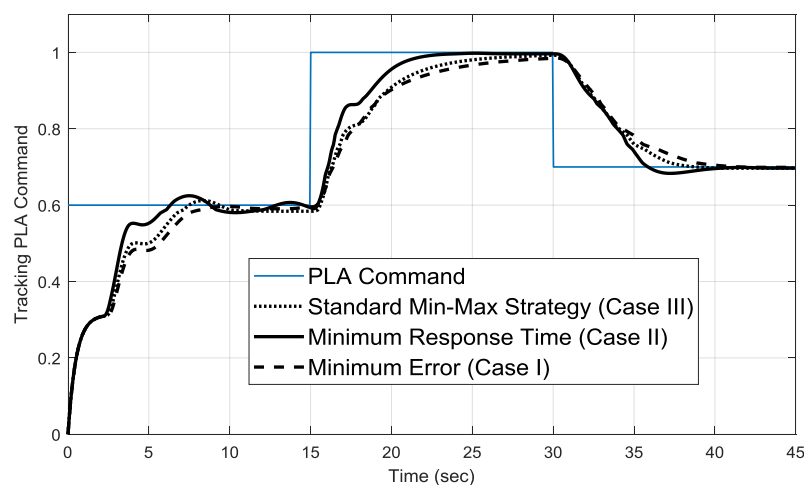

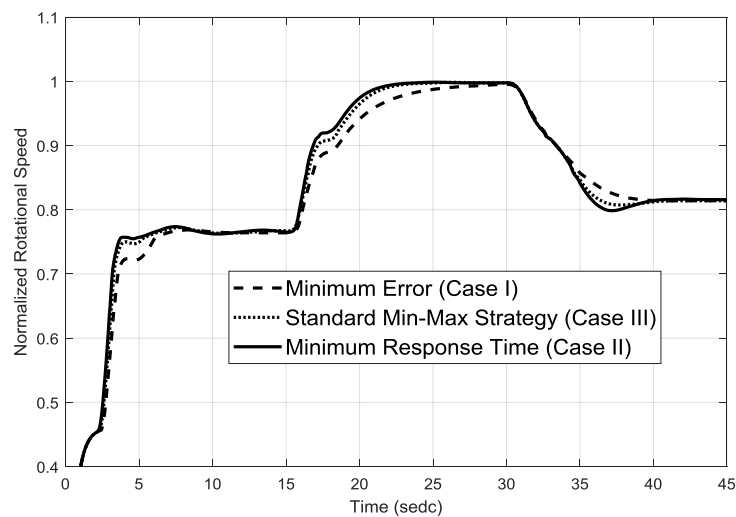**Figure 7.** Tracking the PLA command by different optimal cases.

Figure 8. Variation of engine rotational speed in different optimal cases.
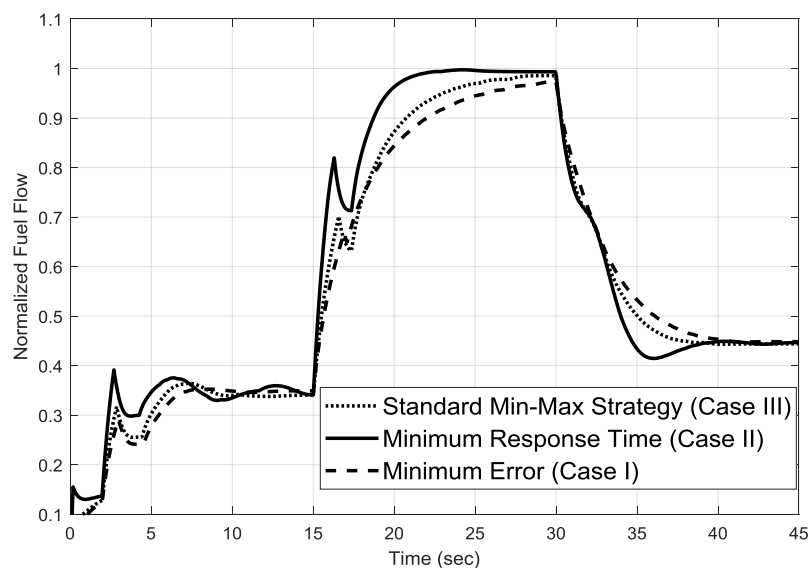

Figure 9. Total fuel flow to the engine in different optimal cases.

Finally, case III results fall between cases I and II results. It means both error and response time will be considered simultaneously when the standard Min–Max selection strategy will be used. This strategy is not the best in command tracking nor in maneuverability. However, if the performance index is defined as weighted combination of tracking and maneuverability, it would perform better than the other cases.

Figure 7 confirms the satisfaction of steady state and transient control modes by the optimal controllers. In other words, the pilot requirements are tracked with minimum error (steady state control mode) and in a short response time (transient control mode). In order to confirm the satisfaction of the physical limitation control mode, the variation of engine rotational speed for three cases are shown in Figure 8. This figure shows the smooth and safe variation of the engine rotational speed in all three cases without any over-speed for the engine. Therefore, the physical limitation control mode is also satisfied by the enhanced Min–Max control structures.

Finally, to confirm the feasibility of the obtained results, the total fuel flow to the engine (actuator output) is shown in Figure 9 for the three cases. This figure confirms that the outputs of modified controllers are smooth, feasible, and implementable without any fluctuation and disturbance. Thus,

this figure confirms the practicality of the proposed approach in design and optimization of industrial Min–Max control strategies for gas turbine engines.

4. Discussion

The presented results show that using fuzzy norms in Min–Max control algorithm for gas turbine engines can enhance the performance of the controller and the engine. However, there are some challenges and issues in this regard that should be addressed before this approach could be considered as a methodological approach for all types of gas turbine engines. The main challenges can be summarized as follow:

- The number of variables: the control modes for GTE can be summarized as a steady-state control mode (to satisfy the pilot demand), transient control mode (to satisfy an acceptable response time) and physical limitation control mode (to protect the engine against malfunctions). In an industrial control strategy for a turbojet engine, four different transient control loops are designed. One of them is in charge of the pilot demand (pilot lever angle (PLA) control loop) and three of them give guarantee about safe operation of the engine to protect the GTE against physical damages. However, the number of transient control loops would be increased in turbofan engines (two and three spool engines) and industrial gas turbine engines respect to many more constraints and parameters that should be considered for these types of GTEs. Therefore, the number of required runs would be increased noticeably, and it may not be affordable to solve the problem using direct search method.
- Control loop gains: another issue is that when the Min–Max selection strategy is changed, it could not be claimed that the tuned gains are optimal. In other words, after changing the selection strategy, control loop gains should be tuned again to get the maximum potential of the control structure. In this approach, we could get a Pareto Front from a set of possible cases rather than having just two or three cases. However, adding these parameters to the problem will increase the complexity of the problem noticeably and may not be affordable easily.
- Objective functions: the other issue is the performance indices defined for the problem. This paper considered the steady state error and the response time to the pilot command. However, there are many more objectives that could be considered for the controller enhancement like total fuel consumption in a mission, emission level, robustness and responses to the uncertainties etc. Addressing these objectives also needs a methodological approach and a problem formulation.
- Effects of uncertainty: the main structure of the proposed controllers are the same with the industrial Min–Max controllers which is robust and reliable. However, after replacing the simple mathematical functions with fuzzy norms, the controller should be tested again under uncertain conditions (e.g., different weather and flight conditions) to confirm the ability of the proposed approach in dealing with uncertainties.

A potential solution to deal with the above-mentioned issues is to formulate a methodological approach for a framework development for this problem. This approach will be able to formulate the problem as a comprehensive engineering optimization problem with all parameters included in objective function formulation for any type of GTEs. Then, using a meta-heuristic optimization algorithm, both controller loops gains and Min–Max strategy norms could be optimized simultaneously. Moreover, different indices could be defined for the objective function in both weighted single objective and multi-objective features. However, the size of the problem and the mixed variables types (discrete for norms and continuous for gains) would be main issues for development of this framework.

The main achievement of this study is to confirm that considering fuzzy norms for the Min–Max selection strategy is a high potential field for the performance optimization of GTE control systems. It could be the first step to connect the fuzzy sets with the industrial Min–Max control approach.

5. Conclusions

This paper focuses on using union and intersection fuzzy sets in the Min–Max selection strategy of gas turbine engine control systems to enhance the controller and engine performance. The main idea is to use S-norms for union and T-norms for intersection sets to calculate the appropriate fuel flow for the GTE to satisfy all engine control modes simultaneously. A single spool turbojet engine is selected as a case study with a Min–Max control system including four transient control loops. The Min–Max selection strategy has two unions and one intersection to investigate. Thus, 125 different cases simulated and tested on track-ability and maneuverability indices. The results of the simulation show that use of Einstein and Hamacher norms will enhance the PLA tracking and response time of the engine respectively. The limitations of the used method are the lower number of control loops in turbojet engines in comparison with other types of GTEs, fixed control loop gains, and limited objective indices tested in simulations. The potential solution suggested for these issues is to define a framework for defining the idea of using fuzzy sets in GTEs industrial controller as an engineering optimization problem. In this framework the fuzzy sets as well as control loops gains could be defined as optimization variables and more indices like emission level and total fuel consumption could be added to the objective function. The main achievement of the paper is to confirm the high potential of fuzzy norms to be used in industrial GTEs Min–Max control algorithms.

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