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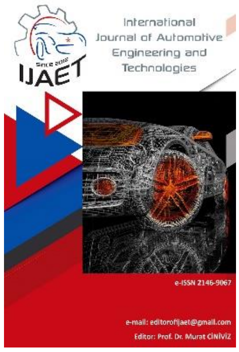

Original Research Article

Lean-burn air-fuel ratio control using genetic algorithm-based PI controller

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ABSTRACT

Maximizing the fuel economy while lowering exhaust emissions highly depend on precise air-fuel ratio (AFR) control. The major challenge in the control of AFR is the time-varying delay, which is an inherent reason for performance degradation and instability. For analysis, the time delay is approximated by Padé approximation, leading to a non-minimum phase system that exhibits the difficulty of controlling due to its zeroes in the right half side of the s-plane. Moreover, dealing with uncertainties in fuel-path dynamics and minimizing the effect of external disturbances are key goals in the minimization of harmful emissions and maximization of fuel economy. This study puts forward an AFR control strategy in lean-burn spark-ignition (SI) engines by proposing a genetic algorithm (GA)-based proportional-integral (PI) control technique. The proposed PI controller aims at dealing with the aforementioned design challenges. The PI controller gains, namely, proportional (K_p), integral (K_i) gains are obtained with the proposed GA algorithm based on minimization of an objective function. The GA-based PI controller's performance is analyzed with several methods in time-domain study. According to the obtained results, it has been revealed that the proposed GA-based PI controller improves the reference air-fuel ratio tracking performance in the existence of the time-varying delays in the closed-loop system, exhibiting good disturbance rejection properties, and is robust against system uncertainties. Thus, it can be effectively used for the accurate regulation of AFR under various operating conditions in SI engines.

Keywords: Air-fuel ratio, genetic-algorithm, PI control, time-delay systems, non-minimum phase systems.

1. Introduction

Due to the stringent requirements for engine emissions in recent years, research in reducing emissions and enhancing fuel economy has received significant attention. Lean-burn spark-ignition (SI) engines offer better improvements in tailpipe emissions and fuel economy among conventional spark-ignition engines. It is of a great importance to maintain air-fuel ratio (AFR) at up-stoichiometric value for reduced carbon monoxide and hydrocarbons but leading to increased nitrogen oxide (NO_x), stored in three-way-catalyst (TWC). TWC conversion efficiency heavily depends on the AFR reference. In fact, TWC is located downstream the universal exhaust gas oxygen (UEGO) that requires to integrate after-treatment system dynamics in maintaining the AFR reference, thus posing challenges in engine control methods. This is due to feedback control, using the signal from the UEGO sensor in the exhaust stream to regulate the AFR value. This introduces an engine speed-dependent time-varying delay for exhaust gas exiting the cylinders to be measured in UEGO sensor for the AFR control system. Due to the time-varying delay, wide operation ranges of the engine, nonlinearities, and parameter variation, achieving an optimal performance remains a difficult engine control system problem for lean-burn engines. To this end, we investigate engine-speed dependent lean-burn SI analysis to propose a suitable control technique in this work.

There has been a great number of efforts addressing the AFR control in literature [1-3]. The authors propose a parameter-varying proportional-integral-derivative control method in [4]. The work in [5] proposes an adaptive stoichiometric AFR control. A generalized predictive control is proposed for the AFR regulation by taking time delays, nonlinearities, and parameter variations into account in the closed-loop in [6]. The work [7] addresses an experimental AFR control with the unknown system dynamics estimator. In the lean-burn AFR problem, there are many contributions. A second-order sliding mode control is utilized in the AFR problem considering the negative impacts of time-varying delay, measurement noise, and canister purge disturbance in [8]. Authors propose a fuzzy sliding-mode control strategy to maintain AFR reference in the presence of time-varying delay, uncertainties, and disturbances in [9]. A linear parameter varying (LPV) control of the AFR problem is investigated by presenting the engine model as an LPV time-delay system. Their goal is to track the AFR set-point changes to the stoichiometric AFR by minimizing the effects of disturbances and time-varying delays [10-12]. It is important to take into account the state delay in the controllers such that the expected control performance is achieved.

Among many types of controllers used for engine control, the proportional-integral (PI) controller is the most widely used controller due to its simple structure and design, low cost in maintenance, effectiveness, and intrinsic characteristics against model nonlinearities, uncertainties, and parameter variations [13]. The PI controller has two parameters, so-called proportional gain (K_p) and integral gain (K_i). Precise tuning of these parameters is needed to obtain optimal system performance. In case of poor tuning, bad performance or even instability is inevitable. Soft computing is a good strategy to design and optimize the PI controller gains. It has many advantages, for example, many design considerations can be incorporated in a unified way [14]. Even though heavy computational burden and convergence to an optimal solution receive critics by researchers, for a small-scaled problem, for instance, PI controller parameter optimization is presenting no issue in computation. Genetic Algorithm (GA) is a type of soft computing, which is an evolutionary algorithm to solve many optimization problems. Many fruitful applications are reported [15-18]. In GA, candidate solutions are presented by a population of chromosomes. Using a fitness function, their quality is evaluated at each iteration. In the next step, the selection mechanism chooses the best ones as parents. Through crossover and mutation mechanism, parents produce offspring. Found offspring are a new solution to the problem. These steps are repeated until the optimal solution has been found in a pre-defined error bound.

In this brief, the problem of the AFR regulation is investigated in SI engines using a control strategy based on the GA-based PI controller for the first time. Major highlights of this work are summarized as follows.

1. A simple and straightforward control system design based on a heuristic optimization for the robust AFR control in the existence of time-varying delay, system parameter variations, and external disturbances is introduced.
2. An extensive simulation study to validate the control strategy is put forward.
3. Convergence to an optimal solution is found, thus GA’s reliability and fast optimization speed are obtained.

The paper is structured as follows. Section 2 describes the system dynamics and time-delay model for the control design and puts forward the new GA-based PI controller. Section 3 illustrates the simulation results and an extensive discussion is provided. Lastly, we draw the conclusions in Section 4.

2. Modelling

Precise control of the AFR becomes necessary to minimize the effect of emission gases converted to relatively less harmful compounds in the TWC. Thus, the TWC is a key component on the exhaust after-treatment part, which reduces the tail-pipe emission to meet government's strict legislation. In order to achieve this, proper modeling is necessary for the AFR regulation. The TWC operates efficiently when the fuel matches to air charge in stoichiometric proportion. In this work, only air-fuel dynamics are demonstrated. The engine air-fuel path can be modeled as the structural properties of the air-fuel path. This path includes several considerations to be taken into account from wall wetting dynamics to the UEGO sensor dynamics. A schematic description of the fueling path is shown in Figure 1.

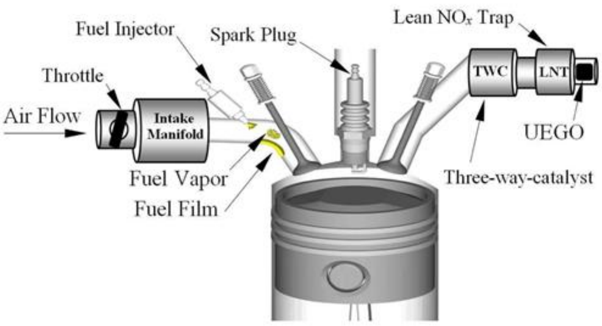

Figure 1: Air-fuel path in SI engine adopted from [8].

As the fuel is injected into the cylinders, some of the amounts directly evaporate, which form fuel film in the intake port. The rest of the fuel puddle injected into the cylinder also evaporates. This situation is described as the so-called wall-wetting effect in the system. The vaporized fuel mixes with the air and forms the air-fuel mixture. After the combustion, the exhaust gases exit the cylinder, they mix with the previously existing exhaust gases and travel through the exhaust manifold and reach the UEGO sensor location. Also, in a multi-cylinder engine, the exhaust gases coming from the individual cylinders enter the exhaust manifold at different times. Thus, time-varying delay in the design consists of two parts: i) cycle delay T_{cyc} due to the four strokes of the engine stated as $T_{cyc} = 720/(360/60)N = 120/N\ (secs)$ where N is the engine speed, and ii) exhaust gas delay T_{ext} where the time it takes for the exhaust gases to reach the UEGO sensor location given as $T_{ext} = \vartheta/\dot{m}_a$ where $\dot{m}_a$ is the air-mass follow and variable ϑ is to be determined with experiment [19]. Then the total time-varying delay is $T = T_{cyc} + T_{ext}$. Also, the UEGO sensor dynamic has a first order lag $G(s) = 1/(ks+1)$ with k is the time constant. After having taken into account all these considerations, we limit the discussion on the modeling of having a proper model for control design purposes. Thus, the air-fuel path dynamics including the UEGO sensor dynamics with the total time delay is expressed as

$$k\dot{y}(t) + y(t) = u(t - T) \tag{1}$$

where $y(t)$ and $u(t)$ are the actual and input AFR, seen in Figure 2.

2.1. PI control and time-delay modeling

The PI controller with its proportional (K_p) and integral (K_i) gains is given in the form of a transfer function in Eq. (2).

$$G_{PI}(s) = \frac{u(s)}{e(s)} = K_p + \frac{K_i}{s}. \tag{2}$$

In Eq. (2), the PI gains need to be properly tuned to obtain the best system performance, i.e, short transient and stability for the closed-loop system, demonstrated in Figure 2. Ziegler-Nichols method has been extensively studied for optimal tuning of the PI controller parameters. However, these parameters need to be manually tuned until prescribed system specifications are met. This motivates us to utilize a global optimization strategy for the PI controller parameters selection over the entire operation ranges.

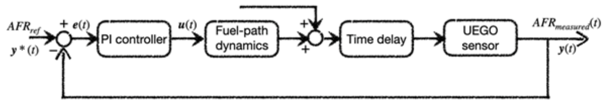

Figure 2: Closed-loop structure.

$$e^{-Ts} = \frac{1-\frac{T}{2}s}{1+\frac{T}{2}s}. \tag{3}$$

The Padé approximation is introduced to approximate the time delay, leading to a transfer function presentation so-called a non-minimum phase system. For the control of AFR in this study, the delay dynamics is approximated by a first of Padé approximation as shown in Eq. (3): Recall that T is the time delay in the AFR control problem. A higher-order Padé approximation might have been used at the cost of increased complexity in the control design. Using the Padé approximation, the Eq. (1) is rewritten as

$$G(s) = \frac{1-\frac{T}{2}s}{\left(1+\frac{T}{2}s\right)(1+ks)}. \tag{4}$$

This transfer function is called as a non-minimum phase system and introduces control design challenges due to the zeros being in the right half side of the s-plane.

2.2. Objective function/fitness function

In this study, the designed PI controller aims to optimally improve the dynamic behavior of the closed-loop system. The objective function should include percent overshoot M_p, rise time t_r, settling time t_s, and steady-state E_{ss} control criterias. They are the main performance indicators for the AFR control problem to have the minimum values of these criteria to a unit step response. In this study, the performance is measured using an integral time-weighted squared error (ITSE) function of the tracking error for a step reference under time-delay and disturbances, combined with a measure of the energy of the incremental control in Eq. (5).

$$ITSE = \int_0^t t\left|AFR_{ref} - AFR_{measured}\right|^2 dt = \int_0^t t|e|^2\, dt. \tag{5}$$

2.3. Genetic algorithm

Genetic algorithm [20] was presented to the science by John Holland in 1975. It is an important heuristic algorithm, which is based on the populations of chromosomes in living things and working according to the evolutionary process in nature. The survival principle of strong individuals is the main goal. GA produces a set of multiple independent solutions. This set of solutions is called the population. Populations are made up of strings of numbers called chromosomes or individuals. Every element in an individual is a gene. To find the optimum point with the genetic algorithm; reproduction, crossing, and mutation processes are created code based on gene structure. These codes are called chromosomes. These are selected according to the normalized fitness function. This stage is the breeding stage. Then, the crossover phase is started. In the crossover stage, chromosomes are crossed to produce new individuals. By crossing, it is transmitted to new generations with superior features. In order to reach the global optimum, it is important to carry superior features to new generations. Also, the mutation is performed by changing any bit of information on the chromosome. The above-mentioned process steps are repeated until the termination criteria is met.

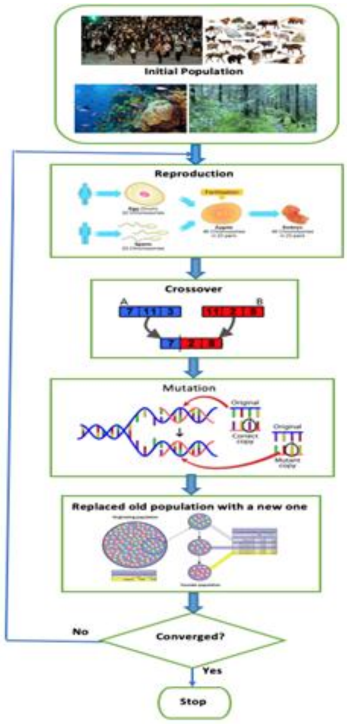

Figure 3: Genetic algorithm structure [21-27].

In this study, two parameters of the PI controller need to be optimized under a multi-objective optimization within a certain bound. The basic operations are summarized as follows.

I) Initialization: Initial population.

II) Individual evaluation: The fitness of each individual is calculated.

III) Selection: Passing the optimized individuals to the next generation through pairing and crossing.

IV) Crossover operation: Exchanging of design parameters between the paired individuals.

V) Mutation operation: Exchanging the gene value between the paired individuals.

VI) Termination: When no significant chance is observed in evaluation of the fitness function is achieved.

The GA flow chart visually demonstrates the above process in Figure 3.

3. Results and Discussion

As stated, we use the ITSE fitness function in the optimization of the PI parameters that are calculated with GA algorithm with selected a sample time of 0.001 secs and the total time of simulation duration is 10 secs. GA is known for finding a global solution. It generates a set of population points at each iteration. This generation is a random process thus the solution is highly affected according to the random population generation. The tuning parameters for the GA are: number of variables is being 2, population size is set to 50 with the elite count is being 50. Moreover, the crossover fraction is 0.2 along with a maximum generation as being 25. The optimization of the PI controller is stated as follows. By using the fitness function in Eq. (5), the values of K_p and K_i are encoded as a chromosome in GA to minimize the settling time and overshoot based on the response characteristic, shown in Figure 4. New generation is then evaluated their quality based on their objective value. Selection, crossover, and mutation operations are re-performed until design specifications are met.

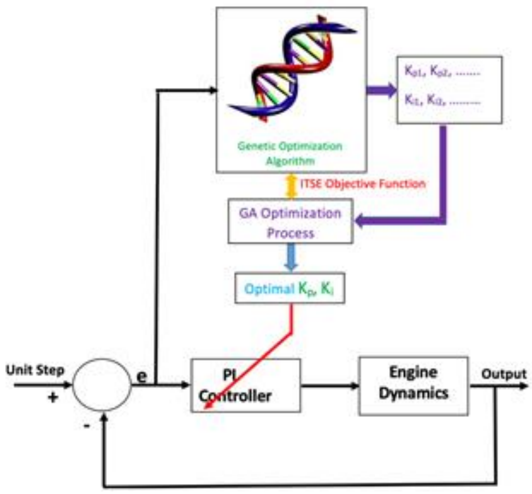

Figure 4: GA solution to find optimal PI controller parameters.

The optimal parameters after several runs in MATLAB software are calculated as $K_p = 0.2356, K_i = 0.2234$. The simulations under different operating conditions are performed to confirm the performance of the proposed control strategy. To this end, the engine time constant is chosen as $k = 0.2$. Time-varying delay is $0.3 \leq T \leq 2.7$ in the design. In addition, the lean normalized AFR ratio is chosen as 1.4. The simulations are performed on a Fujitsu desktop equipped with Intel Core i5 3.0 GHz CPU and 8 GB of RAM running MATLAB 2018a. The step response is one of the common tools for validating a controller performance. To this extent, we first demonstrate the step responses for different uncertainty levels, i.e., $\pm 20\%$ change in the time constant of the fuel-path dynamics in Figure 5. As seen in the plots, GA-based PI controller settles around 4-5 seconds.

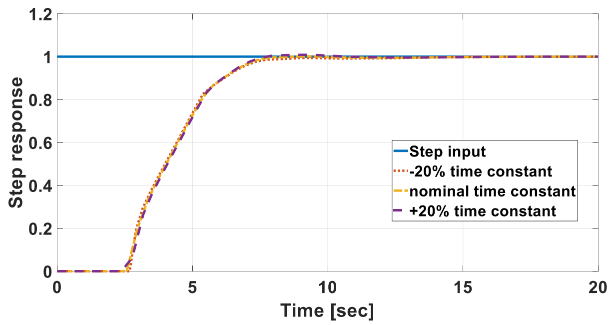

Figure 5: Step response subject to the time constant change.

Results show that higher time constants result in a slight overshoot. However, in the steady-state, both cases represent no changes. This is indeed quite satisfactory result not only in the speed of the response viewpoint but also a robust stability viewpoint in the presence of uncertain system dynamics. The varying delay of the engine restricts performance specifications in the control loop. Therefore, the presence of time delays typically imposes strict limitations on the control design. There are several methods of dealing with the negative impacts of time-varying delays. To ensure that the robust stability of the closed-loop system, similarly to the time constant uncertainty analysis, the simulations are performed for $\pm 20\%$ change of the delay estimation change in Figure 6. Results show that higher-delay estimation error leads to a little faster transient response and no significant change is observed in the steady-state response of the closed-loop system.

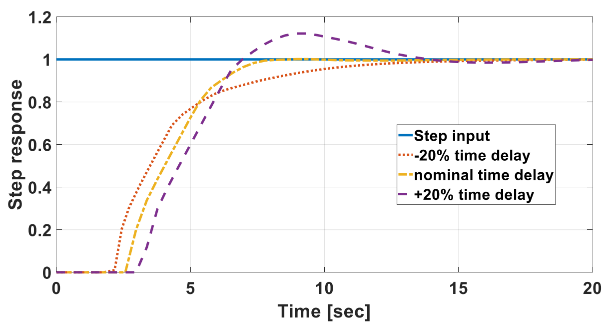

Figure 6: Step response subject to the time-varying delay change.

Conversely, smaller delay estimation error is lower than the actual time delay value and it presents sluggish response in the transient response but no important change is observed in the steady-state response. Based on the above analysis, it is concluded that the proposed GA-based PI controller can be effectively used under different operation conditions.

The main control objective of the AFR problem is to minimize the tracking error in the existence of external disturbances and delays [8, 28]. It is worth mentioning that there are not reported results of the heuristic optimization-based PI controller design to quantitatively compare the AFR results to the best of author's knowledge, yet this article is intended to open a new research direction for heuristic optimization-based PI controller design for the AFR control. Then the canister purge and fuel injector disturbance profile is given in Figure 7. The closed-loop tracking performance of the designed controller is demonstrated in Figures 8-11. The following simulation results demonstrate the tracking enhancement of the controller. As observed in Figure 8, the proposed controller provides smooth tracking, which is subject to a 20% change in the time constant. Evidently, transient response to higher and lower time constants leads to almost no change in response, zoomed in Figure 9. To further investigate the controller performance in a practical setting, AFR system responses to a 20% change [1, 4] in the time-varying engine delay are evaluated in Figure 10. It is trivial to demonstrate that even if the delay takes the maximum value, i.e., $+20\%$ the controller stabilizes the plant as expected, a slight overshoot is observed with satisfactory tracking in the presence of external disturbances [2, 8, 12], as shown in Figure 11. It is observed that there is no significant change even when we assume a -20% change in the time-varying delay, demonstrating that the system response is a bit sluggish over transient conditions. Figures 12-15 show the corresponding control inputs subject to a 20% change in the time constant and time-varying delay. Control input for $\pm 20\%$ change in the time constant is almost the same as that of the nominal case, which means no significant fuel economy deterioration during the period of fuel injection [8, 9], seen in Figures 12-13. Moreover, Figure 14 shows that the effect of the change in time-varying delay on the corresponding control signal, which leads to an increase over transient conditions. An increase in fuel consumption is observed for $+20\%$ change in the time-varying delay over transient conditions, zoomed in Figure 15. Nevertheless, control inputs exhibit robustness against disturbances and parameter variations in the AFR fuel-path dynamics [4, 12, and 28]. It is clearly stated that the proposed GA-based PI controller can be effectively employed under various working conditions [6].

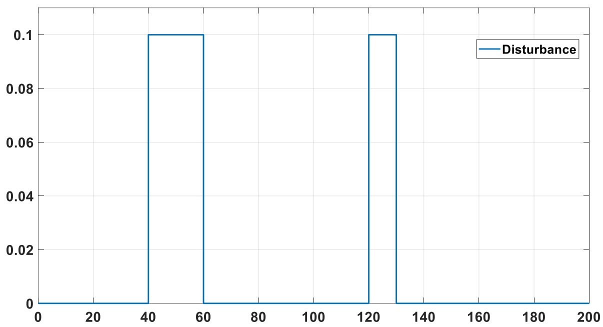

Figure 7: Fuel injector and canister purge disturbance profile.

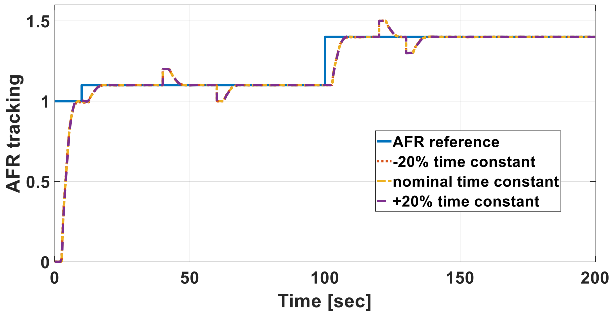

Figure 8: Output tracking response subject to the time constant change.

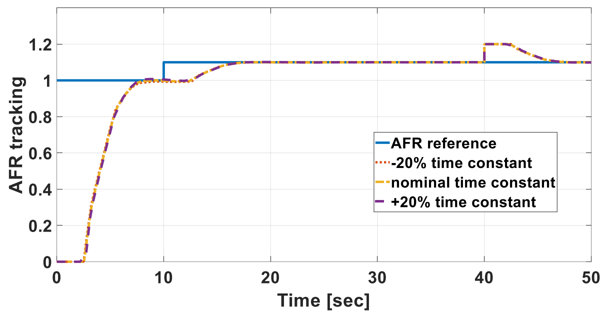

Figure 9: AFR output tracking response subject to the time constant change (zoomed between [0 50] seconds).

4. Conclusion

In this paper, a genetic algorithm (GA)-based proportional-integral (PI) control methodology for air-fuel ratio (AFR) control of lean-burn spark-ignition engines with the engine time-varying delay is introduced. The fuel-path dynamics is modeled as a first-order system with the time-varying delay where the Padé approximation is utilized to present the overall system as a non-minimum phase system. GA-based optimization algorithm is used to tune the PI controller parameters where the optimization is performed offline using a simulation model of the fuel-path dynamics with time-varying delay. Then the optimized PI controller is applied to the system.

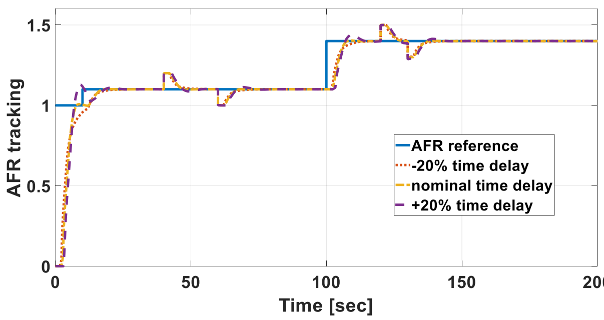

Figure 10: AFR output tracking response subject to the time-varying delay change.

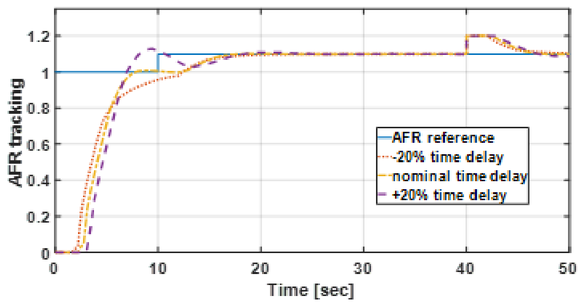

Figure 11: AFR output tracking response subject to the time-varying delay change (zoomed between [0 50] seconds).

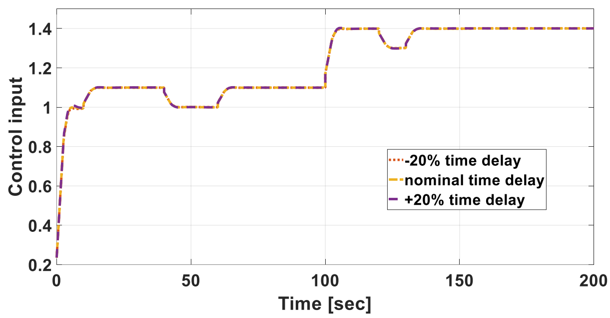

Figure 12: Control input subject to the time constant change.

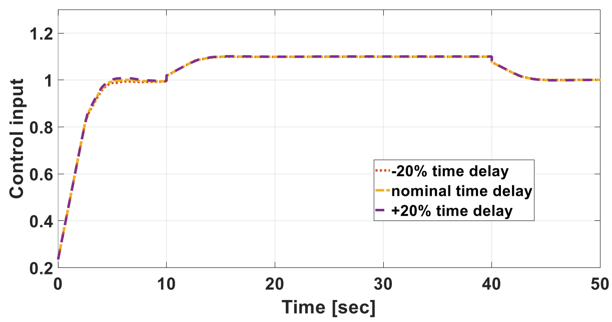

Figure 13: Control input subject to the time constant change (zoomed between [0 50] seconds).

Time response results to a given step input are used to validate the controller performance under different working conditions to test the

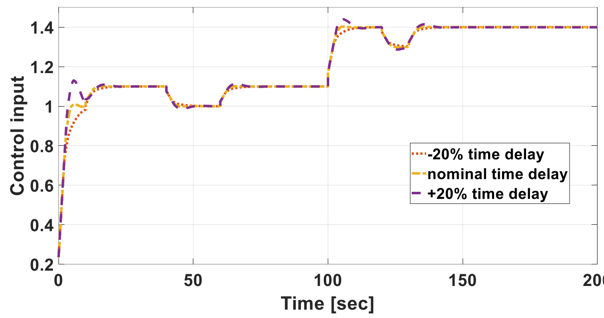

Figure 14: Control input subject to the time-varying delay change.

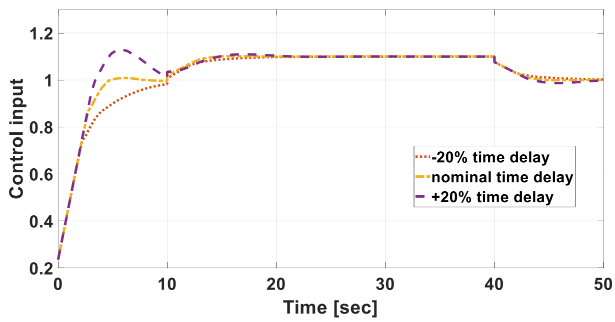

Figure 15: Control input subject to the time-varying delay change (zoomed between [0 50] seconds).

controller robustness. We first demonstrate the step responses for different uncertainty levels, i.e., $\pm$ 20% change in the time constant of the fuel-path dynamics. It is observed that transient response to higher and lower time constants leads to almost no change in response. Moreover, a $\pm$ 20% change in the time-varying delay bounds is tested where higher delay estimation errors result in a little faster transient response yet no significant change is observed in the steady-state response of the closed-loop system. Since the main control objective of the AFR problem is to minimize the tracking error in the existence of external disturbances and delays, the closed-loop system performance against uncertainty in the time constant and time-delay under the canister purge disturbance is studied. To this aim, the closed-loop performance is evaluated in the presence of various operating conditions, i.e., the AFR system responses to a $\pm 20\,\%$ change in the engine time constant as well as to a $\pm 20\,\%$ change in the time-varying engine-speed-dependent delay under the fuel purge disturbance. The GA-based PI controller shows robustness against the ± 20 change in the time delay and time constant. Further, we study the control inputs subject to a 20% change in the time constant and time-varying delay. It is revealed that no significant fuel economy deterioration during the period of fuel injection is observed. Thus, control inputs exhibit robustness against disturbances and parameter variations in the AFR fuel-path dynamics, demonstrating that the proposed GA-based PI controller can be effectively applied under various working conditions. It has been concluded through the simulation study that the proposed controller is capable of regulating the closed-loop AFR under system parameter and time-varying delay changes as well as external system disturbances.

5. References

1. Tafreshi, R., Ebrahimi, B., Mohammadpour, J., Franchek, M.A., Grigoriadis, K. and Masudi, H., "Linear Dynamic Parameter-Varying Sliding Manifold for Air–Fuel Ratio Control in Lean-burn Engines", IET Control Theory & Applications, vol.7 issue 10, pp.1319-1329, 2013.

2. Wang, P., Zhu, C. and Gao, J., "Feedforward Model Predictive Control of Fuel-Air Ratio for Lean-burn Spark-Ignition Gasoline Engines of Passenger Cars", IEEE Access, vol.7, pp.73961-73969, 2019.

3. Kumar, M. and Shen, T., "In-cylinder Pressure-based Air-Fuel Ratio Control for Lean Burn Operation Mode of SI Engines", Energy, vol.120, pp.106-116, 2017.

4. Ebrahimi, B., Tafreshi, R., Masudi, H., Franchek, M., Mohammadpour, J. and Grigoriadis, K., "A Parameter-Varying Diltered PID Strategy for Air–Fuel Ratio Control of Spark Ignition Engines", Control Engineering Practice, vol.20 issue 8, pp.805-815, 2012.

5. Jiao, X., Zhang, J., Shen, T. and Kako, J., "Adaptive Air–Fuel Ratio Control Scheme and Its Experimental Validations for Port-Injected Spark Ignition Engines", International Journal of Adaptive Control and Signal processing, vol.29, issue 1, pp.41-63, 2015.

6. Meng, L., Wang, X., Zeng, C. and Luo, J., "Adaptive Air-Fuel Ratio Regulation for Port-Injected Spark-Ignited Engines Based on a Generalized Predictive Control Method", Energies, vol.12 issue 1, pp.173, 2019.

7. Na, J., Chen, A.S., Huang, Y., Agarwal, A., Lewis, A., Herrmann, G., Burke, R. and Brace, C., "Air-Fuel Ratio Control of Spark Ignition Engines with Unknown System Dynamics Estimator: Theory and Experiments", IEEE Transactions on Control Systems Technology, vol. 99, pp.1-8. 2019.

8. Ebrahimi, B., Tafreshi, R., Mohammadpour, J., Franchek, M., Grigoriadis, K. and Masudi, H., "Second-order Sliding Mode Strategy for Air–Fuel Ratio Control of Lean-Burn SI Engines", IEEE Transactions on Control Systems Technology, vol.22, issue 4, pp.1374-1384, 2013.

9. Wu, H.M. and Tafreshi, R., "Fuzzy Sliding-mode Strategy for Air–Fuel Ratio Control of Lean-Burn Spark Ignition Engines", Asian Journal of Control, vol.20, issue 1, pp.149-158, 2018.

10. Zope, R.A., Mohammadpour, J., Grigoriadis, K.M. and Franchek, M., "Air-fuel ratio control of spark ignition engines with TWC using LPV techniques", In Dynamic Systems and Control Conference, vol. 48920, pp. 897-903, 2009.

11. Zope, R., Mohammadpour, J., Grigoriadis, K. and Franchek, M., "Robust fueling strategy for an SI engine modeled as an linear parameter varying time-delayed system", In Proceedings of the 2010 American Control Conference, IEEE, pp. 4634-4639, 2010.

12. Wu, H. M., & Tafreshi, R., "Air–fuel ratio control of lean-burn SI engines using the LPV-based fuzzy technique", IET Control Theory & Applications, vol.12, issue 10, pp.1414-1420, 2018.

13. Wati, D. A. R., & Hidayat, R., "Genetic algorithm-based PID parameters optimization for air heater temperature control", In 2013 International Conference on Robotics, Biomimetics, Intelligent Computational Systems-IEEE, pp. 30-34, 2013.

14. Nagaraj, B., Subha, S., & Rampriya, B., "Tuning algorithms for PID controller using soft computing techniques", International Journal of Computer Science and Network Security, vol.8, issue 4, pp.278-281, 2008.

15. Wang, F., Chen, Z., & Song, G., "Monitoring of multi-bolt connection looseness using entropy-based active sensing and genetic algorithm-based least square support vector machine", Mechanical Systems and Signal Processing, vol.136, 106507, 2020.

16. Wen, Q., Liu, G., Wu, W., & Liao, S.,

"Genetic algorithm-based operation strategy optimization and multi-criteria evaluation of distributed energy system for commercial buildings", Energy Conversion and Management, vol. 226, 113529, 2020.
17. Qin, L., Huang, W., Du, Y., Zheng, L., & Jawed, M. K., "Genetic algorithm-based inverse design of elastic gridshells", Structural and Multidisciplinary Optimization, pp. 1-17, 2020.
18. Köse, E., Abaci, K., Kizmaz, H., Aksoy, S., and Yalçin, M. A., "Sliding mode control based on genetic algorithm for WSCC systems include of SVC", Elektronika ir Elektrotechnika, vol.19 issue 4, pp. 25-28, 2013.
19. Zhang, F., Grigoriadis, K. M., Franchek, M. A., & Makki, I. H., "Linear parameter-varying lean burn air-fuel ratio control for a spark ignition engine", Transactions of the ASME, vol. 129, pp. 404-414, 207.
20. Holland, J. H., "Adaptation in Natural and Artificial Systems", Mich. Univ. Press. Ann Arbor, MI, USA, 1975.
21. https://www.sciencemag.org/news/modern-humans-lost-dna-when-they-left-afri ca-mating-neandertals-brought-some-back, 10/2017
22. https://tr.pinterest.com/pin/706502260268183167/
23. https://www.worldwildlife.org/stories/an-end-to-great-barrier-reef-dumping-is-imminent/01/2015
24. https://www.helsinki.fi/en/researchgroups/population-genetics-and-biodiversity
25. https://becominghuman.ai/understanding-genetic-algorithms-a-use-case-in-organizational-field-2087c30fb61e/2/12/ 2017
26. https://evolution.berkeley.edu/evolibrary/article/0_0_0/mutations_04
27. https://courses.lumenlearning.com/boundless-biology/chapter/population-genetics/
28. Amin, A. A., & Mahmood-ul-Hasan, K., "Robust active fault-tolerant control for internal combustion gas engine for air–fuel ratio control with statistical regression-based observer model", Measurement and Control, vol. 52, pp. 1179-1194, 2019.