



COMPARATIVE APPROACH FOR OPTIMIZATION OF FUEL ECONOMY IN DIESEL CONTROL SYSTEM

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Abstract

This paper on the improvement of fuel consumption using an intelligent neuro-based MPC of a heavy-duty vehicle, is focused on analyzing the performance of various machine actuator controller techniques such as Model Predictive Control (MPC), Adaptive Model Predictive Control and (Adaptive-MPC) and Artificial Neural Network Based-MPC. This study reviewed various research works conducted on this field of study for the improvement of this system and equally reviewed the electronic diesel control system, diesel fuel injection actuator system and electronic engine control system. Then, the techniques analyzed in this paper were also discussed. The result achieved in this study presented the artificial neural network based-MPC technique as the most efficient with an improvement performance of 47.6%. This result shows that the technique is the most efficient among the others for improving the fuel/energy conservation in heavy-duty vehicles and is recommended for adoption.

Keywords: Adaptive-MPC, ANN, Heavy-Duty Vehicle, Neuro-based, Fuel Consumption

1. INTRODUCTION

Over the years, the use of Heavy-Duty Vehicles (HDV) has evolved with great technological advancements which seek to enhance its performance efficiency and fuel consumption rate. One major area of the vehicle which has experienced major attention is the engine, due to the high demand for more energy management to

reduce fuel consumption and also reduced environmental pollution(James, 2021).

According to Bosch (2011) engines are of two major categories which are gasoline-based engines and diesel-based engines. The former is associated with smaller cars, while the latter is for heavy-duty vehicles. This diesel engine is popular today due to its ability to manage fuel better than the

traditional gasoline engine; however, the rate at which this fuel is conserved can be better managed to achieve optimal efficiency and better fuel economy. This triggered many research publications over time immemorial, proposing the use of many approaches which are capable of improving fuel economy and better engine efficiency.

Traditionally, requirements such as driving at a constant speed, good tyre pressure, slow and steady gearing, and cruise control among others, are capable to achieve the aim of fuel economy and have been established as procedures to manage the use of fuel in HDV (James, 2021). Furthermore, the use of air-fuel mixture, ignition timing, and idle speed were mechanically set and dynamically controlled by pneumatic and mechanical means to improve Engine Management System (EMS); however, the need for an EMS which is more efficient, intelligent, and autonomous triggered the evolution of Electronic Engine Management System (EEMS) (Hellstrom et al., 2013).

This EEMS makes use of Engine Control Unit (ECU) technology which employed a series of sensors and actuators to control the performance of the engine. This ECU employ techniques such as high-pressure injection control, compression and induction air cooling, and exhaust gas recirculation for

the management of engines. These techniques all have their pros and cons (Chartier et al., 2011). However, the use of high-pressure injection control has remained the most effective for fuel economy (Hellstrom et al., 2013).

The injection system is responsible for the supply of fuel directly to the engine based on the real-time data collected from its online during the vehicle translation. The pattern of this data is determined by many factors such as how well the vehicle is maintained, driving behavior, and road condition among others, and is feedback to the ECU for processing and control of the injection system.

This has been achieved using many approaches which involve a Programmable logic controller (PID) (Olanrele et al., 2014), dynamic programming (Rodriguez and Fathy, 2018), optimization-based Genetic algorithm (Dai-Duong et al., 2018), Local based speed control, Model Predictive Control (MPC), Pontryagin Minimum principle among others. However, they all have their advantages and disadvantages. Nevertheless, the use of MPC provided better performance when compared to the rest, due to their ability to control multi-nonlinear input systems. However, when these multi-nonlinear parameters change

with time, the MPC cannot update with the changing condition of the parameters of the constraint and this has limited its efficiency as a reliable system for ECU management. To address this problem, most of the state-of-the-art algorithms employed a dynamic programming approach to make the MPC adaptive; however, despite the success achieved, there is still great room for improvement. This research, therefore, proposes to help achieve it using an Artificial Neural Network-based approach to improve the MPC.

2. LITERATURE REVIEW

In Tri et al. (2014) a model predictive control approach was proposed for the improvement of fuel consumption on a hydraulic hybrid vehicle. The study used the proposed control system to address the problem of series hydraulic hybrid vehicles via the regulation of engine speed, velocity, torque, and pressure accumulation to a standard reference value which improves the vehicle's overall efficiency. This was achieved with MPC. The fuel economy rate was compared with that of the Proportional Integral Controller (PID) and the result showed that the MPC performs better with a percentage improvement of 10.43%, even though there is still room for improvement in the rate at which fuel is conserved.

Taghavipour et al. (2012) presented research on an optimal power management strategy for power split plugs in hybrid electric vehicles. In the research, MPC was proposed, developed, and used to improve energy efficiency in the vehicle under study. This was used to reduce the rate at which fuel was consumed on the vehicle and then compared with the dynamic programming approach the percentage improvement is 14.4% which is very good but still gives room for more improvement.

Panday and Bansal (2014) presented a review on the optimal energy management strategies for a hybrid electric vehicle. The study surveyed the various algorithm proposed over the years to improve the management of energy on HEV and also their limitations. The study revealed the importance to reduce fuel consumption HEV as it has both economic and environmental importance as it reduced climate change.

Yan et al., (2012) presented a hybrid electric vehicle-based MPC control strategy for the management of energy. This was achieved by the MPC using torque and engine transient characteristics as the control parameters to ensure they are within the reference set point. The result measured with other states of the art algorithm like the Dynamic Programming (DP), showed an

improved performance of 4.54% for fuel economy, which despite its success gives room for improvement.

Ivan and Dirk (2018) presented a predictive cruise control model for heavy-duty vehicles. The study revealed that to conserve energy and save fuel in vehicles, the operating principles of the engine must be adjusted using aerodynamics or speed variation. The study used a predictive cruise control technology to achieve the latter which employs load parameters to estimate the ideal vehicle speed and allow marginal variation in the speed setpoint. This was achieved with a neuro-based dynamic programming approach and implemented for use on heavy-duty trucks. The result when evaluated showed that the fuel conservation rate achieved is 47.6%. However, despite the success, there is still room for improvement.

Murphey et al. (2012) presented research on intelligent hybrid vehicle power control systems using machine learning techniques. The study reviewed the various algorithms for control of HEVs and took a position with a machine learning algorithm. The study established that machine learning algorithms can improve very energy consumption efficiency and recommend more research.

Adithya (2018) presented a Heavy Energy Vehicle (HEV) fuel optimization system using an interval back-propagation-based dynamic programming technique. The research presented a novel approach that manages energy consumption of HEV via the quantization of the energy storage states (state of charge) in a set of intervals based on a dynamic programming approach. The system was implemented with MATLAB and evaluated using comparative analysis with a rule-based technique. The result showed a percentage improvement of 35.9% in energy conservation against the rule-based.

In Du et al. (2019), fast Q learning was used to develop an adaptive energy management system for HEV. This was done using the reinforcement learning technique. The system was implemented and tested. The result showed that Q learning has a fast convergence speed, and can save about 16% of computation time.

Ezemobi et al., (2022) presented a study on the application of adaptive model predictive control including battery thermal limitations for fuel consumption reduction in P2 hybrid electric vehicles. This work optimized the consumption of fuel in HEV of the automotive powertrain. However, the result from this study presented that the energy

consumption was improved by 15.7% which is associated with the predictive ability of the adaptive MPC technique.

3. ELECTRONIC DIESEL CONTROL (EDC) SYSTEM

The EDC is a hybrid electro-mechanical control system architecture that is made up of four main sections which are the actuator sensors, the electronic control unit, the engine, and then the injection system. The actuator sensors are the torque position sensor which monitors the position of the

engine, the vehicle speed sensor to determine the engine speed, the clutch and brake sensor to determine the throttle performance, the oxygen sensor to monitor the air to fuel ratio, temperature sensor to monitor the engine temperature, pulse sensor to monitor the timing of the injection systems. All these actuator sensors are connected to the electronic control system to monitor the engine performance as shown in the modeling diagram of figure

1;

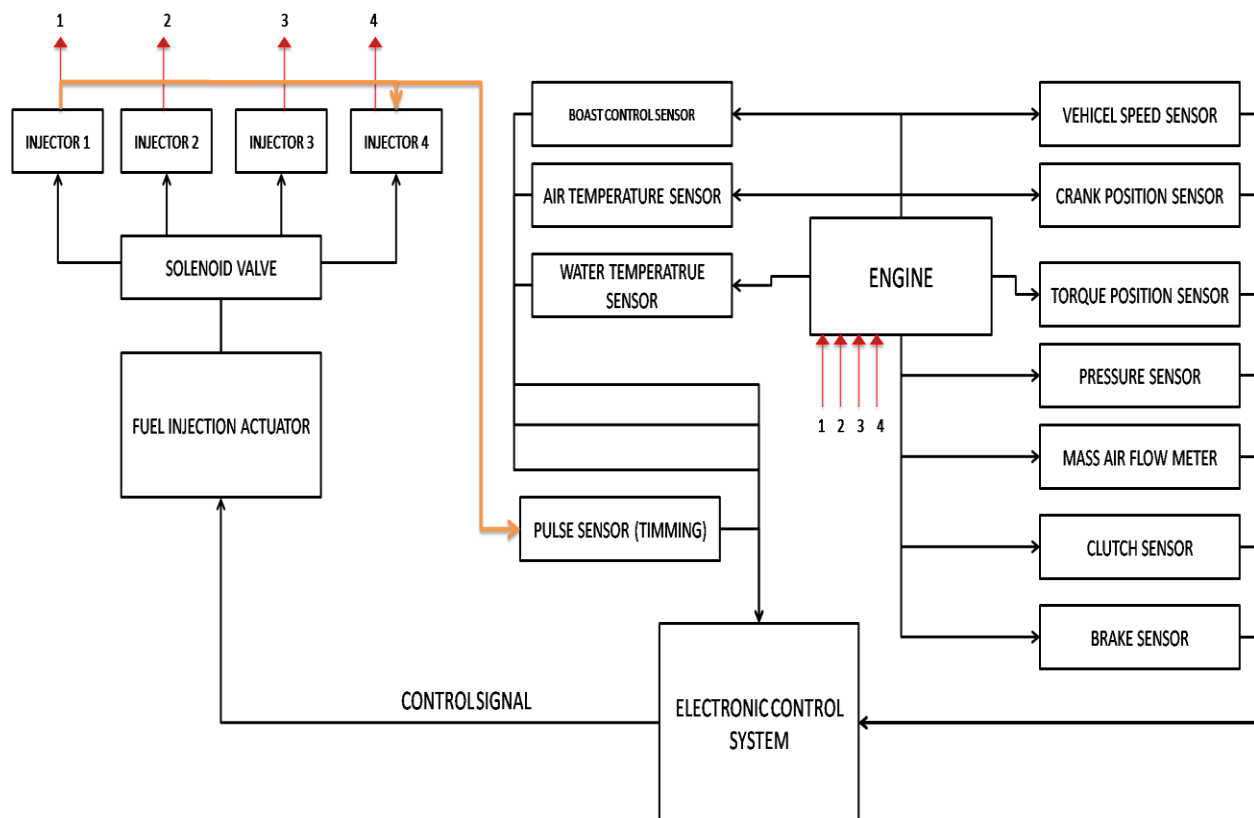


Figure 1: Modelling diagram of the Electronic Diesel Control System

The modeling diagram of the EDC in in figure 1 shows the relationship between the control system actuator, injectors and the diesel engine. After data of the engine was collected by the actuator sensors, they are fed to the PID based control system for processing and then control the timing of the injection actuator which then supplies controlled fuel to the engine.

3.1. The Diesel Fuel Injection Actuator System

The fuel injection system is part of the DCS which supplies regulated fuel to the engine for operation. This was achieved via the injection of compressed air and pressure into the combustion chamber. The diesel fuel injection system was modelled using the fuel injection pump, high-pressure lines, injection nozzles, feed pump and fuel filter as shown in the modelling architectural diagram in figure 2;

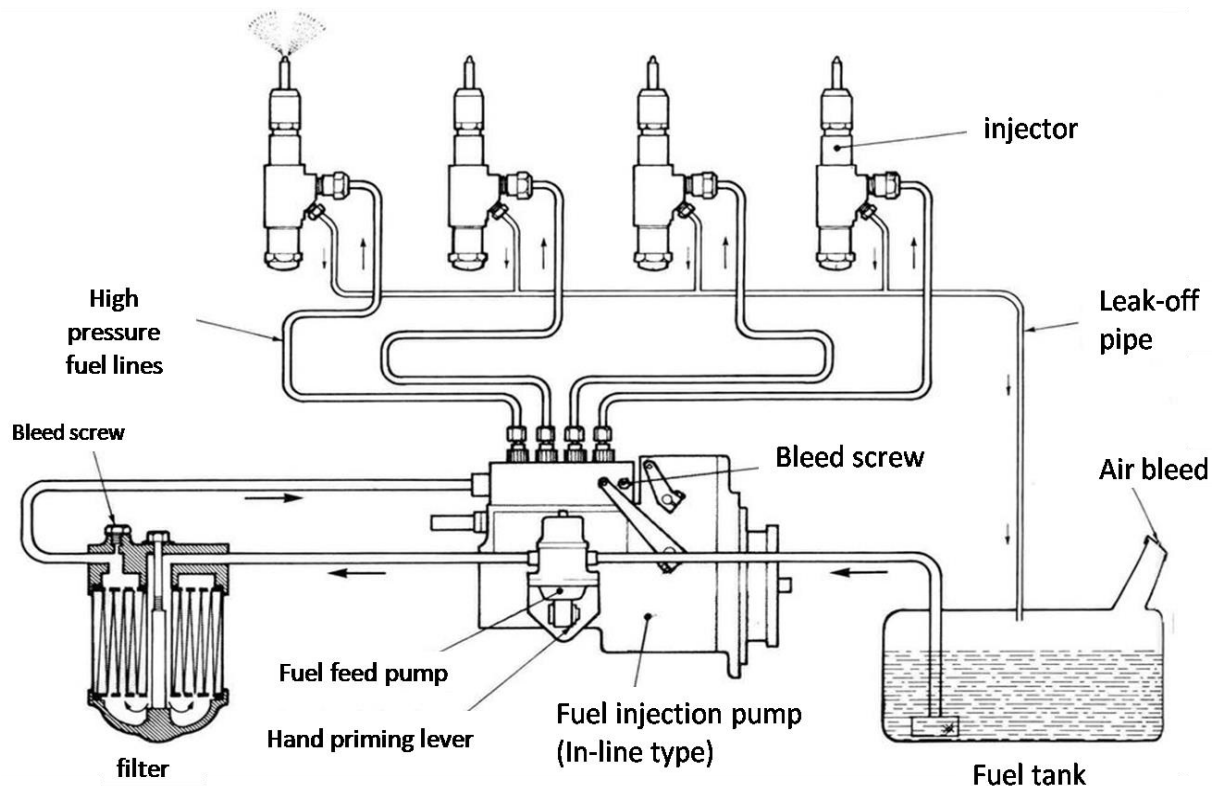


Figure 2: Architectural model of the diesel injection system (Riggs, 2015)

The model was developed of a four-stroke cycle injectors system that accumulated

high-pressure fuel and injects to the engine cylinder at timing control based on the

engine angular speed, torque and other engine parameters processed by ECU. The fuel from the fuel tank is filtered and fed through to the injector pump via the feed pump. This fuel is then pressured at the injector and delivered to the combustion chamber in an atomized system where combustion occurs. The excess fuel is returned to the fuel tank via the leak-off pipe. The injector model developed suffers many limitations as it supplies constant fuel to the engine despite the multivariable constraints attributed to it. This as a result leads to excess fuel consumption and also poor efficiency as the fuel supply is supposed to be based on the engine requirements and not on a constant rate. Hence the research developed in the next section a control system that was able to consider the multi-input variable of the engine and then use the data to control the actuator system.

4. THE INJECTOR CONTROL SYSTEMS

This section presents the actuator control techniques which are being proposed for the improvement of the fuel consumption as presented in this study. The techniques reviewed are model predictive control

(MPC), Adaptive -MPC and Artificial Neural Network based-MPC.

4.1 Model Predictive Control System

Model predictive control (MPC) relies on dynamic models of the process, most often linear empirical models obtained by system identification. The MPC can predict future events and take control actions accordingly. MPC is nearly universally implemented as digital control, although there is research into achieving faster response times with specially designed analogue circuitry.

It is an advanced method of process control that is used for the control of the technical process while satisfying a set of constraints. The MPC e main advantage of is the fact that it allows the current timeslot to be optimized while keeping future timeslots in an account (Wang et al., 2020). This is achieved by optimizing a finite time-horizon, but only implementing the current timeslot and then optimizing again, repeatedly, thus differing from Linear-Quadratic Regulator (LQR).

4.2 Adaptive Model Predictive Control

The adaptive MPC are set of MPC which can update their behaviour based on system dynamics. It is an advanced control strategy based on the optimization of an objective

function within a specified horizon and has been recognized as the winning alternative for constrained multivariable control of industrial systems (Marshiana et al., 2019). However, the characteristics of many industrial systems are highly nonlinear and time-varying. Therefore, the algorithms obtained by MPC design techniques which are based on a linear mathematical model of the controlled process are not very efficient because these methods cannot guarantee stable control outside the range of the model validity.

For this reason, adaptive algorithms which would be based on a continuous model updating process and redesign of the MPC strategy before a new control action is applied to the real system would be the preferred ones. Up to now the development of such algorithms is very much restrained to systems with large sampling time because of their high computation time (Yan et al., 2012). However, the recent availability of inexpensive multi-core computers makes us rethink the possibility of developing adaptive MPC algorithms.

4.3 Artificial Neural Network (ANN) Based MPC

Many works A recent approach to modelling nonlinear dynamical systems is the use of neural networks (NN). The application of neural networks (NN) for model identification and adaptive control of dynamic systems has been studied extensively (Udit et al., 2014). NNs can approximate any nonlinear function to an arbitrarily high degree of accuracy.

The adjustment of the NN parameters results in different shaped nonlinearities achieved through a gradient descent approach on an error function that measures the difference between the output of the NN and the output of the true system for given input data or input-output data pair (training data) (Sabahi, 2011).

5. COMPARATIVE ANALYSIS

This section presents findings from the studies conducted on the techniques applied for the improvements of fuel/energy consumption performance by the three actuator control techniques discussed in the previous section. The results achieved by Taghayipour et al. (2012), Ezemobi et al. (2022) and Ivan and Dirk (2018) are presented on table 1 representing the techniques they applied for this performance improvement.

TABLE 1: PERFORMANCE RESULTS

Author	Technique	Performance Improvement (%)
Taghayipour et al. (2012)	MPC	14.40
Ezemobi et al. (2022)	Adaptive-MPC	15.70
Ivan and Dirk (2018)	Artificial Neural Network Based-MPC	47.60

The result presented in table 1 show how the different techniques have performed in the subject energy/fuel consumption

improvement. This result will be analyzed and presented in figure 3, for a clearer illustration of the improvements achieved with the techniques.

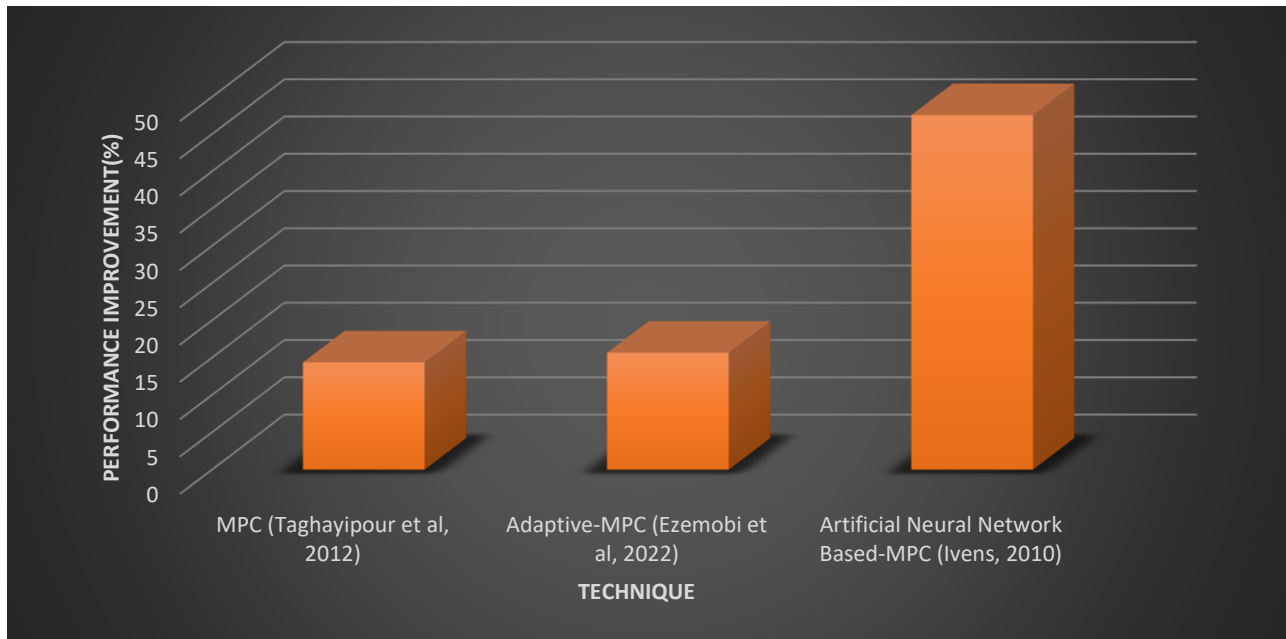


Figure 3: Analysis of the Performance Improvement

From figure 3, it can be seen that the Artificial Neural Network Based-MPC has the highest and the best energy/fuel consumption improvement of 46.6%, which

is followed by Adaptive-MPC with an improvement of 15.7%.

6. CONCLUSION

This study on the improvement of fuel consumption using an intelligent neuro-based MPC of a heavy-duty vehicle, is focused on analyzing the performance of various machine actuator controller techniques such as Model Predictive Control (MPC), Adaptive Model Predictive Control and (Adaptive-MPC) and Artificial Neural Network Based-MPC. This study reviewed various research works conducted on this field of study for the improvement of this system and equally reviewed the electronic diesel control system, diesel fuel injection actuator system and electronic engine control system. Then, the techniques analyzed in this paper was also discussed. The result achieved in this study presented the artificial neural network based-MPC technique as the most efficient with an improvement performance of 47.6%. Adithya (2016) also presented a back-propagation neural network based-MPC which has an accuracy of 35.9%. This shows that the technique is the most efficient among the others for improving the fuel/energy conservation in heavy-duty vehicles and is recommended for adoption.

7. REFERENCES

- Adithya R. (2018) “Hev Fuel Optimization Using Interval Back Propagation Based Dynamic Programming” George W Woodru_ School of Mechanical Engineering Georgia Institute of Technology,
- Bosch, R. G. (2011). Bosch Automotive Handbook, 8th Edition. Wiley, Chichester, West Sussex, England.
- Chartier, C., O. Andersson, B. Johansson, M. Musculus, and M. Bobba (2011). “Effects of post-injection strategies on near-injector over-lean mixtures and unburned hydrocarbon emission in a heavy-duty optical diesel engine”. SAE Int. J. Engines 4:1, pp. 1978–1992.
- Dai-Duong Tran, Omar Hegazy, Joeri Van Mierlo, Rafael Smijtink, Jonas Hellgren, Olof Lindgarde, Think Pham and Steven Wilkins (2018); Modeling and Co-design Optimization for Heavy Duty Trucks; Conference Paper: The 31st International Electric Vehicles Symposium and Exhibition & International Electric Vehicle Technology Conference 2018, At Kobe, Japan.

- Du G, Zou Y, Zhang X. Intelligent energy management for hybrid electric tracked vehicles using online reinforcement learning. *Applied Energy*, 2019, 251.
- Ezemobi, E.; Yakhshilikova, G.; Ruzimov, S.; Castellanos, L.M.; Tonoli, A. Adaptive Model Predictive Control Including Battery Thermal Limitations for Fuel Consumption Reduction in P2 Hybrid Electric Vehicles. *World Electr. Veh. J.* 2022, 13, 33. <https://doi.org/10.3390/wevj13020033>
- Hellström, E., D. Lee, L. Jiang, A. G. Stefanopoulou, and H. Yilmaz (2013). "On-board calibration of spark timing by extremum seeking for flex-fuel engines". *IEEE Trans. Control Systems Technology* 21:6, pp. 2273–2279.
- Ivan Mareev and Dirk Uwe Sauer (2018); Energy Consumption and Life Cycle Costs of overhead Catenary Heavy-Duty Trucks for Long-Haul Transportation; *Energies* 2018, 11, 3446;
- James M. (2021) "How to improve the fuels economy of a diesel vehicle engine" articles; available at <http://offroadauseeie.com>
- Liangcheng Suo, JiaminRen ,Zemeng Zhao and Chi Zhai (2020) "Study on the Nonlinear Dynamics of the Continuous Stirred Tank Reactors"; China Coal Energy Research Institute Co., Ltd., Xi'an 710054, suoliangc@chinacoal.com (L.S.); Processes ISSN 1436
- Marshiana. D, Vinothkumar.C, Ramadevi. R, Ajit. G (2019) " design and optimization technique for controller control" *Design Of Controller Techniques And Optimization For Nonlinear ChemicalProcess: ISSN2277 8615*
- Murphey L, J. Park, Z. Chen, M. L. Kuang, M. A. Masrur, and A. M. Phillips, Intelligent hybrid vehicle power control part i: Machine learning of optimal vehicle power," *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 8, pp. 3519{3530, 2012.
- Olanrele, O.O., Olaiya, K. A., Aderonmu, M.A., Adegbayo, O.O. and Sanusi, B.Y. (2014); "Development of a Dynamic Programming Model for Optimizing Production Planning" *International Journal of Management Technology*, Vol.2, No.3, pp.12-17, September 2014.

- Panday A. and Bansal H (2014) "A review of optimal energy management strategies for a hybrid electric vehicle," *International Journal of Vehicular Technology*, vol. 4, pp 431-439.
- Riggs, J. B. (2015) "Nonlinear Process Model-Based Control of a Propylene Sidestream Draw Column". *Ind. Eng. Chem. Res.* 29,
- Rodriguez, Manuel and Fathy, Hosam (2018); *Speed Trajectory Optimization for a Heavy-Duty Truck Traversing Multiple Signalized Intersections: A Dynamic Programming Study*; 2018 IEEE Conference on Control Technology and Applications (CCTA), Copenhagen (Denmark), 21-24 Aug 2018.
- Sabahi Galler (2011) used a new adaptive non-linearize control based on the neural networks approach, In Friedman RF, Adams B (eds) *The followers of Horus*. Oxbow Books, Oxford, England, pp 19–26
- Taghavipour A., Azad N., & McPhee (2012). An optimal power management strategy for power split plug-in hybrid electric vehicles. *International Journal of Vehicle Design* 60(3/4):286 – 304
DOI:[10.1504/IJVD.2012.050085](https://doi.org/10.1504/IJVD.2012.050085)
- Tri-Vien Vu, Chih-Keng Chen and Chih-Wei Hung (2014). A Model Predictive Control Approach for Fuel Economy Improvement of a Series Hydraulic Hybrid Vehicle. *Energies* 2014, 7, 7017-7040; doi:10.3390/en7117017; energies ISSN 1996-1073
- Udit Mamodiya, Priyanka Sharma (2014)" *Review in Industrial Automation*" *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)* e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 9, Issue 3 Ver. IV (May – Jun. 2014), PP 33-38
- Wang, B.; Wang, Z.; Chen, T.; Zhao, X.(2020) "Development of Novel Bioreactor Control Systems Based on Smart Sensors and Actuators". *Front. Bioeng. Biotechnol.*
- Yan F., J. Wang, and K. Huang. (2012). Hybrid electric vehicle model predictive control torque-split strategy incorporating engine transient characteristics. *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 6, pp. 2458-2467, 2012.