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Simultaneous optimization of fuel and electrical energy consumption in forward looking Hybrid electric vehicle

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ABSTRACT

Recently, number of Hybrid Electric Vehicles (HEV) is on the rise due to concerns over environmental issues. By combining fuel and electricity as two sources of power, this type of vehicle is capable of bettering fuel economy and lowering emission. In this work, fuel and electrical energy consumption of a parallel hybrid electric vehicle are investigated through TEH-CAR urban drive cycle. For this purpose, a forward looking model is developed in AVL CRUISE M. To ensure adequacy of the model and take engine gas path components' dynamic interaction into account, a crank based model with individual cylinders is utilized. Furthermore, a throttle filter is presented to slow down engine's response and also, allow the electric motor to have the larger share of delivering power in transients. Finally, genetic algorithm is used to find optimal values for throttle filter parameter and electric motor load ratio, in order to have minimal overall fuel and electrical energy consumption. The optimization results show 1.2% of fuel and 20.2% of total energy consumption reduction in comparison with conventional torque assist.

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1. Introduction

Due to strict emission regulations, conventional propulsion systems are being replaced by Hybrid ones, since transportation is responsible for 30% of the total greenhouse gases emission [1-2]. Another important aspect, of course, is fuel consumption. Internal Combustion Engines (ICEs) undergo many dynamic processes, especially over urban driving conditions, when throttle angle hovers around it's lower range and there are frequent stops, ICEs have poor efficiency [3]. Therefore, by introducing Electric Motor (EM) into propulsion systems, one can achieve higher overall efficiency by tuning the collaboration of them.

Many researches have been conducted under control strategy title over the years to find the optimal control parameters. For example, one of the most influential parameters on fuel consumption is the power ratio between the two main sources. Methods like Dynamic Programming (DP) can give us the global optimal value for such control parameters at any given moment, but they require all the effective variables to be known [4]. Therefore, they are usually used only as a benchmark. On the other side of control strategy spectrum, rule-based and fuzzy logic-based methods are widely used, since they can be easily implemented, but they also require extensive knowledge to be able to operate the powertrain to work optimally. For this purpose, optimization techniques are used broadly in automotive control applications. Nikzadfar et al. [5] formulated an optimization problem in which fuel consumption (FC) and number of gear shifts are reduced without mitigating drivability through NEDC. Same authors in [6], investigated performance of a number of Bio-inspired Meta- Heuristic Algorithms in deriving PID controller parameters for engine idle speed control. Genetic Algorithms (GA) is one of these Bio-inspired Meta- Heuristic Algorithms, which has been adopted from natural biological evolution [7] and is particularly convenient for control strategy problem, since it deals with a highly nonlinear phenomenon. This algorithm can find best possible values for control parameters, through iterative search [8-9]. Montazeri et al. [10] used GA to find optimal parameter of fuzzy rule to achieve lower emission and better fuel consumption at the same time. Similarly, Masih-Tehrani et al. [11] adopted GA for identical purpose in heavy construction equipment and reported that, by controlling engine operating points, significant reduction in emissions and FC can be achieved. Xu et al [12] also adopted the same approach and with implementation of DP, concluded that this method can result in near optimal fuel consumption. Montazeri et al [13] investigated the application of GA for simultaneous optimization of HEV component sizing and control strategy, where a tradeoff between contradictory objectives was achieved.

The equivalent fuel consumption minimization strategy (ECMS) is a well-known method in HEV control strategies, which translates electrical energy consumption (EEC) into equivalent fuel consumption and consequently an optimization problem is formed, which by solving, overall minimum energy cost can be found. Paganelli [14] initially introduced the concept of ECMS in HEV application to reduce the FC. The main difficulty with ECMS is to find an appropriate equivalent factor, since it can vary depending on driving conditions, battery's state of charge (SOC) and etc. [15]. Liu et al. in [16] formulated an ECMS problem by considering both SOC and acceleration, and by means of GA found a correction map which lowers the cost of electricity than fuel when acceleration demand is large, even when SOC is lower than minimum target. This method has proved to have lower FC than conventional ECSM.

Although, all aforementioned works show the impeccable practicality of GA in HEV applications, often utilized backward-looking vehicle modeling with steady-state map-based ICE models. In this work, we've develop a forward-looking mild parallel HEV with crank-based ICE model, which takes adequate details into consideration. Crank angle based approach in CRUISE M enables us to take nonlinear and dynamic response of ICE into account and in turn, achieve closer result to reality, since experimental investigations are highly costly, time consuming and for such iterative researches almost not feasible. Different from ECMS approach, a filter with adjustable parameter is introduced to slow down throttle response and along with a fixed adjustable power ratio for electric motor, as two input parameters, are formulated in an optimization problem and by means of GA, minimum usage is found.

This paper is organized as follows; section 2 describes the procedure of modeling and its collaboration with optimization process. Firstly, vehicle modeling approach in AVL CRUISE M and subsystems are illustrated in detail. Moreover, throttle filter is introduced. Secondly, GA parameters and problem formulation are presented. In section 3, simulation results are provided and discussed. Finally, conclusion is given in section 4.

2. Approach (Methodology)

Fig. 1 demonstrates the procedure used in this work. First, vehicle model is developed in AVL CRUISE M environment. The vehicle model is then extracted as a S-function to be transferred to MATLAB/Simulink environment, where a co-simulation of AVL CRUISE M and MATLAB/Simulink is formed. Based on this model, GA selects a set a two variables and optimization process is done.

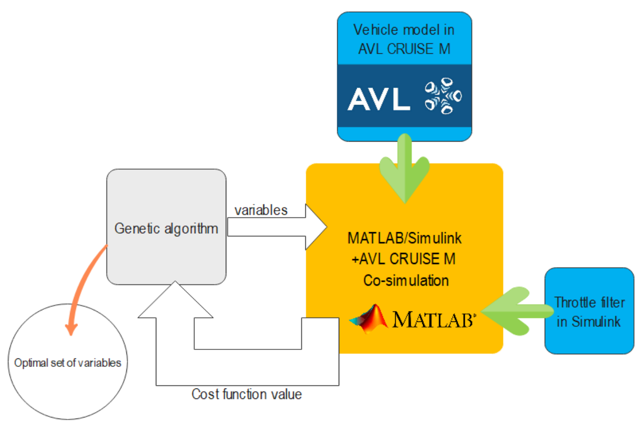


Fig. 1 : graphical schematic of optimization process

2.1. Vehicle model

There are two main types of vehicle modeling: forward and backward looking. [17] The first one begins with driver demand and moves through powertrain to the wheels, whereas the latter is the opposite, ending with propulsion system variables. In backward approach, torque and speed are derived by wheel speed and usually other variables such as fuel rate are calculated through steady-state ICE maps. However, in forward approach, energy route starts from propulsion sources, similar to what happens in real world. To ensure that the vehicle follows the drive cycles, a PID controller serves as a driver.

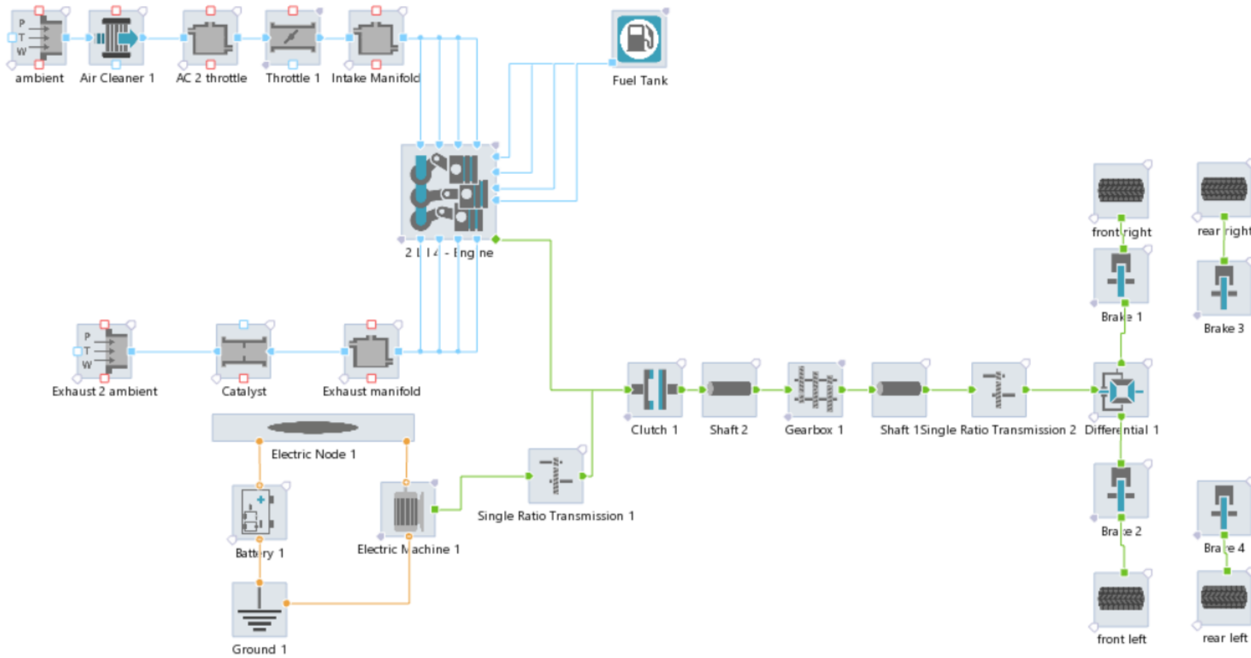


Fig. 2: mild parallel HEV model

Fig. 2 shows the mild parallel HEV model developed in AVL CRUISE M environment. ICE consists of gas path subsystems which have been modeled using mean value approach, namely, air cleaner, throttle, intake and exhaust manifolds and a plenum (from air cleaner to throttle). Instead of quasi-steady assumptions in mass flow through gas path elements, AVL CRUISE M utilizes transient momentum balance equations presented by Katrašnik [18].

In cylinder block, four individual cylinders are modeled to take nonlinear dynamic of ICE into account. Fig. 3 shows modeling of each cylinder. Vibe function is adopted for combustion process which determines the released heat according to crank angle. Generally, there are two types of vibe functions, single and double vibe [19]. This function can be adjusted by two parameters; “m” which determines the heat release and “a” for how much of fuel is burned. In this work, the single vibe function is utilized. Fig. 4 illustrates corresponding rate of heat release at 800 rpm. Intake and exhaust ports also follows same transient momentum balance principles mentioned earlier and are modeled by orifice equation, in which Flow coefficient depends on valve lift. Since engine model is based on crack angle, valve lift is determined by a map (see Fig. 6). Generated heat is then divided into 3 parts; first part leaves the cylinder as exhaust gas energy, second is transmitted into cylinder block through thermal

connections (shown by red connections in Fig. 3) and the last part generates the engine output torque. Additionally, frictional forces are considered to be speed related (see Fig. 5). Crank angle based approach in CRUISE M enables us to take nonlinear and dynamic response of ICE into account and in turn, achieve closer result to reality, since experimental investigations are highly costly, time consuming and for such iterative researches almost not feasible. ICE and gas path general specifications are listed in ***Table 1***.

On the other side, Since EMs have relatively faster dynamics, a map-based approach has been implemented for electrical parts. Fig. 7-a shows EM full load torque-speed graph and battery’s open circuit voltage. EM only works in first torque-speed quarter, meaning that no regenerative braking is considered. At every time

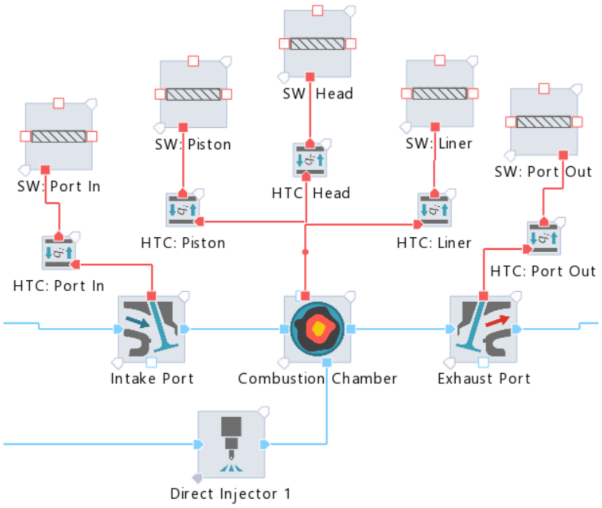


Fig. 3: in-cylinder model

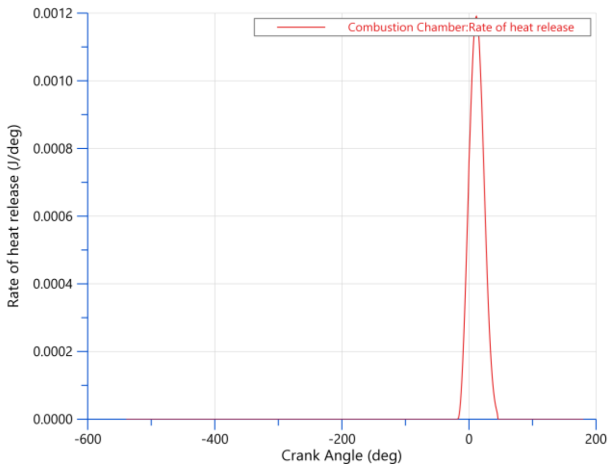


Fig. 4 : Rate of Heat Release (ROHR) over a crank angle cycle

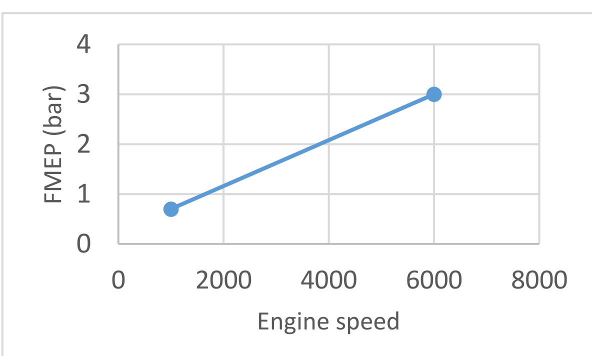


Fig. 5 : Engine friction according to speed

step, a load signal between 0 and1 is sent to EM and based on speed, generated torque is calculated. Consequently, battery block defines the electrical energy derived by EM. Gearbox has a set of gear ratios that are selected based on velocity and transmit power to the wheels. Brake blocks determine braking torque based on brake pressure (a linear function of brake pedal), friction coefficient, piston surface, disc effective surface and its efficiency. ***Table 2***, provides the general vehicle information.

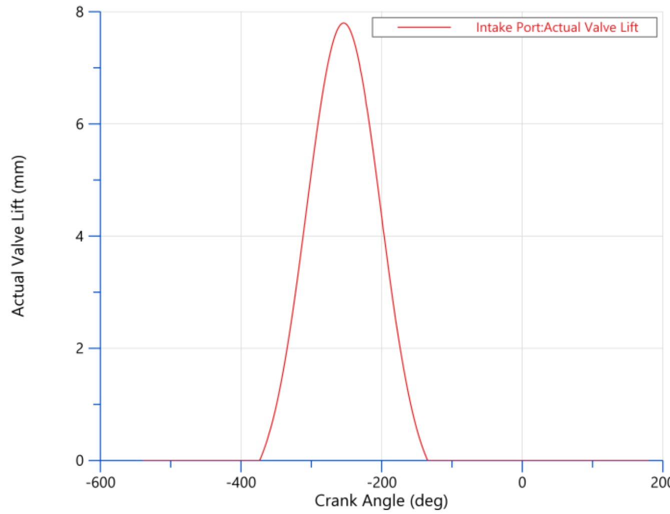
Table 1: ICE components general specifications

Air cleaner(core volume, length, hydraulic diameter, flow coefficient)	1.794 l, 300mm, 10mm, 0.95
Air cleaner to throttle plenum (core volume)	2.09 l
Throttle (body diameter, shaft diameter, rest angle, flow coefficient)	55 mm, 11 mm, 5°, 1
Intake manifold	8.5 l
Exhaust manifold	21 l
Catalyst (core volume, length, hydraulic diameter, flow coefficient)	4.1 l, 300mm, 10mm, 1
Engine (size, number of cylinders, bore, stroke, compression ratio, type of injection, air fuel ratio)	1.7, l, 4 , 80 mm, 85 mm, 10, direct, 1
Maximum torque and power	145 N.m (4000rpm) 80 kW (6000rpm)
Vibe parameters (m, a)	1.96, 6.9

Table 2: Vehicle components general specifications

Gearbox (gear ratios)	5 speed 3.45, 1.84, 1.25, 1, 0.82
Transitional gear ratio (final gear ratio)	3.53 (12.178)

EM torque coupler ratio	2.5
Wheel (moment of inertia, friction coefficient, reference wheel load, radius)	0.95, 4512 N (front), 2100 N (rear), 317.19 mm
weight	1322 kg
Brake	1800 mm2
(friction coefficient, effective friction radius, efficiency, moment of inertia)	0.25, 130 mm, 0.99, 0.02 kg.m2
Battery maximum charge	10 A.h
Air drag (frontal area, drag coefficient)	2.16 m2, 0.3



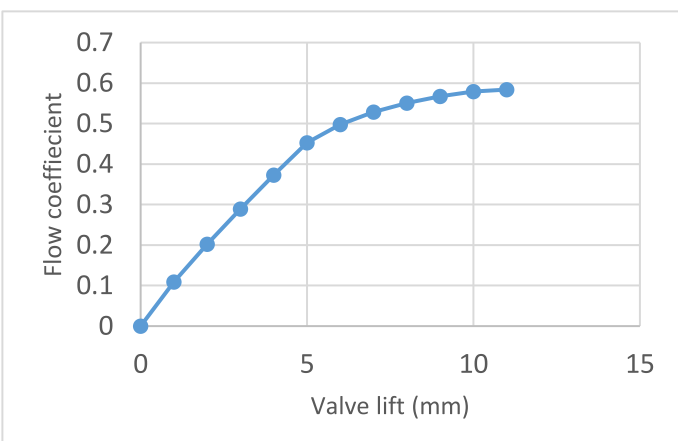


Fig. 6 a) intake port valve lift according to crank angle, b) flow coefficient according to valve lift

The vehicle model is then extracted as a S-function to be transferred to MATLAB/Simulink environment. In this co-simulation, throttle signal, which is initially determined by the PID controller, is distorted by the following transfer function:

$$C(s) = \frac{a}{s+a} \qquad (1)$$

Which has a unit dc gain but slows down as “a” decreases. Fig. 8 demonstrates step response of this filter for different values of “a”. It should be mentioned that, EM load signal does not undergo through this filter, mainly because it’s only used to slow down power demand from ICE and in turn, decrease fuel consumption. Consequently, M would be responsible to compensate the wer torque over transients. Another control arameter is load ratio “r” between ICE and EM. g. 9-a depicts the mentioned signal routing. In der to have a comparison, a conventional ethod, where EM only assists ICE at celeration times is considered as well (see Fig. b).

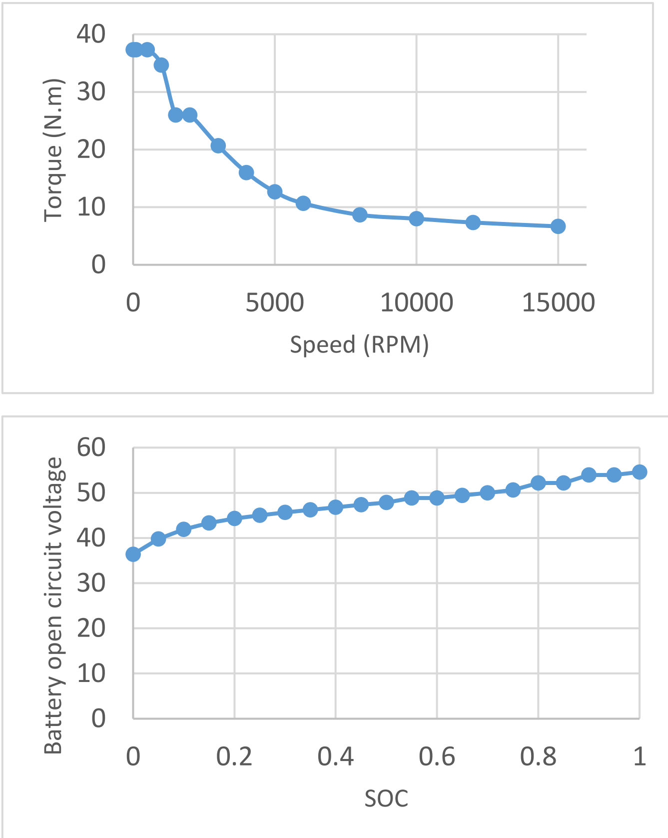


Fig. 7 a) EM full load torque-speed graph, b) Battery open circuit voltage map

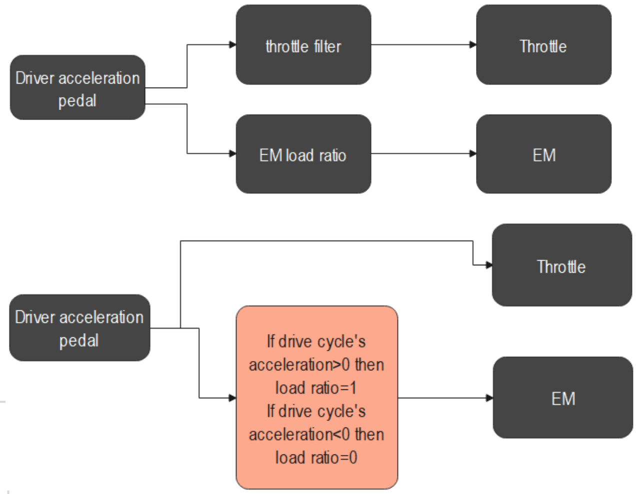


Fig. 9: a) acceleration signal routing with throttle filter, b) torque assist acceleration signal routing

.2 Genetic algorithm and problem formulation

Our objective is to reduce the fuel and electrical nergy consumption simultaneously. As mentioned previously, two main variables are, EM load ratio "r" and throttle filter parameter "a". Accordingly, cost function is set to be:

$$J(a,r) = w_1 \frac{\int FC}{FC_n} + w_2 \frac{\int E}{E_n}$$

(2)

Where FC is the fuel consumption and E is electrical power drawn from the battery. and are

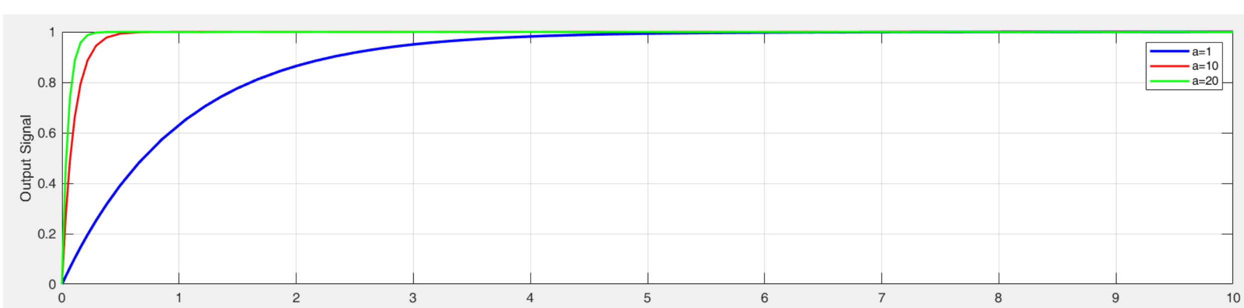


Fig. 8 : step response of throttle filter

employed to normalize and are derived over drive cycle, as variables are set on random value. In addition, weight factors can be implemented to impose priority of fuel economy or electrical power consumption. Here, they are considered to be equal to 1. ***Table 3*** shows variable bound values. It must be mentioned that, since performance is not considered directly in cost function, lower EM load ratio value is demanded by acceleration time limit while "a" is at its lowest. Intentionally, this bound was selected externally, so that it wouldn't slow down the optimization process. Both variables "a" and "r" are fixed through drive cycles.

Table 3: optimization variables bound

Variables	Lower bounds	Higher bounds
THROTTLE FILTER PARAMETER, A	1	20
EM LOAD RATIO, R	0.5	1

GA has two operators, known as crossover and mutation. [2-23] Algorithm starts with an initial population, then fitness value of each individual is calculated as their performance with regards to the cost function. From there, through every iteration, those two operators produce the next generation population, also known as children. ***Table 4*** shows the parameters of GA.

Table 4: GA parameters

POPULATION	20
SELECTION	roulette
CROSSOVER FUNCTION	Heuristic
CROSSOVER FRACTION	0.9
MUTATION FUNCTION	Adaptive feasible
ELITE SIZE	1
GENERATIONS	20

Optimization toolbox by MATLAB is utilized to perform the algorithm. Heuristic crossover function creates children that randomly lie on the line containing the two parents, a small distance away from the parent with the better fitness value, in the direction away from the parent with the worse fitness value. While, Adaptive feasible, as mutation function, randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation. **Fig. 1** shows the collaboration of GA and HEV co-simulation in MATLAB/Simulink in search of the optimal variable values.

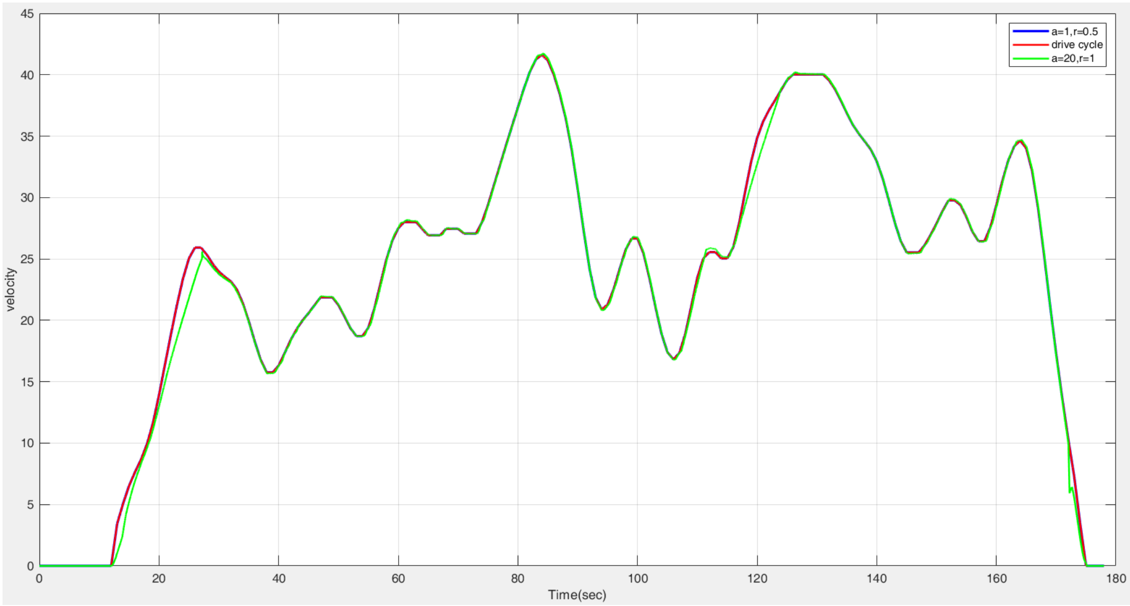


Fig. 10 : performance of PID controller as driver with different GA variable values

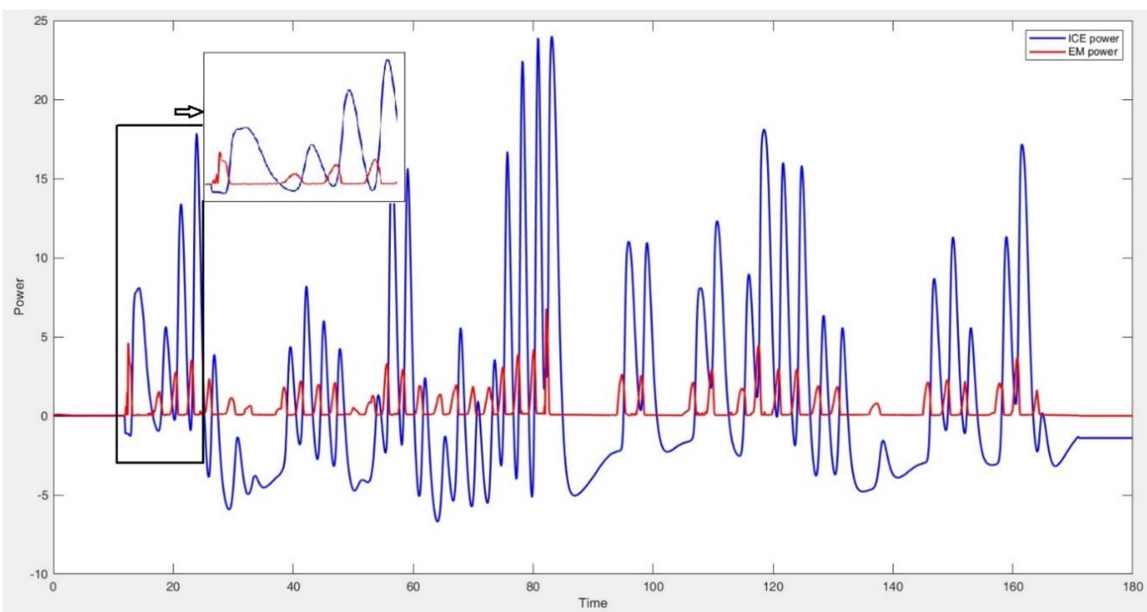


Fig. 11: EM and ICE power (kW) over THE-CAR urban with a=1, r=0.5

3. Results

TEH-CAR urban driving profile [24] was selected as a dynamic cycle to be used in optimization. Considering the model detail and the total computation time, the first part of this cycle, which is almost 180 seconds and starts and ends with zero, is chosen as our designated driving cycle. PID controller makes sure that vehicle will follow the velocity profile with any given sets of variables. Fig. 10 illustrates the adequate PID performance for both lower and higher bounds. It must be noted that driver has a substantial effect on forward looking modeling results. It determines whether driving is done aggressively or mildly. Also, unlike backward modeling approach where exact required torque is determined according to velocity, vehicle velocity fluctuates around desired profile as driver (PID controller) tries to figure out appropriate acceleration and brake pedal. Fig. 11 depicts ICE and EM power over drive cycle, with a=1, r=0.5. As previously mentioned, throttle filter puts a delay on ICE response and in this manner EM is responsible for the beginning of transient response. Also, it's interesting to see how as EM instant torque kicks in, negative values of ICE power are visible, since EM is also propelling ICE in these acceleration time periods.

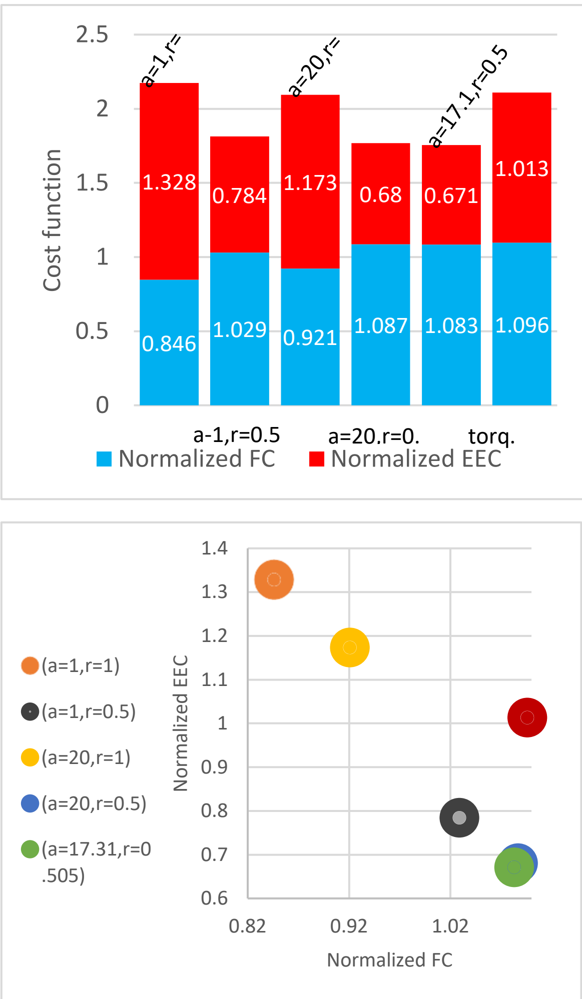


Fig. 12 **:** a) cost function for different sets of variables and torque assist, b) normalized values of FC and EEC comparison

Cost function values for different sets of variables and aforementioned torque assist are represented in **Fig**. 12-a. These numbers reflect fuel and electrical energy consumption. Generally, with higher values for "a" throttle response would be faster and therefore, larger FC is expected, while higher values for "r" would mean electrical share is more, therefore ICE with filtered throttle would use less fuel. However, with a constant value for each variable, changes in FC and EEC are different. For example, at r=0.5, by changing "a" from 1 to 20, FC increases by 5.63%, while EEC decreases by 15.29%. Also, at a=1, by changing "r" from 0.5 to 1, FC decreases by 21.63%, while EEC increases by 69.38%, which means larger changes in EEC is possible by smaller changes in FC. This can be explained by the fact that transients, especially aggressive ones, have major effect on FC. Therefore, by allowing EM to accelerate both the engine and the vehicle, at the very beginning of every transient, can highly reduce the FC. Thereupon, maximum fuel economy can be attained by setting both "a" and "r" at their maximum. *Fig. 13* illustrates GA progress in search of Optimal point, which was found to be at a=17.31 and r=0.505, with values very close to a=20 and r=0.5. It must be considered that this result is achieved when both EEC and FC weights are equal to 1 in the cost function, meaning that both are equally valuable. Moreover, in comparison with conventional toque assist (mentioned in Fig. 9-b), FC in all cases are less, since throttle movements are not damped and it shows the efficacy of presented filter.

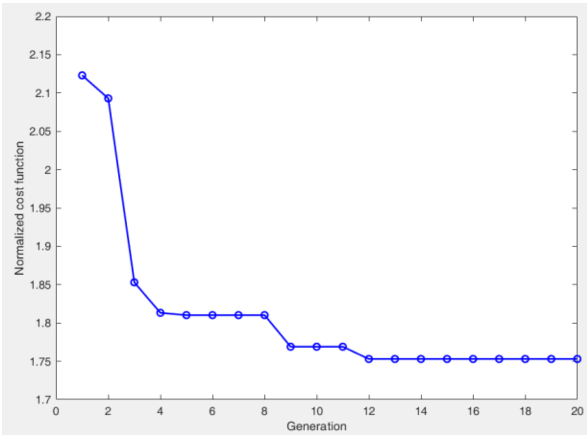


Fig. 13**:** GA progress

4. Conclusion

In this work, we aimed to find the relation between FC and EEC and also, the optimal energy consumption, when both are equally valued. For this purpose, first a forward looking parallel HEV model was developed. To ensure adequacy of the model, a crank based ICE model with individual cylinders was utilized. Secondly, a novel throttle filter with an adjustable parameter "a" is used to slow down ICE response and also, to allow the EM to have the larger share of delivering power in transients. EM load ratio "r" was selected as the second control variable, to determine required power from EM according to load demand. It can be concluded that, changes in FC and EEC happens by unequal margin at different "a" and "r". Optimal point was found to be closer to "a" at its higher bound and "r" at its lower bound, since more EEC reduction can be achieved with less FC, when they are equally valued. Also, it would be more convenient to have EM partially helping ICE with a filtered throttle at all time, instead of injecting torque only when vehicle is accelerating. According to **Fig.** 12-a, this way 1.2% of fuel and 20.2% of total electric energy consumption reduction can be achieved in comparison with conventional torque assist.

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