International Journal of Automotive and Mechanical Engineering
ISSN: 2229-8649 (Print); ISSN: 2180-1606 (Online)
Volume 16, Issue 3 pp. 7007-7018 Sept 2019

Hybrid Hydraulic Vehicle Parameter Optimisation using Multi-Objective Genetic Algorithm

A. F. Hawary[1] and M. I. Ramdan[2]

[1]School of Aerospace Engineering, Universiti Sains Malaysia
*Email: aefaizul@usm.my
Phone: +6045995894; Fax: +6055996911
[2]School of Mechanical Engineering, Universiti Sains Malaysia,
14000 Nibong Tebal, Penang, Malaysia

ABSTRACT

The hybrid hydraulic vehicle (HHV) setup combines compressed-fluid energy in parallel with internal combustion engine (ICE) to deliver the propelling energy to the wheels. During power assist mode, the compressed fluid assists the ICE to propel the vehicle at relatively less energy, hence improving fuel economy. Obviously, in this case the engine torque and fuel economy are two conflicting parameters in which high-torque operation results in poor fuel economy. These conflicting objectives cannot be solved using a classical single-objective optimisation method. Therefore, a multi-objective genetic algorithm (MOGA) is proposed to optimise the power split between an ICE and a hydraulic motor to improve fuel economy. The simulation runs on three operating modes namely, engine only, power assist and regenerative modes considering both highway and city drive cycles. Using a single unified formulation, the objectives can be simultaneously optimised through a systematic search algorithm within a diverse parameter space to provide a set of non-dominated solutions along the Pareto optimal front. Overall, the HHV contribution is significantly observed at low-torque operations when the hydraulic motor assists the ICE in both drive cycles. In conclusion, the improvement achieved by the HHV in terms of fuel economy is recorded as much as 5.55% for highway and 6.50% for city drive cycles.

Keywords: Multi-objective optimisation; genetic algorithm; hybrid hydraulic vehicle

INTRODUCTION

The main source of energy in automobile industries all over the world today is depending on internal combustion engines (ICE) that run on fuel. In future, the increasing demand of fuel worldwide is expected to be more than the reserve could supply. This situation forces automotive industries and researchers to explore alternative energy sources to minimise fuel consumptions through hybrid systems [1]. Alongside Hybrid Electric Vehicle (HEV) counterpart, Hybrid Hydraulic Vehicle (HHV) systems if combined with conventional ICEs could offer a promising saving in fuel consumption [2],[3]. In addition, HHV provides a quick recharge through a regenerative braking [3]. A basic setup for HHV utilises an ICE and high-pressurised accumulator (HPA) as alternative energy storage that is generated from ICE and regenerated during braking to assist the engine when needed, thus reducing the engine load. This scenario not only improves fuel efficiency but also reduces the vehicle emissions at the same time. For this to work a proper torque optimisation is needed to regulate the power split between HPA and ICE.

Such strategies aim to maximise the fuel economy while still satisfying the torque requirement. Common algorithms used for optimising energy of the hybrid system include Energy Following [4] and Thermostatic [5]. The former utilises the energy from an ICE and regulates it based on the energy requirement. Whereas the latter switches the power from HPA, and ICE based on the State of Charge (SOC). Under thermostatic strategy, the engine turns on when the pressure reaches the low limit of SOC then turns off when HPA reaches the SOC high limit depending on the most efficient speed and torque level according to the performance of the engine. For real time optimisation, fuzzy logic controller [4] and energy-flow analysis [6] are among the popular methods. Under real-time optimisation, the actual output torque is regulated based on real-time energy demand and SOC. However, the progressiveness of locating the optimal solution in real-time requires expensive computations. Therefore, static optimisations such as Dynamic Programming, fuzzy logic, Genetic Algorithm are among the reliable strategies to optimise proper splits between the hydraulic and ICE power using an established efficiency map.

A lot of work has been done involving multi-objective optimisation problems such as Vector Evaluated Genetic Algorithm (VEGA) [7], NSGAII [8] and MOGA [9]. These methods divide a population into disjoint subpopulations that are governed by different objective functions, however, VEGA seems to be able to find only extreme solutions on the Pareto front. Among these three methods, multi-objective genetic algorithm (MOGA) is found to be the preferred method since it offers more flexible and robust searches.

For conventional ICE engines, the amount of torques is directly proportional to the amount of fuel burnt. As for HHV, an optimal power split is important to improve the fuel economy while still offering the torque required. Therefore, in this paper, MOGA is used to optimise the power split between ICE and a hydraulic motor to provide a trade-off between engine torque and the fuel economy. Based on that, the optimal split between two energy sources that results in a better fuel economy can be observed throughout the engine RPMs. This paper is organised as follows; the multi-objective genetic algorithm followed by the hybrid hydraulic component and ICE model with MOGA implementation. Finally, the optimisation results are discussed and followed by a conclusion.

Multi-Objective Optimisation

In general, multi-objective optimisation (MOO) is a method that optimises a problem with many objectives. A generic MOO problem has long been studied in great details, both in the control and the operational research community. Usually, a classic representation of MOO solution is presented using Pareto-optimal approach due to its conflicting problem. The notion of Pareto efficiency is useful in MOO that refers to Pareto frontier or Pareto set or Pareto front where the optimal solution lies. In conventional multi-objective optimisation techniques, the importance of objectives are combined through multiple attributes using weighted-sum method. It expresses the relative importance of the objective and balances their involvement in the overall utility measure using real values of weighting coefficients. However, in real multi-objective optimisation, each objective is treated independently without any preference hence the obtained solution is not influenced by a priori knowledge. For that, an evolutionary method such as genetic algorithm is capable to handle the complexity of the multi-objective problem.

Genetic Algorithm (GA)

The concept of GA is based upon the survival of the fittest inspired by the theory of natural evolutions. A dynamic meta-heuristic search is needed to identify a superior solution within the diverse space through selection, crossover and mutation operators [10]. These three operators are applied in every generation during the evolution process. Selection is a process of choosing the parent candidates e.g., tournament, roulette wheel, rank based, probability based, and random based. A tournament selection from random samples is sufficient to provide a new parent candidate for every generation before mating or crossover takes place. Crossover through its swapping features creates new offspring such as uniform, single point and multiple point. The fitness of the new offspring will be determined using a fitness function. It would replace the current candidate if a fitter candidate is found during the evolution processes. Then, the mutation takes place to further evolve where the genes are slightly altered. The degree of alteration depends on the mutation rate. An algorithm that features meta-heuristic and random can ensure global convergence although the problem has multiple local minima as shown in Figure 1.

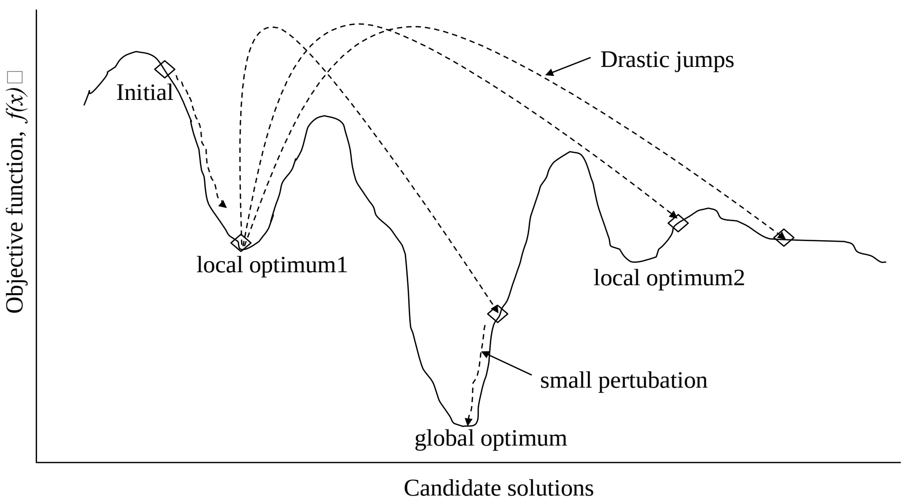

Figure 1. A search space with a global optimum and local optima.

Multi-Objective Genetic Algorithm

The main difference between MOGA and conventional single-objective genetic algorithm (SOGA) is that the objectives are not aggregated into a single-and-parameterised objective. The objectives are treated equally without predetermined weight vectors. Therefore, the solution of MOGA is not biased to any objective and hence best presented using Pareto-optimal solution. The fundamental definition of Pareto-optimal for multi-objective genetic algorithm is described in Eq.(1) as follows:

$$\begin{cases} min/max\, F(x) = [f_1(x), f_2(x), \ldots, f_n(x)] \\ s.t. \quad g(x) \geq 0 \quad i=1, 2, \ldots m \end{cases} \tag{1}$$

where $F(x)$ is a multi-objective function vector, $f_n(x)$ is a set of objective functions, x is input vector, $g(x_i) \geq 0$ is a set of nonlinear inequality constraint if and only if there is no $x \in X$, which lets $F(x_i) \geq F(x_*)$, the solution of $x_* \in X$ is said to be Pareto optimal.

Hybrid Hydraulic Vehicle Model

Unlike conventional ICEs, HHV utilises two propelling energy - ICE and accumulated compressed fluid using high-pressure accumulator (HPA) [11]. ICE produces power through continuous, controlled explosions that push down pistons connected to a rotating crankshaft and delivers the power to the wheel through a gearbox. The latter uses hydraulic pump-motor (HPM) to drive the wheel. A portion of rotating crankshaft power (depending on the mode of operations) drives a hydraulic pump to harvest some energy and store it into an HPA. The operation is simplified into four modes namely, ICE mode, power-assist mode (HPA+ICE), recharging mode and regenerative mode. For optimisation purposes, recharging mode is disabled and regenerative mode depends on full braking forces. The regenerative braking system is used to recuperate kinetic energy from hydraulic pump during braking and store it into an HPA. Based on the torque demand, the algorithm must decide which operation mode to use, then determine the appropriate split between power sources to obtain a good trade-off between fuel economy and the engine torque. A rule based valve control in HPA is used to harmonise the power between two operation states - recharge state and release state based on the state of compression (SOC).

In this study, the model of HHV is built upon the Perodua MYVI 1.3L using K3-VE gasoline engine paired with an integrated hydraulic motor-pump (HPM) that powers the wheels in motoring-mode and regenerates braking energy in pumping-mode. A complete setup of HHV model is depicted in Figure 2, and the important parameters are shown in Table 1.

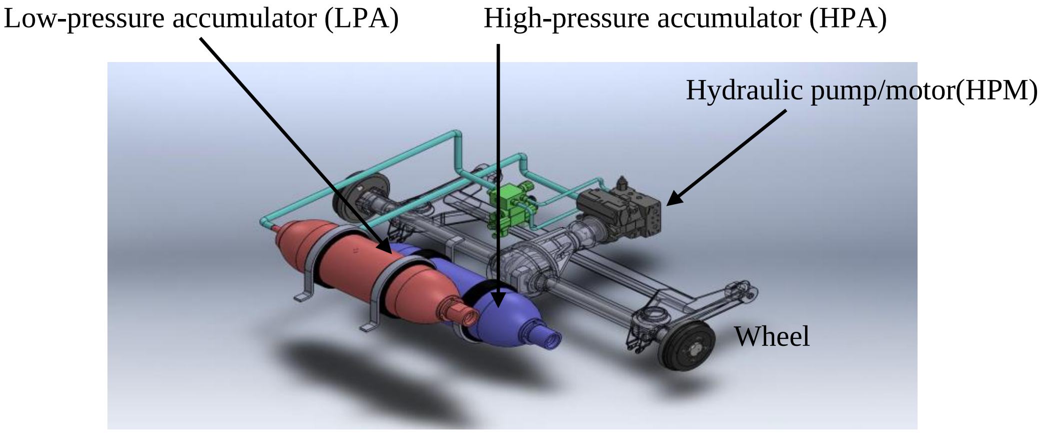

Figure 2. Hybrid hydraulic vehicle setup [2].

Driving force at the wheel, F_{wheel} is the sum of forces due to air drag, road slope, rolling resistance and acceleration as formulated in Eq. (2).

$$F_{wheel}=[F_{air}+F_{slope}+F_{rolling}+F_{acceleration}] \tag{2}$$

The wheel angular speed ω_{wheel} (rad/s), is calculated using Eq. (3) where r_{tyre} is the radius of the tyre (m) and $v_{vehicle}$ is the vehicle speed.

$$\omega_{wheel}=\frac{v_{vehicle}}{r_{tyre}} \tag{3}$$

Table 1. Perodua Myvi parameters (automatic) [12].

Parameters	Symbol	Values	
Maximum engine torque	T_{engine}	1.3L, 64 kW	116 (Nm)
Total ratio (gear ratio x final drive ratio)	G_{ratio}	1st gear	11.01
		2nd gear	6.15
		3rd gear	4.03
		4th gear	2.81
Efficiency of mechanical components	η_t		0.95
Efficiency of hydraulic components	η_{hyd}		0.6
Tyre radius	R_{tire}		0.288 m
Frontal area	A		2.306 m^2
Air drag coefficient	C_d		0.32
Air density	ρ		1.225kg/m^3
Mass of vehicle + driver	m		1055 kg
Mass of hydraulic components	m_{hyd}		238 kg
Coefficient of rolling resistance	C_r		0.01
Mass of 40 cc/rev pump/motor (Bosch Rexroth A4VG40)	m_{PM}		31 kg

The torque required to drive the wheel is given by Eq. (4) and Eq. (5) [2],

$$\tau_{wheel}=[F_{air}+F_{slope}+F_{rolling}+F_{acceleration}]\, r_{tyre} \tag{4}$$

$$\tau_{wheel}=\left[\frac{1}{2}\rho v^2 C_d A+m\, g \sin\alpha+m\, a+C_r m\, g\right] r_{tyre} \tag{5}$$

The wheel torque, τ_{wheel} is driven by the input torque from an ICE, τ_{engine} and the torque produced by HPM, T_{motor} is given by Eq. (6),

$$\tau_{engine}+\tau_{motor}=\tau_{wheel}/G_{ratio} \tag{6}$$

Internal Combustion Engine and Hydraulic Hybrid Parameters

The ICE mode uses engine to propel the vehicle as in conventional drive train. This mode is used when the SOC is less than 30% and when the wheel torque is bigger than the maximum torque provided by the HPM. The torque of engine follows the torque of wheel as in Eq. (7).

$$\tau_{engine}=\frac{\tau_{wheel}}{G_{ratio}\eta_{transmission}} \tag{7}$$

The power assist mode enables HPM to add torque to the drive train (thus, lowering the engine load) and assists the engine to propel the vehicle as shown in Eq. (8).

$$\tau_{engine}=\frac{(\tau_{wheel}\text{-}PDx\eta_{mech.})}{G_{ratio}\eta_{transmission}} \tag{8}$$

This mode is used when the SOC is between 30% and 100% and the maximum HPM torque is bigger than the wheel torque. The speed of engine follows the speed of wheel as shown in Eq. (9).

$$\omega_{engine} = \omega_{wheel} G_{ratio} \tag{9}$$

The hydraulic hybrid system in the simulation consists of two main components namely, an HPM and two accumulators (HPA and LPA). A variable 'x' is introduced to vary its torque and switch the HPM to pumping or motoring mode. During the motoring mode, the HPM drives the load by using the pressure in high-pressure accumulator (HPA) as shown in Eq. (10) and Eq. (11).

$$\tau_{motor} = PDx\eta_{mech.} \tag{10}$$

$$Q_{motor} = \frac{\omega Dx}{\eta_{hyd.}} \tag{11}$$

During pumping mode, an external torque drives the HPM to pump hydraulic fluid from low-pressure accumulator (LPA) to HPA using Eq. (12) and Eq. (13).

$$\tau_{pump} = \frac{PDx}{\eta_{mech.}} \tag{12}$$

$$Q_{pump} = \omega Dx\eta_{hyd.} \tag{13}$$

where P is pressure of the HPA, Q is volumetric flow rate, D is displacement of the PM, and x is fraction of the maximum HPM capacity. The HPM is subjected to friction loss, represented by the mechanical efficiency η_{mech}, and leakage loss, represented by the volumetric efficiency η_{hyd}. The motor mode and pumping mode are expected to work between $-1 \leq x \leq 1$. The former operates when x is positive and switches the former when x is negative. Both operations operate at 100% when x =1 and $x = -1$. Pressure drops in the connecting lines (such as hoses, unions, fittings and bends) are neglected, because they are relatively small compared to the pressure difference between HPMs.

It is important to recall that HPA is an energy storage component that stores potential energy in the form of a pressurised hydraulic fluid between 6.9 MPa and 25 MPa. Within the HPA, a 6.3 L dry nitrogen gas compression bladder is used to pre-charge one side of the accumulator. An LPA is the same accumulator as the HPA, but it operates as a reservoir to contain the low-pressure hydraulic fluid. The LPA's mass is included in the overall vehicle mass, but only the HPA is modelled in the simulation.

An adiabatic (polytrophic) model is used for expansion and compression of the nitrogen bladder inside the HPA. As the initial volume of oil in the accumulator is known, the Euler's method is used to calculate the volume of the oil in the accumulator at each time step, as shown in Eq. (14). The negative sign convention at the HPM flow (Q_{PM}) is established because it normally works in motor mode ($x > 0$), in which it takes the fluid away from the accumulator.

$$V_{oil}\,(k+1) = V_{oil}(k) - (Q_{PM})\Delta t \tag{14}$$

Once the volume of oil in the HPA and the initial pressure (6.9 MPa pre-charged pressure) are known, the HPA pressure is calculated using Eq. (15 to 17). The state of charge (SOC) represents the ratio of the current potential energy to the full potential energy stored in the HPA, i.e. a fully charged accumulator has a SOC of 100%. The total fuel consumption along the time steps is used to calculate the fuel economy of the vehicle operating on every drive cycle using Eq. (18).

$$P_{gas}(k)=\left(\frac{V_{gas,\ initial}}{V_{gas}(k)}\right)^{\gamma} P_{gas,\ initial} \tag{15}$$

where,

$$V_{gas}(k)= V_{total,\ acc}-V_{oil}(k) \tag{16}$$

$$SOC\ (k)=\frac{P_{gas}(k)-P_{min}}{P_{max}-P_{min}} \tag{17}$$

$$Fuel\ economy\ (km/l)=\frac{Total\ distance\ travelled}{Total\ fuel\ consumed} \tag{18}$$

METHODOLOGY

MOGA is configured in accordance to the fitness function used in the optimisation process based on Eq. (8) and Eq. (18) as listed in Table 2.

Table 2. Objective functions for HHV optimisation

Function #	Objectives	Optimise function
$f_1(X)$	Engine torque, τ_{engine}	maximised
$f_2(X)$	Fuel economy	maximised

Table 2 shows two objective functions that need to be maximised. A solution is said to be superior if both objectives are maximised, but this is not always the case due to the conflicting problem. Therefore, the solutions are best presented using Pareto optimal. Furthermore, the solution is subject to some constraints and limits as listed in Table 3. MOGA aims to optimise the following functions by treating them equally without any weight vectors involved as shown in Eq. (19).

Table 3. Constraints and number of genes in the chromosome.

Parameters, (X)	Unit	limits	# genes (bits)
Engine speed, ω	RPM	$850\leq\omega\leq4946$	10
Pump torque, τ_{pump}	%	$0\leq\omega\leq127$	7
Gear ratio, G_{ratio}	N/A	1 - 4	2

$$\begin{cases} min.\ F(X)=f_1(X),f_2(X) \\ s.t.\ g_j(X)\geq0 \quad j=1,\ 2,\ \ldots J \end{cases} \tag{19}$$

where X is a list of corresponding decision parameters belonging to each function $f_i(X)$, $g_j(X) \geq 0$ being a group of nonlinear inequality constraint.

Optimal fuel economy can be achieved through a good balance between the engine torque and the HPM torque. Three decision variables and their corresponding limits are defined to form a chromosome for genetic algorithm optimisation as shown in Table 3. Chromosome representation describes the genes of each individual in the form of a string. The number of bits defines the resolution for of each parameter. Based on these variables, the genes were defined in the chromosome to be 19 bits long in the following order:

$(\omega\ \tau_{pump}|\ G_{ratio}|) = MSB\ (YYYYYYYYYY\ |\ YYYYYYY\ |\ YY)\ LSB$

The structure of the chromosome is in binary form where $Y \epsilon \{0,1\}$, where the genes toward the left represent the most significant bit (MSB) and the genes on the right are the least significant bit (LSB). The speed genes are 10 bits long, equivalent to 1024 decimal values – multiplying this value by 4 equals 4096 to cover the speed range of 850 ~ 4946 (maximum torque is obtained at 5000 RPM). The reason 4 is chosen as the multiplication factor is that changing the engine speed by 1 RPM does not produce a significant difference in torque. The genes for pump torque has 7 bits to evolve within 128 data range that would be multiplied by $100\%/128$ to obtain an actual percentage of SOC. The last two bits on the right represent the number of available gears (4 gears). Once the chromosome is defined, the computational procedure in MOGA was executed in the following order:

Initialisation

Set the initial values of six parameters for genetic algorithm, including the maximal number of generations MAXGEN, the population size NIND, the generation number GEN, the crossover probability P_c, the mutation probability P_m, and the constraint parameters $g(x)$.

Evaluation of fitness function

Compute the fitness value $f_i(X)$ for each chromosome in the ith generation. After validating by the constraints $g(x)$, record and modify the best chromosome to the next generation and update a tentative vector of Pareto optimal solutions.

Reproduction

Compute the reproduction probability P_i and the cumulative probability q_k. Generate a random number r in [0, 1] according to a uniform distribution. Operating the reproduction process with the parameter P_i, q_k and r, a new generation will be produced.

Crossover

For each selected pair, apply a crossover operation to generate two new strings. Generate a random number as r in [0, 1] according to a uniform distribution in turn. Set up a parent chromosome population based on the parameter P_c and r. Select two chromosomes in the parent chromosome population and a breakpoint for each chromosome in random. Compute the crossover process for all parent chromosomes.

Mutation

The mutation increases the diversity of the population by introducing random variation to the population. Generate a random number as $r_1, r_2, r_3, \ldots r_n$ in [0, 1] according to uniform distribution in turn.

Convergence

If the present generation number ith equals to the maximum number of generations MAXGEN, optimisation processes are said to be converged to an optimal solution.

Sorting

Sorting is the process where the solutions are ranked according to their superiority to be the non-dominated solution at the Pareto front. In this paper, we used the MOGA ranking [9] to identify the non-dominated solution. A summarised method described above is depicted in Figure 3.

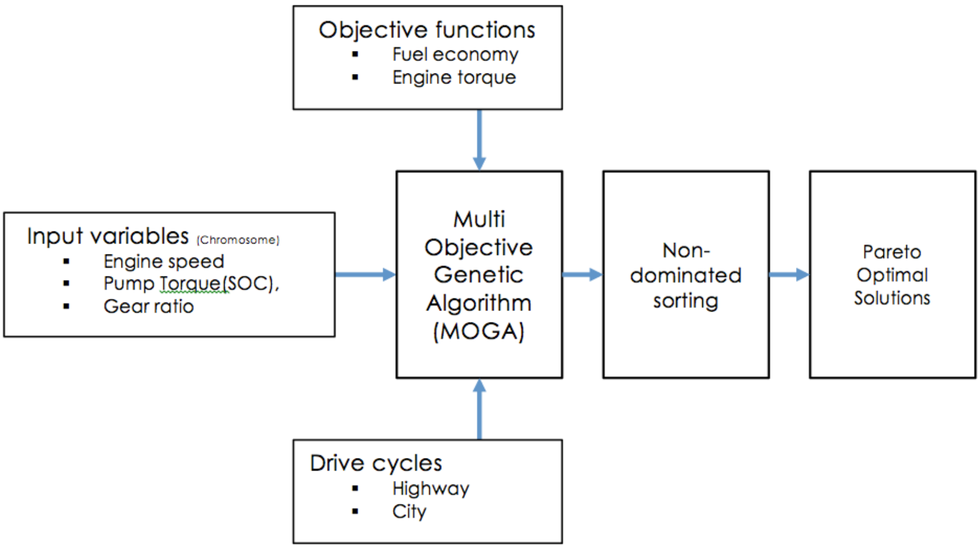

Figure 3. A summarised block diagram for the optimisation process.

SIMULATION RESULT

The mathematical model HHV is used to simulate the parameter optimisation using MOGA. The simulation runs on both city and highway drive cycles that originated from Malaysian roads in Alor Setar, Kedah [2]. Basically, the city drive cycle consists of 1738 s of low speed (maximum speed of 19.5 m/s) with high-frequency stop-and-go driving conditions. The highway drive cycle, on the other hand, consists of 2878 s of high speed (maximum speed of 33.37 m/s) with less frequent stops. Figure 4, Figure 5 and Figure 6 show a set of trade-off results between engine torque (Nm) and fuel economy (km/l) for both HHV and conventional ICE engine (without HHV).

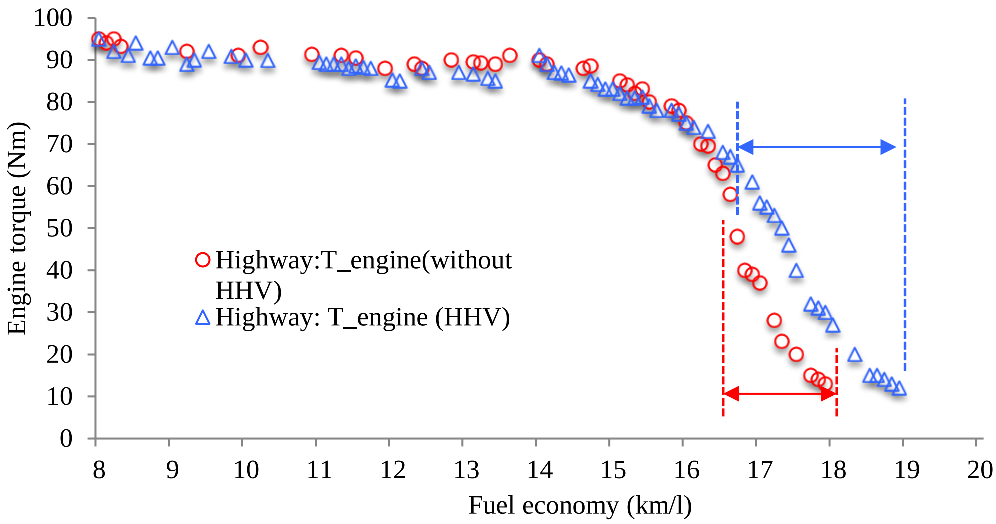

Figure 4. Trade-off solution between HHV and conventional ICE on highway drive cycles.

Figure 4 shows that for the highway drive cycle; the engine torque for ICE and HHV demonstrate similar performance above 70 Nm where the fuel economy varies from 8 to 16 km/l. It is observed that above 70 Nm, the vehicle is mainly powered by the ICE engine, hence there is no significant difference in fuel-saving from both systems. However, at the lower torque operation of below 70 Nm, the HHV has demonstrated a better fuel economy in the range of 17~19 km/l as compared to ICE 16.5~18 km/l. The improvement is due to the power assistance from HPM to lighten the engine load. The slight improvement in fuel economy is expected because highway driving demands higher torque that utilises more ICE engagement.

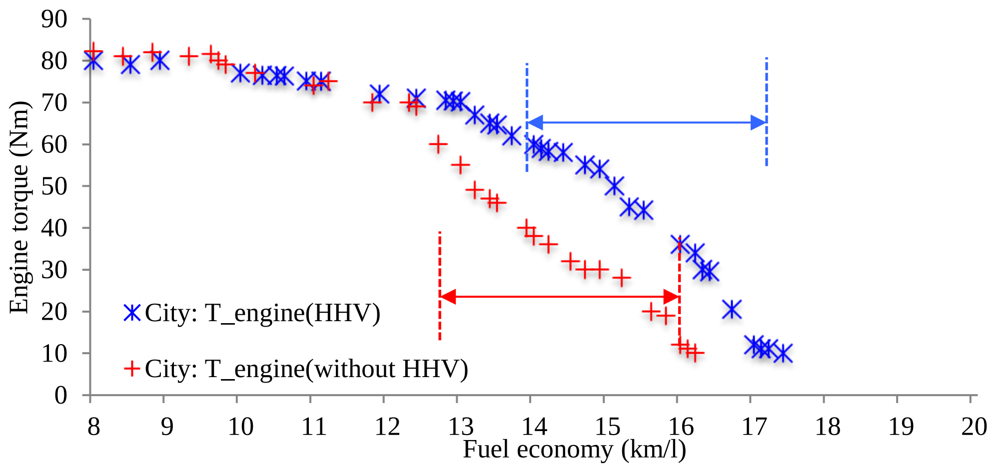

Figure 5. Non-dominated solution trade-off between HHV and conventional ICE on city drive cycle.

In Figure 5, a similar pattern is observed for high-torque above 70 Nm. However, at low torque below 70 Nm the fuel economy for HHV in city driving is much improved as compared to ICE engines particularly where fuel economy is achieved between 14 ~ 17.5 km/l as compared to 13 ~ 16 km/l. This scenario is highly expected since, in city drive cycle, the vehicles operate at low torque start-stop condition and hence charging up the hydraulic pump and offering more assistance from the hydraulic motor to relief the ICE load.

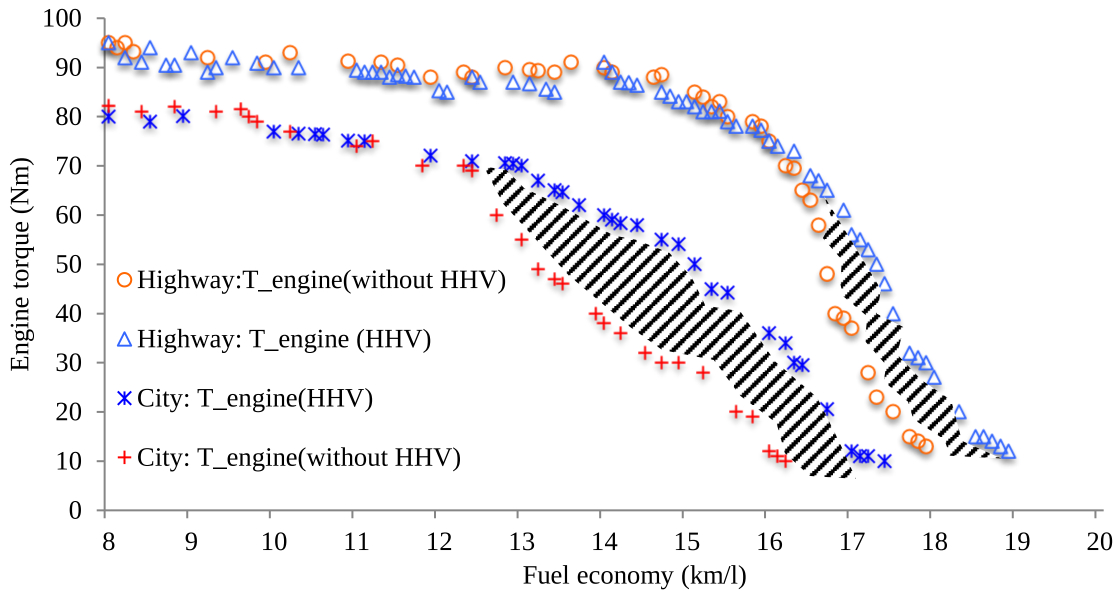

Figure 6. Non-dominated solution trade-off between HHV and conventional ICE highway and city drive cycles.

Figure 6 shows a combined solution for both highway and city drive cycles. It is observed that HHV offers a slight improvement in term of fuel economy for both highway and city driving over conventional ICE engine particularly at low-torque operations indicated by shaded areas. In comparison, the fuel economy has improved on city drive cycle as compared to highway drive cycles. Indirectly, it indicates that the engagement of hydraulic motor and pump are more frequent on a city drive cycle.

CONCLUSION

The results demonstrate that the multi-objective genetic algorithm (MOGA) provides a useful representation of the solutions in terms of Pareto optimal. The algorithm can be used to evaluate the performance from multi-objective perspective between engine torque and fuel economy for both non-HHV and HHV setups. From the results, a slight improvement in fuel economy is observed from HHV at lower torque mode (mostly at low engine RPM) due to the engagement of the hydraulic motor. However, at higher torque, the result for HHV and non-HHV are almost aligned since the motor does not assist the engine at this point. It is observed that the estimated fuel economy achieved by HHV setup is within the range of 0.5 ~ 1 km/l for highway and 1 ~ 1.5 km/l for city drive cycles. Although this improvement is small, driving HHV vehicle with 50 litres fuel would travel more than 50 extra kilometres – which is considered a significant saving. Therefore, it is concluded that MOGA has provided a set of compromised solutions (Pareto optimal solutions) between engine torque and fuel economy for HHV setup. It also demonstrates that, the fuel economy for HHV has improved about 5.55% for highway and 6.5% for city drive cycles while maintaining the required torque.

ACKNOWLEDGEMENT

The work described in this paper is funded by Universiti Sains Malaysia RUI grant 1001/pmekanik/8014032 under the supervision of Dr Muhammad Iftishah Ramdan.

REFERENCES

[1] Calabrese G. The Greening of the Automotive Industry. Basingstoke: Palgrave Macmillan UK, 2012.

[2] Ramdan MI. Perodua Myvi engine fuel consumption map and fuel economy vehicle simulation on the drive cycles based on Malaysian roads. In: MATEC Web of Conferences. 2017, p. 01044.

[3] Huang C-J, Du M-S, Tsai G-L. Comparison of Fuel Economy between Hydraulic Hybrids and Hybrid Electric Vehicles. Manufacturing Science and Technology 2015; 3: 57–65.

[4] Leon Quiroga JA, Gonzalez Mancera AL, Garcia Bravo JM. A Fuzzy Logic Controller for a Hydrostatic Transmission for an Electric Hybrid Bus in Bogotá, Colombia. In: Proceedings of the ASME/BATH 2017 Symposium on Fluid Power and Motion Control. ASME/BATH 2017 Symposium on Fluid Power and Motion Control. Sarasota, Forida, USA. October 16–19, 2017. 2017, p. V001T01A042.

[5] Peng J, He H, Xiong R. Rule based energy management strategy for a series–parallel plug-in hybrid electric bus optimized by dynamic programming. Applied Energy 2017; 185: 1633–1643.

[6] Hofman T, van Druten R. Energy analysis of hybrid vehicle powertrains. In: Proc. IEEE Int. Symp. Veh. Power Propulsion. 2004, pp. 1–8.

[7] Schaffer JD. Multiple objective optimization with vector evaluated genetic algorithms. In: Proceedings of the 1st International Conference on Genetic Algorithms, Pittsburgh, PA, USA, July 1985. 1985, pp. 93–100.

[8] Deb K, Pratap A, Agarwal S, et al. A fast and elitist multiobjective genetic algorithm: NSGA-II. Evolutionary Computation, IEEE Transactions on 2002; 6: 182–197.

[9] Fonseca CM, Fleming PJ. An overview of evolutionary algorithms in multiobjective optimization. Evolutionary computation 1995; 3: 1–16.

[10] Goldberg DE. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley Longman Publishing Co., Inc., 1989.

[11] Zhang Z, Chen J, Wu B. The control strategy of optimal brake energy recovery for a parallel hydraulic hybrid vehicle. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 2012; 226: 1445–1453.

[12] Perodua. 2013. Specification of Perodua Myvi. Retrieved from https://paultan.org/2008/10/10/2008-perodua-myvi-se-full-details-and-prices; 30 October, 2017.