Multi-objective optimization of virtual formula powertrain design for enhanced performance and fuel efficiency

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Abstract

Formula 1 is considered an important motorsport event that has driven the development of cutting-edge automotive technology. Similarly, virtual formula competition is introduced at the university level to harness technological advances for automotive development among universities. Performance and fuel efficiency have always been two conflicting objectives in determining the optimal powertrain design. In this paper, state-of-the-art multi-objective evolutionary algorithms (MOEAs) are employed to optimize the vehicle powertrain design based on competing event and the on-track performance through software in-the-loop optimization approach. Unlike conventional powertrain optimization approach where the powertrain design is optimized again standard urban driving profiles to achieve optimum driving performance and fuel consumption which is not suitable to be employed to optimize race car powertrain design. The powertrain design is optimized and benchmarked in multiple dynamic test events i.e. Acceleration, Autocross and Endurance. Each event measures different performance parameters (i.e. lap time and fuel consumption) A total of nine design parameters are optimized in this study. Three design parameters (employed to formulate the progressive gear calculation of six gear ratios), five gear shifting rpm (revolutions per minute) and an aerodynamic downforce scale value (for front and rear downforce). Two stages of optimization solution are proposed to handle such complicated design requirement. NSGA-II was identified as the most efficient algorithms among the MOEAs employed in this study; especially in terms of computational time, Pareto distribution and Pareto design. Overall, the optimized powertrain design showed significant improvement in all events i.e. energy efficiency was increased by 13.7% for the endurance event while lap time was reduced by 0.7 and 1.2% in the acceleration and autocross events, respectively.

Keywords Powertrain design · Multi-objective evolutionary algorithm · Vehicle performance · Fuel efficiency

1 Introduction

Lately, energy independence and climate change have triggered a surge in the development and sales of electric vehicle (EV). However, the onslaught of EVs are nowhere near ready to take over its heavyweight contender, gasoline-powered vehicles, in the near future. Further development of the internal combustion engine (ICE) remains top priority in the current transition stage from ICE to EV [1]. This poses a great challenge to car manufacturers as continuous improvement of gasoline-powered

vehicle efficiency, without compromising its performance, is required to sustain and attract more clientele. This stringent condition is also applied to vehicles featured in the Formula 1 race, where vehicles no longer focus solely on performance but also on energy conservation and recovery [2]. Similar to Formula 1, Virtual Formula is a competition which is built upon the well-established Formula SAE (Society of Automotive Engineers) event. These events aim to promote the growth and development of automotive technologies in universities by providing a virtual platform for engineers to design and simulate the performance of

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their designed vehicles. The competition requires engineer to optimize their respective vehicle within the design constraint provided by the rules and regulations. The vehicle will compete in the following events i.e. acceleration, autocross, skidpad, and endurance. Each event requires different aspect of performance tuning via different powertrain designs. For instance, the powertrain system is configured to deliver a fast acceleration response in the acceleration event while it provides dynamic performance under the autocross category, whereas the endurance event requires the powertrain design to be energy efficient. However, the skidpad event will not be included in this study since the powertrain design has insignificant impact on handling performance.

Powertrain design plays an important role in determining the fuel consumption and performance of a vehicle. Conventionally, powertrain design is optimized based on various standard driving cycles, such as the FTP-75 test cycle used in the United States, ECE+ EUDC test cycle used in the European Union, and 10-15 mode cycle used in Japan [3–6]. Each type of driving cycle consists of different simulated driving profiles to mimic the daily usage of vehicles driven in designated environment. As a result, the efficiency of a powertrain design is highly dependent on the driving cycle employed [7]. However, the driving cycle for a performance vehicle on the race track is not widely available, and hence this poses a challenge for engineers trying to optimize formula racing vehicles. Additionally, most research studies are simply focused on the optimization of fuel consumption via the gear shifting strategy or gear ratio tuning without taking into account the performance of the vehicle [4, 8–11]. Furthermore, researchers paid more attention to passenger and commercial vehicle in which vehicle performance is not a critical aspect of the vehicle design. In contrast, a formula racing vehicle has stringent conditions necessary to account for performance and fuel consumption. Therefore, complex optimization such as the integration of aerodynamic drag and downforce with the powertrain optimization becomes a necessary factor to be considered. This will greatly influence the performance of the vehicle. To date, the advancement of multi-objective evolutionary algorithm (MOEA) has successfully supported the solving of complex nonlinear optimization problems. The optimization problem is treated as a black box without implicit mathematical derivation, which makes it suitable to optimize vehicle performance as the explicit derivation of the vehicle performance is complex. In the past decade, various applications involving MOEA showed great potential in solving complex vehicle designs [12–21]. This paper aims to demonstrate the application of evolutionary algorithms to optimize the powertrain and aerodynamic design of racing vehicles. The optimization utilizes the driving profiles from various

events via simulation prior to the tuning of gear shift schedule for the enhancement of vehicle performance and fuel consumption.

2 Vehicle and powertrain modelling

The formula racing vehicle used in this study is a rear wheel drive with a six-speed gear box and rear limited slip differential. The detailed specification of the vehicle is shown in Table 1. It is equipped with an ICE which has a maximum output of 78 kW at 12,150 rpm. The brake-specific fuel consumption (BSFC) of the engine is presented in Fig. 1.

The engine is efficient when it is operated at low rpm, however the fuel consumption increases parabolically with increasing torque demand. In the powertrain design, it is ideal to have a wide spread of gear ratios to cover different regions of torque demand as required by the vehicle at different speeds. Generally, the initial gear has the largest ratio and it is selected based on the maximum traction which the vehicle can adapt. It affects the maximum acceleration of the vehicle and provides the initial starting torque to drive the vehicle. Whereas, final gear ratio determines the top speed which the vehicle can achieve. The intermediate gear should be selected as such that it provides a large enough stepping in which the maximum permissible engine speed will not be exceeded when the next lower gear ratio engages the maximum engine torque. Such contradictory aspects of the gear design resulted in two formal methods employed in

Table 1 Vehicle dimension and base powertrain specification

Information	Values
<i>Vehicle data</i>	
Length	1.7 m
Total mass	223 kg
Mass distribution percentage (front: rear)	50:50
Centre of gravity height	0.277 m
Unloaded wheel radius	0.26035 m
Tire vertical stiffness	200 kN/m
Aerodynamic downforce scale	1
<i>Powertrain data</i>	
1st Gear ratio	3.5
2nd Gear ratio	1.95
3rd Gear ratio	1.55
4th Gear ratio	1.28
5th Gear ratio	1.142
6th Gear ratio	1.061
Transmission gear ratio	2.5
Final drive ratio	3.6
Uniform upshift timing	14,850 rpm

Fig. 1 Internal combustion engine torque curve and brake-specific fuel (BSFC) consumption mapping

designing the gear ratio steps i.e. geometrical gear steps and progressive gear steps. Geometrical gear steps are mainly employed in commercial vehicles as it provides lower specific power output i.e. all gears are evenly spread across the design speed range. In this study, progressive gear design calculation is selected as it is mainly employed for either passenger or performance vehicle design. The powertrain has more gears at higher speed than at low speed. The progressive gear steps are formulated as shown in Eq. (1):

For ratio of each gear i_n in gear $n = 1$ to $z = 6$ (for a six-speed transmission gear box)

$$i_n = i_z \varphi_1^{(z-n)} \varphi_2^{0.5(z-n)(z-n-1)} \quad (1)$$

where i_z is the smallest gear ratio or final gear ratio, φ_1 = base ratio, and φ_2 = selected progression factor. Instead of assigning six different gear ratios as the optimization design parameter, this progressive method can reduce the input parameters from six to just three design variables i.e. i_z , φ_1 and φ_2 .

In terms of the aerodynamic influence towards acceleration performance of a powertrain design, it can be easily demonstrated by solving the required traction or torque required from a vehicle at a given speed [Eq. (2)].

$$T_{req} r_{dyn} = mg(f_R \cos \theta + \sin \theta) + \frac{1}{2} \rho_{air} C_d A v^2 + m \lambda a \quad (2)$$

where T_{req} = torque required, r_{dyn} = dynamic tire radius, m = vehicle mass, f_R = rolling resistance, g = gravitational acceleration, θ = road inclination, ρ_{air} = density of air, C_d = drag coefficient, A = projected frontal area of the vehicle, v = vehicle velocity, a = vehicle acceleration and λ = scale of acceleration. In the Virtual Formula competition, the track employed in both Autocross and Endurance events has a flat road profile with zero inclination

and negligible rolling resistance compared to the drag force component (Eqs. 3–4). At higher velocity, the torque required is proportional to the square of velocity in aerodynamic drag force component as well as the magnitude of acceleration. In the simulation environment, the drag force ($F_{drag}(v)$) is modelled as a function of downforce scaling to mimic the tuning of aerodynamic design for a formula vehicle.

$$C_{fdrag_{scale}} = 0.5 + (0.27 \times C_L)^{3.5} \quad (3)$$

$$F_{drag}(v) = C_{fdrag_{scale}} \times \frac{1}{2} \rho_{air} C_d A v^2 \quad (4)$$

where $DF_{front/rear}$ = downforce scale values, and $C_{fdrag_{scale}}$ = drag force scale. The downforce scaling is limited to the range of 1–6. The relationship between drag force scale and downforce scale is shown in Fig. 2.

By gaining downforce, the vehicle can gain higher traction force on the rear wheel which increases acceleration. However, this comes at the cost of higher torque requirement to compensate for the drag force incurred at higher velocity, and hence result in poor fuel consumption. Such complex nonlinear interaction between vehicle dynamic and aerodynamic design complicates the optimization process through the conventional way of manually determining the gear ratio and its respective shift timing.

The base powertrain gear ratio is designed with progressive gear steps and it has a uniform shifting schedule at maximum revolution of the engine i.e. 14,850 rpm. The speed profiles and traction curve demand (Eq. 2) of the base powertrain design are analysed and shown in Fig. 3. It is shown that the gear shifting is poorly designed based on the gear shift activity at a maximum engine revolution of 14,850 rpm which resulted in high fuel

Fig. 2 Relationship between drag force scale, down force scale (a) and its corresponding force values (b)

Fig. 3 Base powertrain performance—**a** speed profiles and **b** traction curve

consumption. Furthermore, the overall gear ratio spread is not wide enough for the 6-speed design to meet the required torque demand at both low- and high-end speed requirements. Therefore, a two-stage optimization process is proposed to optimize the powertrain design. Firstly, the gear ratio with fix shifting is optimized against acceleration test to obtain an optimum vehicle speed profiles that is required for different test events. Then it will be further fine tune with its shifting mechanism to obtain a compromise result between the lap time and energy consumption. This will increase the convergence speed of optimization in each stage as the total number of parameters required for each stage can be minimized.

3 Multi-objective optimization formulation

Acceleration event is chosen for the optimization study. Changes in the powertrain design have directly impacted the acceleration time, vehicle top speed and fuel consumption. Unlike other track events, lap time or fuel consumption are dependent on the vehicle performance such as handling, braking, and acceleration. Evaluation of such events is not straightforward and decomposition the of the relationship between measured performance and the respective subsystem design of the vehicle is complicated. Therefore, a Design of Experiments (DoE) was applied for the optimization of this study. In total, there are five parameters involved

in this study i.e. i_z , $\varphi_1\varphi_2$, Shf_{rpm} (uniform shifting rpm), and Dfs (downforce scale). The correlation matrix was calculated based on the Spearman rank coefficient [22] to assess monotonic relationships among the measured objectives (Fig. 4).

The Spearman rank value ranges between -1 and 1 in which values closer to 1 concludes that both objectives are a perfect monotone function of the other. Otherwise, a value closer to 0 shows that both objectives are not related. In this study, it is observed that the maximum velocity is inversely proportional to the lap time for the Acceleration event. Where minimize the time required would also lead to increase in the vehicle maximum velocity. However, the performance of lap time and fuel consumption are conflicting. The correlation test proved that the performance of the powertrain can be optimized by only considering two objective functions i.e. lap time and fuel consumption. Therefore, the primary optimization process will optimize the gear design parameters i.e. i_z , φ_1 , φ_2 , Shf_{rpm} (uniform shifting rpm), and Dfs against lap time and fuel consumption as shown in Eq. 5:

$$\text{minimize } \{t_{\text{acc}}, \text{fuel}_{\text{acc}}\} \quad (5)$$

where t_{acc} = acceleration lap times, fuel_{acc} = total fuel consumption.

Subjected to $x_n \in R, n = 1$ to 5 . For $x_n = i_z, \varphi_1\varphi_2, \text{Shf}_{\text{rpm}}$ and Dfs

The optimization problem was solved by applying various state-of-the-art MOEAs i.e. non-sorting genetic algorithms such as-NSGA-II [23] and NSGA-III [24], competitive mechanism based multi-objective particle swarm

optimizer with fast convergence (CMOPSO) [25], and reference vector guided evolutionary algorithms (RVEA) [26]. The selection of a suitable MOEA is highly dependent on the complexity of the optimization problem. Each algorithm is designed with a specific strategy to obtain the Pareto solution, where there is no single algorithms which is robust in solving all type of problem as stated in "No free lunch theorem" [27]. NSGA-II was well proven to be a robust optimization method that can be used as benchmark algorithms for many engineering applications. In the past decade, NSGA-III has been introduced as an improved version of NSGA-II in which the crowding distance-based method was replaced with the reference vectors-based niching method. On the other hand, CMOPSO and RVEA are considered recent development evolutionary algorithms which possess competitive advantages over the NSGA-II when tested on benchmark problems [28]. The coding was performed through PlatEMO in MATLAB [29]. PlatEMO is a platform which gathers all the MOEAs in a uniform package which eases the implementation of the optimization process in conjunction of VI-Grade (vehicle simulation tools). The integrated coding of the MOEAs with the VI-Grade simulation is as shown in Fig. 5.

The fine-tuning stage was performed after the primary optimization has obtained the Pareto solution. The best optimized solution was selected for fine tuning the respective timing for each gear shifting rpm (Eq. 6).

$$\text{Minimize } \{t_{\text{acc}}, \text{fuel}_{\text{acc}}\} \quad (6)$$

where t_{acc} = acceleration lap time, fuel_{acc} = total fuel consumption.

Fig. 4 Correlation matrix of measured objectives against Spearman rank correlation function

Fig. 5 Software-in-the-loop optimization flowchart **Fig. 6** Autocross and Endurance race track

Subjected to $x_n \in R, n = 1$ to 5. For $x_n = \text{Shf}_{\text{rpm}}$ for gear 1 to 5.

In the fine-tuning stage, the setup of the optimization processes is similar to the primary run, except that the optimized design's parameters are now focused solely on the respective timing of each gear shifting rpm. Each MOEAs run has a stopping criteria of 2000 evaluations with a population size of 20. Lastly, the optimized solution was benchmarked again with the Autocross and Endurance events. Both events have a similar track shown in Fig. 6.

In the Endurance event, an efficiency rating was employed to measure the efficiency of the vehicle as formulated in (Eq. 7).

$$\text{efficiencyrating} = (T_{\min} \times V_{\min}) / (T_{\text{team}} \times V_{\text{team}}) \quad (7)$$

where $T_{\min} = 70$ s, $V_{\min} = 0.15L$, T_{team} = team best lap time, and V_{team} = team overall fuel consumption.

4 Results and discussion

In the primary optimization process, a comparison study was performed among the selected MOEAs to examine their respective algorithms in locating the best optimized Pareto solution. The Pareto solution found throughout the iteration by the MOEAs is shown in Fig. 7.

It is noticeable that the distribution of Pareto solution obtained through NSGA-II and CMOPSO are superior against other algorithms. In contrast, the Pareto solution obtained through NSGA-III only converges at the edge when the time taken is less than 4.5 s. The Pareto distribution obtained through NSGA-III is compromised by the low number of function evaluation, similar to the benchmark study conducted by Tanabe et al. [28]. It requires higher evaluation counts to improve its distribution. Therefore, the NSGA-III method is not suitable for this optimization problem since the computation of the simulation solution is expensive. On the other hand, RVEA failed to obtain a good Pareto distribution. Overall, NSGA-II outperformed other algorithms as it is capable of obtaining a good Pareto distribution as compared to other MOEAs. The Pareto distribution for NSGA-II is closer to the true Pareto solution as highlighted in the red circle

Fig. 7 Comparison plot of Pareto solution obtain by RVEA, CMOPSO, NSGA-II and NSGA-III

Table 2 Time elapse for tested MOEAs

	NSGA-II	NSGA-III	RVEA	CMOPSO
Time (h)	4.4246	4.5211	4.541	6.9936

Table 3 Score of various events based on lap time

Events	Score, points	Measured parameters	Correlated objectives function
Acceleration	75	Lap time	t_{acc}
Autocross	100	Lap time	
Endurance	325	Lap time	
Efficiency	100	Fuel consumption	$fuel_{acc}$

in Fig. 7b. Furthermore, the solution was obtained with relatively shorter computation time as summarized in Table 2.

Even though the performance provided by CMOPSO and NSGA-II were comparable in the terms of the Pareto distribution and solution, the overall computational time for the optimization is 1.6 times slower than NSGA-II. Therefore, NSGA-II is selected for the fine-tuning stage due to the better Pareto distribution and faster optimization time.

Selection of the best optimized solution in the primary stage is based on the weighted score of the objectives function's contribution towards each event score. The score points of the competition are summarized in Table 3.

Acceleration time has a significant impact on the lap time in the Acceleration, Autocross and Endurance events. In addition, total fuel consumption of a vehicle has an impact on the energy efficiency used to evaluate vehicle

Table 4 Best optimized solution in the primary stage

Parameters	Values
i_z	0.7566
φ_1	1.2845
φ_2	1.1528
Shf_{rpm}	11,500
Dfs	1.8464

efficiency. Therefore, the selection criteria are formulated as follows:

$$Weighted\ Score = \sum \left(\frac{(75 + 100 + 325)}{600} \times normalize\ t_{acc} + \frac{100}{600} \times normalize\ fuel_{acc} \right) \quad (8)$$

The objectives function of t_{acc} and $fuel_{acc}$ are normalized into a range of [0 1]. The design with the highest weighted score was selected and summarised in Table 4.

In Fig. 8, it is demonstrated that the optimized power-train design has a wider gear ratio which covers all speed range compared to the base design (Fig. 3). The optimized shifting rpm limits the engine revolution overdrive after reaching the peak engine output, which resulted in a significant improvement in terms of fuel consumption.

The best optimized solution parameter showed in Table 4 was selected for further fine tune its performance. In fine tuning stage, each gear shifting rpm was treated independently in the optimization process for its best gear shifting strategy. It was optimized against the similar objectives function as primary stage using acceleration event. It follows by employed the similar weighted score method (Eq. 8) to selected the best optimum gear shifting strategy design. The final optimized

Fig. 8 Primary optimization—best optimize variable **Fig. 9** Pareto solution for fine-tuning optimization using NSGA-II **Table 5** Optimized gear shifting parameter for respective gears

Parameters	Values (rpm)
Shift gear 1	9902.3
Shift gear 2	10,670
Shift gear 3	8024.5
Shift gear 4	9963.1
Shift gear 5	11,245

Pareto solution is shown in Fig. 9. The selected optimized gear shifting parameters were summarized in Table 5 and its respective performance curve is presented in Fig. 10.

By varying the shift time between gears, it could give significant impact on the fuel consumption of the vehicle during acceleration (fuel consumption improved by 89.8% compared to base design). The overall

performance of the optimized design is summarized in Table 6 (performance count in the events are bolded).

It was obvious that through the fine-tuning of shift time between gears, it has provided significant improvement on the vehicle's fuel consumption in all types of events, which includes Autocross (+ 26.1%), and Endurance (+ 13.72%) with minimal sacrifice on the lap time in the acceleration event. The fuel consumption distribution is shown in Figs. 11 and 12 in which the optimized design enabled the vehicle to deliver maximum performance at the most efficient region where the BSFC was within the range of 350–500 g/KWh.

The greatest impact on lap time was observed in the acceleration event after fine-tuning (0.0368 s) as compared to the primary stage tuning. Other events such as Autocross and Endurance did not show any significant difference in lap time.

Fig. 10 Fine tuning optimization—best optimize variable **Table 6** Comparison between base design and optimized design for different events

Events	Base performance	Primary stage optimization	Fine-tuning stage optimization
Acceleration event			
Lap time (s)	4.4276	4.36 (+ 1.53%)*	4.3968 (+ 0.7%)*
Fuel consumption (L)	0.0634	0.04 (+ 36.9%)*	0.0334 (+ 89.8%)*
Autocross event			
Lap time (s)	79.69	78.33 (+ 1.71%)*	78.71 (+ 1.23%)*
Fuel consumption (L)	0.3088	0.256 (17.1%)*	0.2281 (+ 26.1%)*
Endurance event			
Lap time (s)	78.12	76.97 (+ 1.47%)*	77.23 (+ 1.14%)*
Efficiency rating	0.5636	0.5753 (+ 2.1%)*	0.6409 (+ 13.72%)*

*Percentage improvement is calculated based on optimized result against base performance

Fig. 11 Autocross event—Fuel consumption distribution

Fig. 12 Endurance event—Fuel consumption distribution

5 Conclusion

Advancement of simulation software and multi-objectives optimization algorithms have helped to perform design optimization at an early stage via software in-the-loop optimization. This paper demonstrated the possibility of employing the Acceleration event as a base performance measurement to optimize the powertrain design based on acceleration time and fuel consumption of the vehicle. Due to its linear correlation of the objectives function measured across various events including Acceleration, Autocross and Endurance, optimization of the Acceleration event would be sufficient to improve other events as well. In the primary stage of optimization, the progressive gear calculation method was used to generate the six-gear ratio and aerodynamic downforce scale values using the state-of-the-art MOEAs. The comparison study shows that NSGA-II outperformed others algorithms in terms of computational time consumed and Pareto solution obtained. In the subsequent fine-tuning stage, NSGA-II was employed to optimize the shift time between gears. The final optimized design showed a significant improvement over the base design for the respective performance i.e. acceleration lap time (+ 0.7%), autocross lap time (+ 1.23%), endurance lap time (+ 1.14%), and endurance efficiency rating (+ 13.72%). The proposed methodology had demonstrated an alternative approach of optimized preliminary design before prototyping a system. This will greatly reduce the time and cost required to develop multiple vehicle prototypes.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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