Optimization of the Calibration for an Internal Combustion Engine Management System Using Multi-Objective Genetic Algorithms

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Abstract- This paper proposes a multi-objective structure for the optimization of an engine control unit mapping. In this way, first an integrated engine-vehicle model is developed. The objective functions for the optimization problem can be defined from this model. After describing the structure of the optimization problem, two different multi-objective genetic algorithms, namely Distance-based Pareto Genetic Algorithm and Non-Dominated Sorting Genetic Algorithm (together with Entropy-based Multi-Objective Genetic Algorithm), are proposed and implemented. The results demonstrate the superiority of this computerized structure to the manual mapping methods and also more generality of the multi-objective methods compared to single-objective ones.

1 Introduction

The rising demands of better performance and fuel economy by consumers on one hand and the very restrict emission standards on the other, have forced the automotive industry to take prudent measures to face up to these challenges. To reach these ends, the role of vehicle engines and specifically their calibration is crucial. The calibration of an engine, or more exactly calibration of engine control unit (ECU), involves proper adjustments of parameters such as air-fuel ratio, spark advance, injection timing, EGR (Exhaust Gas Recirculation) percent, etc for different engine working conditions.

To fulfill the growing market demands, the level of complexity of internal combustion engines is increasing steadily and the number of the calibration parameters is rising, too. As a result, the classic methods of calibration, by manually setting the parameters on chassis-dynamometers, become more and more complicated, expensive, and time-consuming. Because of the correlation between these parameters and also the confusingly high number of output parameters, it is very difficult to ensure whether the obtained calibration is the best configuration or not.

Because of these problems, almost since the advent of electronics control of internal combustion engines, finding a way for computerizing the calibration process has been extremely appealing. The early efforts started in 1970's [1-3] where Ford and General Motors, two giants of vehicle industry, for the first time introduced an automated process for optimization of engine calibration. They used simple models for the engine and vehicle and also for the optimization algorithms. After this start, many researches have been contributed in this field. References [1-10] just include a few number of the many researches performed in this area. Almost in all of these studies, the approach to the problem was as a single-objective problem with the target of minimizing fuel consumption and satisfying standard emission limits as constraints. In this research multi-objective optimization techniques for simultaneous optimization of distinct objectives is used. As a natural specification of multi-objective methods, there is not a unique result, and the final calibration can be chosen from a set of results. This approach has several advantages, for instance the ability of selecting appropriate calibration for different levels of emissions.

2 Forming the Optimization Problem

In the single-objective optimization approaches such as [1-10], the optimization process usually consists of a constrained optimization problem, namely minimizing vehicle fuel consumption with the emission limit constraints. The vehicle performance (fuel consumption and emissions) depend on the vehicle and driveline specifications, as well as engine variables such as torque, fuel consumption and emission maps. These variables, in turn, depend on the ECU calibration and variables such as engine speed and throttle angle. Thus for obtaining engine fuel consumption and emission in terms of calibration parameters, an engine model is required. Because of highly complex and nonlinear nature of internal combustion engines (especially emission production mechanisms) neither the accurate physical modeling of these variables such as thermodynamic and fluid dynamic models is practical nor are the simple interpolation-based methods convenient for such usage. Therefore, most of the presented models are in the form of black-box models [11]. A very powerful method among black-box modeling techniques is neural network modeling which has been widely used in various branches of science and

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engineering in recent years. The good ability of neural networks for modeling nonlinear phenomena (because they are themselves nonlinear) together with their relatively simple application procedure, is the reason for their wide usage.

For this reason, in the following work, we use a neural network engine model proposed comprehensively in the former research [12]. In that work a neural network model is developed for Paykan-1600HC engine, an Iran-Khodro Co. product. Fig.1 shows the schematic representation of inputs and outputs of this model. As can be seen from this figure, the considered calibration variables are spark advance and air-fuel ratio (lambda/λ). The parameter "load" for a specific engine is only a function of the throttle angle, or identically MAP (Manifold Absolute Pressure), and thus they can be used interchangeably [12]. Also the engine speed, *N*, is a function of the engine's operational condition and is not a calibration parameter. Fig. 2 presents a typical output of this model, where two of four inputs are held constant so that one can represent the output in 3-D space.

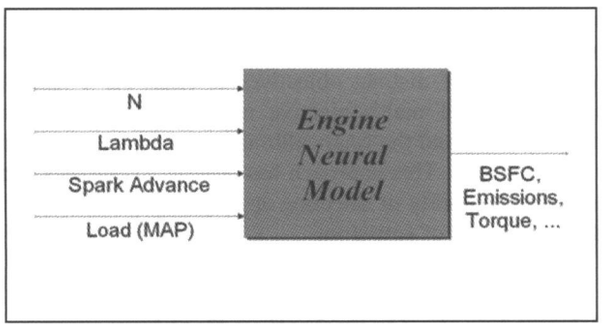

Figure 1. The Engine Model

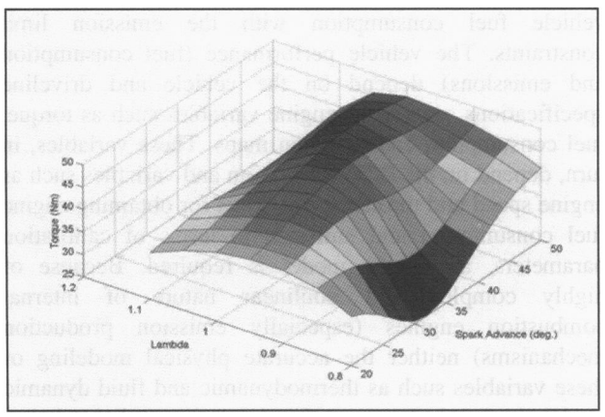

Figure 2. Engine Torque with respect to Lambda and Spark Advance at Engine Speed of 2000 rpm and Load of 45%.

Having this model is not sufficient for the optimization process. Because the objective function is defined in terms of vehicle parameters rather than engine's. As a result, a driveline model is required for converting the engine variables to vehicle variables [12]. The renowned basic formulation of the longitudinal vehicle dynamics for traction force, vehicle speed, and resistance force in terms of engine variables are [13]:

$$F_t = \frac{T\beta\eta}{R} - [(I_e + I_t)(\beta\beta_d)^2 + I_d\beta_d{}^2 + I_w] \times \frac{a}{R^2} \quad (1)$$

$$V = \begin{cases} \dfrac{R\omega_e(1-s)}{\beta\beta_d} & Accelerati\ ng \\ \dfrac{R\omega_e}{\beta\beta_d(1-s)} & Braking \end{cases} \quad (2)$$

$$F_r = \mu_R mg + \frac{1}{2} c_d \rho_{air} A V^2 \quad (3)$$

This basic formulation can be made more and more accurate by using more detailed models for different part of powertrain. These changes can, for example, consider the clutch slip, engine warm-up, etc. In this area, several different commercial softwares have been developed with accurate models and detailed simulation techniques. For this research one of these softwares named ADVISOR was used. ADVISOR is a MATLAB®-based code and can perform the required simulations with acceptable accuracy.

The detailed modeling procedure (for both engine and vehicle) has been proposed in [12] and thus it is not repeated here.

The parameters that are to be optimized are the vehicle's (not engine's) fuel consumption and emissions - which are computed by integration during a specific speed-time profile named as driving cycle. Fig. 3 depicts the diagram for the New European Driving Cycle (NEDC) [14], the driving cycle used for this research.

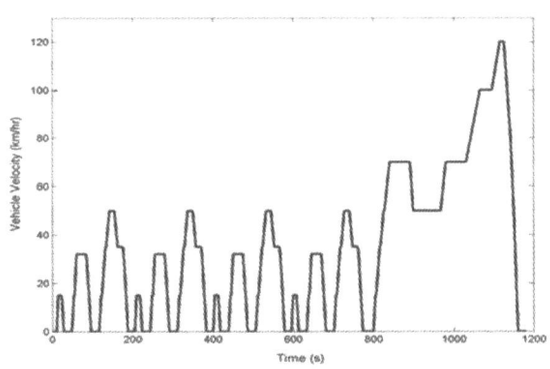

Figure 3. The NEDC Driving Cycle

The simulation results from ADVISOR for Paykan with the base ECU calibration during NEDC are as follows:

$$\begin{cases} \text{Fuel Consumption} = 9.3\ \text{lit/100km} \\ \text{HC} = 0.55\ \text{g/km} \\ \text{CO} = 1.6\ \text{g/km} \\ \text{NOx} = 0.582\ \text{g/km} \end{cases}$$

The objective is to simultaneously optimize these output variables by choosing the best calibration configuration. Assuming 16 discrete values for each of the two inputs engine parameters (which is common) there will be 16×16 points for each ECU maps. Hence, for two input parameters (lambda and spark advance) there are 512 possible input combinations, making the optimization using all of these independent variables unrealistic. The solution often used in similar researches [3,7] is based on the use of Lagrange's multipliers. Thereby, the objective function is defined as:

$$f(N,load,SA,\lambda) = \gamma_f \dot{m}_f + \gamma_{HC}\dot{m}_{HC} + \gamma_{CO}\dot{m}_{CO} + \gamma_{NOx}\dot{m}_{NOx} \quad (4)$$

or identically:

$$f(N,load,SA,\lambda) = \dot{m}_f + \gamma_{HC}\dot{m}_{HC} + \gamma_{CO}\dot{m}_{CO} + \gamma_{NOx}\dot{m}_{NOx} \quad (5)$$

where, the Lagrange's multipliers, γ_i's, are constant throughout the entire map during each step of optimization. For updating Lagrange's multipliers in each step, Cassidy [3] suggests a linear updating equation which is often used in many researches [7-9]:

$$\gamma_i^{new} = \gamma_i^{2} + \frac{\gamma_i^{2} - \gamma_i^{1}}{i_2 - i_1} \times (i^{des} - i^{2}) \quad (6)$$

where i is one of the emissions and superscripts *1* and *2* denote two successive updating steps.

One can see that eq. (6), itself, is an optimization problem which has been simply solved using linear updating. This method is convenient just for very simple and straightforward problems. But the present problem (i.e. updating of the Lagrange's multipliers) is a very complex optimization problem and has many local minimums. Actually, the major challenge in this problem is choosing the best set of Lagrange's multipliers. Therefore an "outer" optimization loop is introduced for obtaining the appropriate γ_i's. The formulation is as following:

$$(\gamma_{HC},\gamma_{CO},\gamma_{NOx}) = \min\{g\} \quad (7)$$

where, g denotes the objective function which is one-dimensional (often vehicle fuel consumption) for single-objective and multi-dimensional (parameters such as fuel consumption and emissions or combinations of them) in multi-objective optimizations. These parameters are the output of vehicle model for which ADVISOR has been used.

Having formulated the optimization problem, one can now apply any (multi-objective) optimization algorithm to find the best configuration(s) of ECU calibration.

3 Optimization Algorithms

For the optimization problem (7) two multi-objective genetic algorithms have been used. The first algorithm is DPGA (Distance-based Pareto Genetic Algorithm) which is one of the most renowned and prevelant multi-objective optimization algorithms. This algorithm has been proposed by Osyczca and Kundu [15,16]. The other algorithm, NSGA (Non-dominated Sorting Genetic Algorithm) [17], is used together with a supplementary algorithm named EMOGA (Entropy-based Multi-Objective Genetic Algorithm) which is proposed by Farhang-Mehr and Azarm [18, 19].

3.1 Distance-based Pareto Genetic Algorithm

The algorithm is based on the definition of distance of a point from non-dominated set. The distance of a point from each member of this set is defined by:

$$d_l(\underline{x}) = \sqrt{\sum_{i=1}^{M}\left(\frac{f_{il}^{\,p} - f_i(\underline{x})}{f_{il}^{\,p}}\right)^2} \quad l = 1,\ldots,l_p \quad (8)$$

The minimum of d_l's is referred to as the distance of a point from the non-dominated set. In this method, the fitness function of each point is assigned proportionally to the distance from the non-dominated set found so far. Therefore, the farther points will have higher fitness and so are more likely to remain in the next generation and help to broaden the search domain.

For fitness assignment, three different modes are considered:

- The current solution is a new member of non-dominated set but does not dominate another member of this set. In this case the fitness function is defined as:

  $$F = p + d(\underline{x}) \quad (9)$$

  where p is a parameter named latent potential, and p_{max} is its maximum value. In this case after this update, p_{max} will be set to F.
- The current solution dominates at least one of the members of non-dominated set. The fitness function is defined as:

  $$F = p_{\max} + d(\underline{x}) \quad (10)$$

  and then if $F > p_{\max} \Rightarrow p_{\max} = F$.
- None of the above conditions are satisfied. Then:

  $$F = \min\{0,[p - d(\underline{x})]\} \quad (11)$$

After each generation p will be set to p_{max} and the genetic operators (selection, crossover, and mutation) will be applied.

3.2 Non-Dominated Sorting Genetic Algorithm

This algorithm is based on the idea of using a parameter named sharing function. This function causes the points which are near together to be assigned lower fitness values. Considering some practical aspects, the sharing function is defined as following [17]:

$$Sh(d)=\begin{cases}1-\left(\dfrac{d}{\sigma_{share}}\right)^{\alpha} & \text{if } d\le\sigma_{share}\\ 0 & \text{otherwise}\end{cases} \tag{12}$$

And "niche count" denotes the sum of sharing functions:

$$nc_i=\sum_{j=1}^{N}Sh(d_{ij}) \tag{13}$$

Then the fitness is updated:

$$F_i'=\frac{F_i}{nc_i} \tag{14}$$

σ_{share} is a parameter that determines the "remote" distance. For the estimation of this parameter the dynamic method of Fleming and Fonseca [20] was used in this research.

NSGA fitness assignment is based on non-dominant classification; that is dividing the population to n separate sets which are ranked with respect to domination. In other words, the first set dominates all other members; the second set dominates the remaining members, and so on. Once the population is classified, the initial fitness is assigned to each set as follows:

$$F_j=F_{\min}'^{\,k-1}-\varepsilon \qquad (k=1,\ldots,n) \tag{15}$$

As can be inferred from the above equation, the initial fitness of the k'th set is considered ε units less then *(k-1)* set's minimum fitness, which is obviously logical.

After fitness assignment via the above procedure, standard genetic operators such as selection, crossover and mutation will be applied to the population to produce the next generation.

3.3 Entropy-based Multi-Objective Genetic Algorithm

Farhang-Mehr and Azarm [18,19] proposed a very interesting idea for increasing the diversity of solution of multi-objective genetic algorithms. Their method is based on the statistical thermodynamics theory for ideal gas. This idea originates from the fact that the particles in an ideal gas in an enclosure, move such that the entropy of becomes maximum. This phenomenon resembles the process of changing the members in a multi-objective optimization problem to obtain better diversity and the enclosure walls act like the variable boundaries.

This algorithm changes the coordinates of population members like as ideal gas molecules expand to maximize the entropy. The velocity of the particles of ideal gas obeys the Maxwellian distribution [21]:

$$f_v=\frac{dN_v}{dv}=\frac{2N}{\sqrt{2\pi}}\left(\frac{m}{kT}\right)^{3/2}.v^2.e^{-\frac{1}{2}\frac{mv^2}{kT}} \tag{16}$$

or with $\lambda = m/2kT$:

$$f_v=4\pi N\left(\frac{\lambda}{\pi}\right)^{3/2}.v^2.e^{-\lambda v^2} \tag{17}$$

In EMOGA, as in NSGA, in each generation the population is first classified with respect to non-domination. Then the progress vector for the i'th member of the m'th set is defined as:

$$\underline{C}_i=\frac{\sum_{k=N_1+N_2+\ldots+N_m+1}^{N_1+N_2+\ldots+N_{m+1}}\underline{Z}_{ki}}{N_{m+1}}-\frac{\sum_{k=N_1+N_2+\ldots+N_{m-1}+1}^{N_1+N_2+\ldots+N_m}\underline{Z}_{ki}}{N_m} \tag{18}$$

The lateral-movement vector is defined as the vector of random direction in the plane normal to the progress vector and with the length obtained from Maxwellian distribution (17).

To permit the population to move towards the Pareto optimal set, the expansion operator is applied not right from the start but after some generations have evolved. Also, for reducing the calculation time, this operator is not applied on the whole population.

4 Optimization Results

Having the proposed structure for calibration optimization, the optimized mapping can be easily obtained for different objective functions. In the most general case, the vehicle fuel consumption together with each emission comprises four objective functions for multi-objective optimization problem. The optimization process has been performed with both DPGA and NSGA-EMOGA methods. The parameters of these algorithms are listed in table 1. Almost all of the parameters are common in both methods. For EMOGA, λ (in eq. 17) has been considered 0.001 and for NSGA, ε (eq. 15) is 0.05.

Due to the limitation in computational platform used for this work (single-processor Pentium IV 2800 MHz with 512 Mb of RAM) the selected individual and generation numbers are almost at the maximum possible level. Each run with current platform took about 100 hours to complete. Therefore, for higher number of these parameters utilizing equipment such as multi-processor systems is inevitable.

For selection, Stochastic Universal Sampling (SUS) was used, which has some advantages compared to other selection methods [22].

Unfortunately, because the results are in 4-dimensional space, the Pareto optimal surface cannot be depicted for these cases. But to exemplify the procedure of choosing

Members	20
Max Generations	21
Bit Number	10
Selection Method	SUS
Coding	Gray
Crossover	Double-Point
Mutation	7%

Table 1. Common parameters of DPGA and NSGA-EMOGA methods

the best configuration for minimum fuel consumption, satisfying the emission level of 10% above Euro-1 standard is used as acceptable emission levels. Euro-1 standard limits are as following:

$$\begin{cases} CO = 2.72\,g/km \\ HC + NOx = 0.97\,g/km \end{cases}$$

The considered emission levels are 10% (case 1) and 20% (case 2) above this limit. In case 1, the minimum fuel consumption found by DPGA method is 8.66 lit/100km while by NSGA-EMOGA is 8.78 lit/100km. In case 2, DPGA results in a minimum fuel consumption of 8.29 and NSGA-EMOGA results in 8.30 lit/100km. A comparison between these results and the base ECU calibration (proposed in section 2) demonstrates the uneven distribution of emissions in the base calibration (low CO, but high fuel consumption, NOx, and HC) and therefore illustrates the superiority of computerized mapping to manual techniques. The output of this procedure is the EMS calibration parameter maps, namely lambda and spark advance. As an example, these maps for case 1 have been depicted in Figs. 4 through 7.

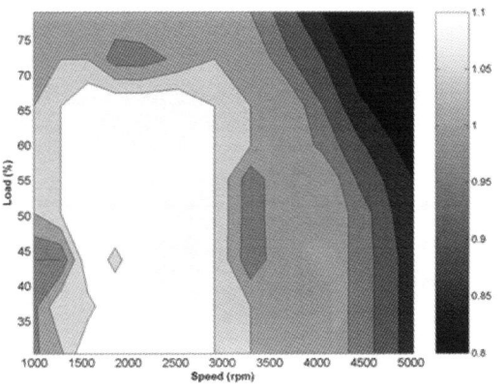

Figure 4. Lambda contours for DPGA - case 1

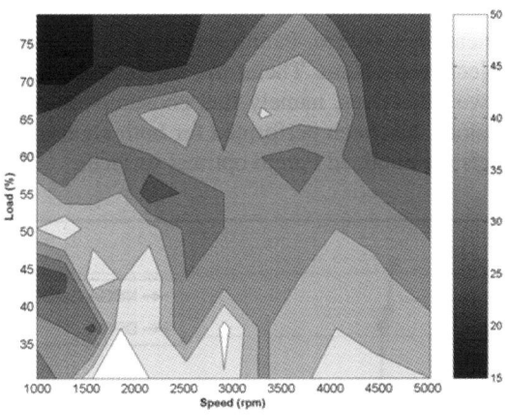

Figure 5. Spark advance contours for DPGA - case 1

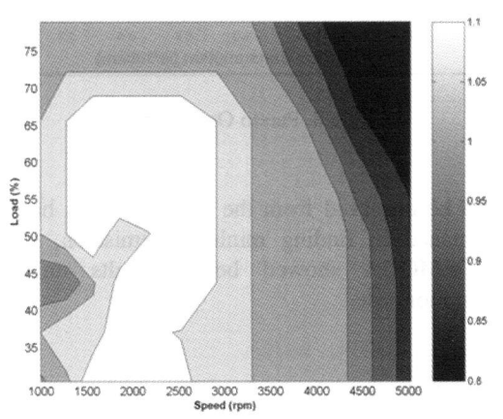

Figure 6. Lambda contours for NSGA-EMOGA - case 1

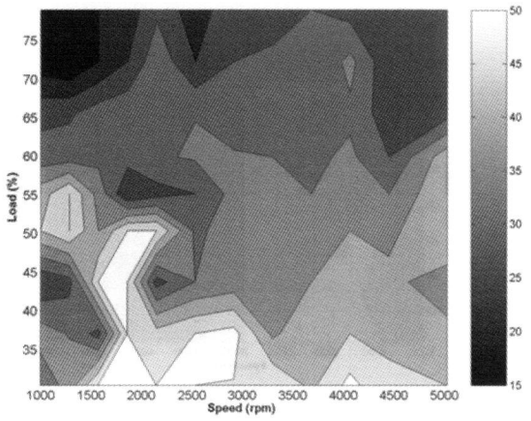

Figure 7. Spark advance contours for NSGA-EMOGA algorithm - case 1

As mentioned before, Pareto set cannot be shown for this 4-objective problem. Therefore, the optimization process for two objectives, namely fuel consumption and sum of emissions, has been performed for both algorithms. Fig. 8 depicts the obtained Pareto optimal surfaces.

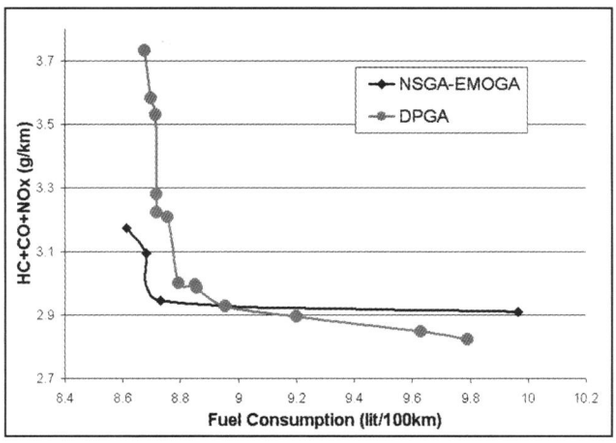

Figure 8. Pareto Optimal Surfaces

As can be observed from the figure, DPGA had a better performance in finding minimum emission, meanwhile NSGA-EMOGA showed better results on the fuel consumption side.

5 Conclusions

In this research, we proposed a structure for multi-objective optimization of ECU calibration parameters. In this way, two different multi-objective genetic algorithms were used for finding the best configuration of calibration parameters. Two case-studies were done on this multi-objective structure. In the first one, the most general problem, optimization of fuel consumption and all emissions, was considered while on the second case-study only two objectives, namely fuel consumption and sum of emissions, were taken into account. In the first study, DPGA had slightly better results, while in the second, two algorithms was more or less alike.

In general, one can say that none of these algorithms have an outstanding superiority to the other and therefore for the optimization problem, each one of them can be used. Although, both of these algorithms and generally speaking the computerized structure has a prominent advantage in comparison with the classic manual methods. On the other hand, compared to single-objective approaches, the proposed structure has the benefit of providing the ability of choosing an appropriate configuration for different emission levels as well as estimating the minimum emission level that the vehicle can provide with acceptable fuel economy.

6 Future Works

In spite of superior results (compared to the manual calibration) achieved in this work, there are still many aspects for further investigation. Definitely the most important matter is utilizing better computational platforms for more individual and generation numbers. On the other hand because the focus in this research was on development of a multi-objective structure for calibration optimization, there was no study concerning the types of MOEA's used or their parameters. Hence these aspects will also remain for future works.

Nomenclature

a	Vehicle Acceleration
A	Vehicle Frontal Area
C	Progress Vector in EMOGA
c_d	Drag Coefficient
d	Distance
f	Objective Function
F	Fitness Function
$\boldsymbol{F'}$	Corrected Fitness Function
F_r	Resistance Force
F_t	Traction Force
g	Gravity – Objective Function
I_d	Final Drive Moment of Inertia
I_e	Engine Moment of Inertia
I_t	Transmission Moment of Inertia
I_w	Wheel Moment of Inertia
k	Boltzman Constant
m	Mass

$\dot{m}_i$	Mass Flow Rate (i = HC, CO, NOx, or Fuel)
N	Number of Ideal Gas Molecules
N_v	Number of Gas Molecules with Speed v
R	Wheel Radius
s	Tire Slip
T	Engine Torque - Temprature
V	Vehicle Speed
v	Velocity of Ideal Gas Particles
x	Members
Z_{ki}	Vector Connecting k'th Member to i'th
β	Gearbox Ratio
β_d	Final Drive Ratio
γ_i	Lagrange's Coefficient (i = HC, CO, NOx, or Fuel)
η	Transmission Mechanical Efficiency
μ_R	Rolling Friction Coefficient
ρ_{air}	Air Density
σ_{share}	Sharing Parameter
ω_e	Engine Speed

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