Designing Heavy-Duty Vehicles’ Four-Parameter Driving Cycles to Best Represent Engine Distribution Consistency

MAN ZHANG1, WENDONG CHENG1, AND YUNBO SHEN1

School of Mechatronic Engineering, Xi’an Technological University, Xi’an 710021, China

Corresponding author: Man Zhang (m15104682686@163.com)

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ABSTRACT

The driving gear affects engine transient cycles. Current methods of designing engine transient cycles need to establish the shift model of the transmission system, and the differences from the actual driving shift law result in the quantitatively low consistency of engine transient test cycles. Then the representativeness and accuracy of the designed engine transient and steady-state test cycles will be worse. By expanding the Markov chain evolution (MCE) framework, in this study, four-parameter driving cycles with gear for heavy-duty vehicles are designed, which can represent the consistency of the engine cycle distribution. The Markov chain model-based multi-parameter state transition with gear information is constructed to be used as constraints to design the genetic operators; engine characteristic model-based parameters are calculated as the constraints for designing the objective function. Multi-parameter vehicle driving cycles are thus generated by the expanded MCE framework and then transformed into engine transient test cycles. The designed driving cycles were verified and analyzed using the data collected from a heavy-duty vehicle. The results showed that the driving parameters and fuel consumption per 100 km between the designed driving cycles and the collected database met the threshold deviation; the correlation coefficients of the distributions related to gear utilization, vehicle specified power (VSP), and engine cycles reached as high as 90%; and multiple results had the same effect as mentioned above. Compared with a conversion method based on the economical shift rule, the fuel consumption rate distribution in this study can be closer to the actual engine running conditions.

INDEX TERMS

Driving gear, engine distribution, heavy-duty vehicle, vehicle driving cycles, fuel consumption.

NOMENCLATURE

MCE Markov chain evolution
VSP Vehicle specified power/ (Kw/ton)
WHSC World harmonized steady-state cycle
TPM Transition probability matrix
PKE Positive kinetic energy per distance/ (m/s²)
OD-C Collected database of congested condition
DC-C Designed cycle of congested condition
CC-C Contrast cycle of congested condition
OD-F Collected database of free-flow condition
DC-F Designed cycle of free-flow condition
CC-F Contrast cycle of free-flow condition
OD-H Collected database of highspeed condition
DC-H Designed cycle of highspeed condition
CC-H Contrast cycle of highspeed condition
2D-NT Two-dimensional engine speed and torque distribution
3D-NT Three-dimensional engine speed and torque distribution

I. INTRODUCTION

The engine bench test is an important means to evaluate the energy consumption and emission of heavy-duty diesel vehicles. Presently, the European Steady-State Cycle and World Harmonized Steady-State Cycle (WHSC) standards are adopted as engine test cycles for heavy-duty engine emission and fuel consumption in China. However, it is well
known that the fuel consumption and emission level of the regulatory cycles deviate greatly from the results of actual driving cycles [1]–[3]. To promote the renewal of relevant regulations and technologies, it is necessary to study and authenticate engine transient and steady-state test cycles to reflect the actual running situation in China. Many studies have shown that the driving gear affects engine transient cycles [4]–[6]. Engine steady-state cycles based on the specific shift model reduce the accuracy of actual engine performance, and even affect the design of vehicle components [7]. The objective of this study is to design engine transient test cycles considering the influence of the driving gear, which can reflect the actual running condition, to improve the accuracy of evaluating engine fuel economy and emission performance, and provide an approach for rectifying current design methods.

A comprehensive review of many studies shows that there are two types of methods for designing engine transient test cycles. One is the direct method, which is less studied than other methods. The engine transient test cycle is designed by directly using the engine parameter series collected from the engine control unit. Reference [8] used the engine speed and torque to define the micro-trips, and used the micro-trip clustering method to obtain a satisfactory transient test cycle by combining the time series of the speed and torque. However, the method is only suitable for urban roads. The particular driving environment for heavy vehicles is highways. Based on data collected from the engine control unit, [9] used the vehicle speed to define a micro-trip database to determine the engine parameter micro-trip database; micro-trips were combined to obtain engine transient test cycles in different driving modes to analyze the engine emissions between the actual running condition and standard cycles. However, this type of method only uses the speed series to define micro-trips, and the generated engine transient test cycles cause unreasonable situations that the micro-trip connection does not meet the actual road slope design. Therefore, this method is not suitable for designing engine transient test cycles when considering the road slope environment.

The other type of method for designing engine transient test cycles is the conversion method, whose technical route is to convert vehicle representative driving cycles from a large number of actual road tests to engine transient test cycles, which are then transformed into engine steady-state test cycles using a statistical method. The WHSC is designed by the World Transient Vehicle Cycle using the conversion method. In [10], using the segment combination method to design the vehicle cycles including speed and acceleration, a simulation model was established to obtain engine transient cycles using AVL CRUISE software. As a result, the gear proportion and engine distribution were approximately the same as those of the actual condition. In [11], based on vehicle representative driving cycles, engine transient test cycles were obtained using the calibrated transmission system model. However, the researchers indicated that the influence of the driver shift rule led to a large deviation between the calculation result and the test result of the engine cycles. Reference [12] explored the construction of engine transient test cycles of a heavy vehicle, and proposed its technical flow. Based on collected vehicle driving cycles, it is necessary to excavate the inductive shift rule and build the transmission system model to design vehicle shift decision software. However, there are significant variations in the actual driving gears because of large differences in shift strategies and driver intentions. This results in complex engine and transmission system configuration types, and makes the transmission model difficult to calibrate [13]. Additionally, a large number of studies strengthened the representativeness of vehicle driving cycles considering the influence of the road slope on vehicle fuel consumption [14], [15]; however, they did not further analyze the engine distribution. The conversion method cannot design engine transient test cycles without vehicle representative driving cycles. Its advantage is that the influence of vehicle speed, acceleration, and road slope on the generated cycles can be considered. The problem of this type of method is that it is necessary to establish the shift model of the transmission system, which is different from the actual driving shift rule, and the difference results in the quantitatively low consistency of engine transient test cycles. It further reduces the representativeness and accuracy of engine transient and steady-state test cycles.

The contribution of this study is to consider the influence of the driving gear on engine test cycles and avoid the construction of the actual shift model, which is not easy to calibrate using the current conversion method. Based on the Markov chain model, the four-parameter state transition relationship with gear information is constructed as constraints to design the genetic operators; based on the engine characteristic models, the vehicle driving and fuel consumption parameters are calculated as the constraints for designing the objective function. An improved MCE framework is thus designed to generate the multi-parameter vehicle driving cycles with the gear parameter, which can actually reflect the transmission system shift law. Additionally, vehicle driving cycles are converted into engine transient test cycles, which can closely reflect the actual running conditions and ultimately be used for the design and certification of engine steady-state cycles.

This paper is organized as follows: In Section II, the relevant theoretical models are introduced. In Section III, an improved MCE framework is established from two aspects. Based on the Markov chain model, the four-parameter state transition relationship with gear information is constructed as constraints to design the evolutionary operators; based on the engine characteristic models, the vehicle driving and fuel consumption parameters are calculated as the constraints for designing the objective function. In Section IV, the designed results are analyzed and verified in terms of representativeness and engine distribution consistency, and compared with a conversion method based on the economic shift strategy. In Section V, the conclusion and future work are presented.
II. RELEVANT THEORETICAL MODELS

A. ENGINE UNIVERSAL CHARACTERISTICS AND EXTERNAL CHARACTERISTICS MODEL

To calculate the fuel consumption of the collected driving data as the constraint index, engine characteristic models needed to be established. The engine model was generally based on steady-state test data; engine characteristics empirical model was formulated using data polynomial fitting or data interpolation. The engine universal characteristic model is expressed in (1) [16].

\[ b_e (T_e, n_e) = \sum_{i=0}^{n} \sum_{j=0}^{i} \left( a_{i-j} \cdot T_e^{i-j} \cdot n_e^j \right) \]  

where, \( b_e (T_e, n_e) \) is the engine fuel consumption rate, \( g/(kw \cdot h) \); \( n \) is the engine universal characteristics fitting order; and \( a_{i-j} \) is the engine universal characteristic fitting coefficient. The number of coefficients is \((n + 1) (n + 2) / 2\).

The coefficients \( a_{i-j} \) were calculated using the least square method from the test data.

\[
\begin{bmatrix}
a_{0,0} & a_{1,0} & \cdots & a_{0,n} \\
\end{bmatrix}
= \sum_{i=1}^{k} \begin{bmatrix}
k \cdot \sum_{i=1}^{n} T_{ei} \cdot n_{ei}^0 & \cdots & k \cdot \sum_{i=1}^{n} T_{ei} \cdot n_{ei}^n \\
\sum_{i=1}^{k} T_{ei} \cdot n_{ei}^0 & \cdots & \sum_{i=1}^{k} T_{ei} \cdot n_{ei}^n \\
\vdots & \vdots & \vdots \\
\sum_{i=1}^{k} b_{ei} \cdot T_{ei} \cdot n_{ei}^0 & \cdots & \sum_{i=1}^{k} b_{ei} \cdot T_{ei} \cdot n_{ei}^n \\
\end{bmatrix}^{-1}
\]

where, \( k \) is the \( s \) test data point of the universal engine characteristic; \( n_{ei}, T_{ei} \) and \( g_{ei} \) represent the speed, torque, and fuel consumption rate, respectively. These correspond to the \( i \)th point of the universal engine characteristic of the test data.

Equation (3) expresses the polynomial fitting model of external engine characteristics

\[ T_e (n_e) = \sum_{i=0}^{k} c_i \cdot n_e \]  

Here, \( k \) is the external engine characteristic fitting order; and \( c_i \) is the engine external characteristic fitting coefficient \( i = 0, 1, \ldots, k \). In the same way, the least squares method was used to generate the fitting coefficient, as shown in (4):

\[
\begin{bmatrix}
c_0 \\
c_1 \\
\vdots \\
c_k \\
\end{bmatrix}
= \begin{bmatrix}
w \cdot \sum_{i=1}^{w} n_{ei}^0 & \cdots & w \cdot \sum_{i=1}^{w} n_{ei}^k \\
\sum_{i=1}^{w} n_{ei}^0 & \cdots & \sum_{i=1}^{w} n_{ei}^k \\
\vdots & \vdots & \vdots \\
\sum_{i=1}^{w} b_{ei} \cdot T_{ei} \cdot n_{ei}^0 & \cdots & \sum_{i=1}^{w} b_{ei} \cdot T_{ei} \cdot n_{ei}^k \\
\end{bmatrix}^{-1}
\]

where, \( w \) is the number of data points for the external engine characteristic test.

Therefore, the fuel consumption rate of the engine was calculated using (1), based on the engine output torque and speed. The instantaneous fuel consumption of the vehicle was then generated using (5)

\[ q = b 3600 \cdot n_e \cdot T_e \cdot \rho 9550 \]  

Here, \( \rho \) is the diesel density, with a value of 0.84 g/ml.

B. MARKOV CHAIN MODEL FOR VEHICLE DRIVING CYCLES

The conversion method for designing the engine transient test cycles cannot be separated from the representative vehicle driving cycles. The random characteristic of driving cycles, namely the Markov property, provides the foundation for designing driving cycles. The Markov chain follows the definition.

For any positive integer \( n \) and \( i_0, i_1, \ldots, i_{n-1}, i, j \) from \( D \), a random sequence \( X_n \) satisfied (6):

\[ P (X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_0 = i_0) = P (X_{n+1} = j | X_n = i), \quad i, j \in D \]  

where, \( X_0 \) is the initial state; \( X_n \) is the state in the \( n \)th step; \( D \) is the state space; and \( X_n \) is called by the time-homogeneous Markov chain [17]. Equation (7) and (8) express the Markov chain transition probability and the one step state transition probability matrix (TPM).

\[ P (X_{n+1} = j | X_n = i), i, j \in D \]  

\[ P = (p_{ij})_{i,j \in D} \]
III. DESIGN OF FOUR-PARAMETER DRIVING CYCLES BASED ON AN EXTENDED MCE FRAMEWORK

The Markov chain evolution (MCE) framework [18] is used in this study, which combines random simulation sampling with genetic evolution to effectively improve design efficiency. In this study, emphasis should be placed on the improvement of the objective function and genetic operators; thus, the application of the MCE framework is expanded, as shown in Fig. 1. Specifically, based on the Markov chain model, the four-parameter state transition relationship with gear information is constructed as constraints to design the evolutionary operators, and based on the engine characteristic models, the vehicle driving and fuel consumption parameters are calculated as the constraints for designing the objective function. Finally, based on the MCE framework, the initial population of a certain size of driving cycles is evolved iteratively until a satisfactory driving cycle is output.

![Diagram of the MCE method considering performance and driving constraints.](image)

**FIGURE 1. Framework diagram of the MCE method considering performance and driving constraints.**

**A. DESIGN OF GENETIC OPERATORS MEETING THE FOUR-PARAMETER STATE TRANSITION CONSTRAINTS**

Firstly, the multi-parameter state transition matrix including gear information was constructed. The Markov chain requires that the states be discretized. Therefore, constructing a four-parameter Markov chain model included the following steps. The first step was to set the values for the interval and range of each parameter to establish the parameter states. The velocity, acceleration, grade, and gear values ranged from 0 to \( v_{\text{max}} \), \( a_{\text{min}} \) to \( a_{\text{max}} \), from \( g_{\text{min}} \) to \( g_{\text{max}} \), and from 0 to \( g_{\text{max}} \), respectively. The intervals for the four parameters were \( v_{\text{gap}} \), \( a_{\text{gap}} \), \( g_{\text{gap}} \), and 1, respectively. The second step was to establish the idle state, which corresponded to intervals of 0 to \( v_{\text{gap}} \) m/s, from \( -a_{\text{gap}} \) to \( a_{\text{gap}} \) m/s², from \( -g_{\text{gap}} \) to \( g_{\text{gap}} \) %, and from 0 to 0 for velocity, acceleration, grade, and gear values, respectively. The third step was to calculate the states by using interval states to represent the parameter value in a certain interval. The state \( m_t \) of velocity of \( v_t \) in the \( t \) step was:

\[
m_t = \left\lfloor \frac{v_t}{v_{\text{gap}}} \right\rfloor + 1 \tag{9}
\]

The state \( n_t \) of acceleration \( a_t \) in the \( t \) step was:

\[
n_t = \left\lfloor \frac{(a_t - a_{\text{min}})}{a_{\text{gap}}} \right\rfloor + 1. \tag{10}
\]

The state \( g_t \) of road grade \( g_t \) in the \( t \) step was:

\[
p_t = \left\lfloor \frac{(g_t - g_{\text{min}})}{g_{\text{gap}}} \right\rfloor + 1. \tag{11}
\]

The gear itself was an integer, so the gear values plus 1 were used to represent the gear states \( s_t \) in the \( t \) step.

The number of states was then generated using:

\[
M = \left\lfloor \frac{v_{\text{max}}}{v_{\text{gap}}} \right\rfloor + 1, \quad N = \left\lfloor \frac{(a_{\text{max}} - a_{\text{min}})}{a_{\text{gap}}} \right\rfloor + 1, \quad W = \left\lfloor \frac{(g_{\text{max}} - g_{\text{min}})}{g_{\text{gap}}} \right\rfloor + 1 \quad \text{and} \quad s_{\text{max}}+1, \text{for velocity, acceleration, grade, and gear respectively.}
\]

When constructing the four-parameter Markov chain model, the current state \( d_t \) in the multi-dimensional space was calculated by the velocity state \( m_t \), acceleration state \( n_t \), slope state \( p_t \), and gear state \( g_t \):

\[
d_t = m_t + (n_t - 1) \cdot M + (p_t - 1) \cdot N + (g_t - 1) \cdot M \cdot N \cdot W.
\]

Then, the multi-dimensional state space was transformed into a one-dimensional state space. The state transition matrix \( P \) of the four-parameter driving cycles was then solved using the maximum likelihood estimate, shown in (13):

\[
P = \begin{bmatrix}
    P_{11} & P_{12} & \cdots & P_{1j} & \cdots & P_{1N_d} \\
    P_{21} & P_{22} & \cdots & P_{2j} & \cdots & P_{2N_d} \\
    \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
    P_{N_d1} & P_{N_d2} & \cdots & P_{N_dj} & \cdots & P_{N_dN_d}
\end{bmatrix}, \quad i,j \in D
\]

where, \( p_{ij} = N_{ij} / N_i ; \quad N_i = \sum_{j=1}^{N_d} N_{ij} ; \) and \( N_{ij} \) was the number of transitions from state \( i \) to state \( j \). The variable \( N_i \) was the number of transitions from state \( i \) to other states, and \( p_{ij} \) was the transition probability from state \( i \) to state \( j \). The variable \( D \) was the set of states in the one-dimensional space, and \( N_d \) was the number of states in a one-dimensional space.

The four-parameters state transition matrix is used to design the genetic operators, which can refer to [18]. Specifically, the two generated driving cycles were required to satisfy the four-parameter state transition relationship in the crossover operator. The process of constructing a single driving cycle for the initial population was used as a mutation operator, providing new state information for the population.

**B. DESIGN OF OBJECTIVE FUNCTION CONSIDERING DRIVING GEAR AND FUEL CONSUMPTION CONSTRAINTS**

The design goal was to have the specified evaluation indices between the driving cycle sequence and the collected data meet the relative deviation constraints, as shown in (14):

\[
|I_{d\text{t}} - I_{d\text{t}}(X)| \leq e_i, \quad (i = 1, 2, \ldots, n), \quad n = 13 \tag{14}
\]

where, \( X \) is the designed driving cycle; and \( I_d \) is the characteristic parameter value of the collected data; \( I_d \) is the characteristic parameter value of the designed driving cycle; \( e \) is the allowable deviation; and \( n \) is the number of evaluation indices.
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Figure 2. Test driving routes (red-urban road, green-highway, black-suburb road).

Figure 3. Engine universal characteristic diagram of test vehicle.

Table 1. Characteristic parameters of micro-trips.

| Micro-trip | 1     | 2     | 3     | 75    | 76    | 77    |
|------------|-------|-------|-------|-------|-------|-------|
| \(P_i\)%   | 1.852 | 1.159 | 3.922 | 15.62 | 2.688 | 3.106 |
| \(P_a\)%   | 0.929 | 1.325 | 10.78 | 11.32 | 3.763 | 1.863 |
| \(P_d\)%   | 52.91 | 44.87 | 68.63 | 66.79 | 12.36 | 21.73 |
| \(P_c\)%   | 44.97 | 53.80 | 17.64 | 6.641 | 82.25 | 73.91 |
| \(\nu_{max}/m/s\) | 1.771 | 1.839 | 5.840 | 19.25 | 3.487 | 2.011 |
| \(\sigma_{max}/m/s^2\) | 0.563 | 0.492 | 3.426 | 10.46 | 0.424 | 0.414 |
| \(\sigma_{cruise}/m/s^2\) | 0.321 | 0.305 | 0.331 | 0.511 | 0.381 | 0.399 |
| \(\sigma_{accel}/m/s^2\) | -0.257 | -0.347 | -0.458 | -1.199 | -0.416 | -0.297 |
| \(\sigma_{decel}/m/s^2\) | -0.251 | 0.243 | 0.228 | 0.369 | 0.264 | 0.273 |
| \(\sigma_{down}/m/s^2\) | -0.128 | -0.269 | -0.313 | -0.612 | -0.312 | -0.183 |
| \(\nu_{ave}/m/s\) | 0.902 | 0.952 | 4.147 | 11.20 | 2.347 | 1.042 |

Driving indices related to common velocity, acceleration, dynamics, and slope including idle time ratio \(p_i\), %; acceleration time ratio \(p_a\), %; cruise time ratio \(p_c\), %; deceleration time ratio \(p_d\), %; average velocity \(\nu_m\), m/s; average driving velocity \(\nu_{dm}\), m/s; driving velocity standard deviation \(\nu_{std}\), m/s; kinetic energy unit distance \(PKE\), m/s²; average climbing \(g_{am}\), %; average downhill \(g_{dm}\), %; and the velocity and acceleration joint probability distribution correlation coefficient, \(c_{va}\), %.

Considering the constraint of gear parameters for analyzing the gear distribution consistency, a statistic \(\alpha_{AB}\) is introduced as the evaluation index to test whether the probability distribution of two discrete variables is equal.

\[
\alpha_{AB} = \sum_{i=1}^{K} \min \{ A(i), B(i) \} \quad (15)
\]

where \(A\) and \(B\) are two discrete variable distributions, \(0 \leq \alpha_{AB} \leq 1\), which are called the similarity coefficients of two samples. \(\alpha_{AB}\) represents the shared area of the two probability distributions, that is, the overlapping area. Additionally, the value reflects the similarity of the two samples. The larger the value, the higher the consistency of the two distributions. It can directly reflect the consistency of the

Table 2. Principal component contribution and cumulative contribution.

| | Eigenvalue | Contribution/% | Cumulative contribution/% |
|---|------------|----------------|--------------------------|
| M1 | 6.333 | 57.57 | 57.57 |
| M2 | 2.461 | 22.38 | 79.95 |
| M3 | 0.880 | 8.00 | 87.95 |
| M4 | 0.674 | 6.13 | 94.09 |
| M5 | 0.419 | 3.81 | 97.90 |
| M6 | 0.116 | 1.06 | 98.96 |
| M7 | 0.064 | 0.59 | 99.54 |
| M8 | 0.030 | 0.28 | 99.82 |
| M9 | 0.016 | 0.15 | 99.97 |
| M10 | 0.003 | 0.03 | 100 |

Table 3. Scores of each principal component.

| Sample number | First principal component | Second principal component | Third principal component |
|---------------|---------------------------|-----------------------------|---------------------------|
| 1             | 1.757                     | 0.107                       | 0.863                     |
| 2             | 1.459                     | 0.368                       | 0.339                     |
| 3             | 2.316                     | -1.835                      | 1.252                     |
| ...           | ...                       | ...                         | ...                       |
| 75            | 4.318                     | -0.060                      | -1.475                    |
| 76            | 4.073                     | -0.284                      | -1.240                    |
| 77            | 0.405                     | 0.225                       | 0.695                     |
driving gear distribution between the designed driving cycles and the actual driving cycles.

Additionally, the performance index $Q$ of fuel consumption per 100 kilometers was considered to be a reflection of the consistency of engine distribution.

Using normalization, equation (14) can be transformed into (16). Using the auxiliary function shown in (17), equation (16) was transformed into (18). Thus, complex multi-objective function was transformed into a simple single objective function:

$$f_i(X) = \left| 1 - \frac{I_i(X)}{I_{oi}} \right|, \quad \bar{f}_i = \frac{e_i}{I_{oi}} = \Delta_i$$ (16)

$$T_i(X) = f_i(X) + \bar{f}_i - \min(f_i(X), \bar{f}_i)$$ (17)

$$F = \min_{x \in D} \left( \frac{1}{n} \sum_{j=1}^{n} T_j (X) \right)$$ (18)

Here, $T$ is the auxiliary function; $x$ is the cycle state; and $F$ is the objective function of the driving cycles.

IV. VERIFICATION AND ANALYSIS OF DRIVING CYCLES FOR DIFFERENT ROAD TYPES

A. TEST ROUTE AND DATA COLLECTION

This study examined the case study of a heavy-duty vehicle with a total weight of 23 tons. The vehicle was assumed to travel on different road types along the route from Yanji.
City to Jilin City in Northeast China, as shown in Fig. 2. The red lines, black lines, and green lines represent the urban roads, suburb road, and highway road, respectively, with associated travel distances of 26.25 km, 77.02 km, and 337.02 km respectively. The vehicle was equipped with DEWE-50 equipment and acceleration sensor. The CAN bus signal and acceleration sensor signal can be synchronously obtained during driving. Collected parameters included latitude and longitude, vehicle velocity, engine speed, elevation, and other factors. Acceleration information was derived from the vehicle velocity and was processed using low-pass filtering. The road grade was obtained using offline estimation [19]. By omitting the wheel slip and clutch friction, the gear information extraction method was used to determine the relationship between vehicle velocity and engine speed; the driving gear can be determined by calculating the transmission ratio as shown in (19).

\[ v = 3.6 r_R \cdot \omega = 3.6 r_R \cdot \frac{2 \pi n_e}{60} \cdot \frac{1}{i_g \cdot i_0} = 0.377 \cdot \frac{r_R \cdot n_e}{i_g \cdot i_0} \]  

(19)

where, \( v \) is the driving velocity, km/h; \( r_R \) is the wheel radius, m; \( \omega \) is the wheel speed, r/s; \( n_e \) is the engine speed, r/min; \( i_g \) is the transmission ratio; and \( i_0 \) is the transmission ratio of main reducer.

The transmission ratios of each gear and the basic dynamic parameters of the vehicle are found in [20]. The engine output torque was calculated using the vehicle driving equilibrium equation, in (20). The collected data were used to analyze and
TABLE 4. Evaluation indices between the multi-parameter driving cycles of three driving conditions and the original data.

| Index | Original database | Driving cycles | Relative deviation absolute value/% |
|-------|-------------------|----------------|-------------------------------------|
|       | Congested | Free-flow | Highspeed | Congested | Free-flow | Highspeed | Congested | Free-flow | Highspeed |
| $p_e$ | 1.15      | 39.86 | 14.49 | 0.96 | 39.17 | 15.92 | 1.00 | 1.73 | 9.81 | 4.16 |
| $p_s$ | 21.63 | 42.12 | 40.11 | 19.50 | 38.33 | 40.11 | 9.84 | 7.80 | 0.01 |
| $P_r$ | 17.21 | 9.99 | 21.04 | 18.50 | 10.67 | 22.83 | 7.51 | 6.77 | 8.51 |
| $P_i$ | 21.31 | 33.40 | 37.89 | 22.83 | 34.58 | 36.06 | 7.16 | 3.55 | 4.84 |
| $v_e$ (m/s) | 0.902 | 6.422 | 20.41 | 0.895 | 6.394 | 21.32 | 0.81 | 0.43 | 4.46 |
| $v_{in}$ (m/s) | 0.900 | 6.422 | 20.41 | 0.895 | 6.394 | 21.32 | 0.60 | 0.43 | 4.46 |
| $v_{id}$ (m/s) | 1.220 | 4.961 | 5.426 | 1.109 | 4.616 | 4.906 | 9.13 | 6.95 | 9.58 |
| $\text{PK}(\text{m}^3)$ | 0.070 | 0.143 | 0.071 | 0.064 | 0.134 | 0.078 | 8.13 | 6.22 | 9.86 |
| $\text{g}_{\text{MW}}$% | 0.016 | 0.016 | 0.013 | 0.014 | 0.014 | 0.014 | 8.12 | 7.95 | 7.26 |
| $\text{g}_{\text{ME}}$% | -0.015 | -0.015 | -0.014 | -0.013 | -0.016 | -0.013 | 9.92 | 9.86 | 4.07 |
| $\text{O}_{(l/100km)}$ | 43.54 | 31.11 | 28.01 | 43.07 | 33.30 | 26.55 | 1.07 | 7.06 | 5.18 |
| $\text{c}_{\text{av}}$% | 0 | 0 | 0 | 0 | 0 | 0 | 9.32 | 9.98 | 9.86 |
| $\text{a}_{\text{av}}$% | 0 | 0 | 0 | 0 | 0 | 0 | 0.88 | 4.63 | 9.60 |

verify the vehicle driving cycles.

$$T_e (n_e) \cdot i_k \cdot i_0 \cdot n_0 = m \cdot g \cdot \sin \alpha + m \cdot g \cdot f + \frac{1}{2} \cdot C_D \cdot A \cdot \rho \cdot v^2 + m \cdot \delta (i_k) \cdot a_j$$  \hspace{1cm} (20)$$

where, $T_e (n_e)$ is the engine required torque, N·m; $\eta_0$ is the transmission efficiency; $C_D$ is the drag coefficient; $A$ is the windward area of vehicle, m²; $v$ is the velocity, km/h; $m$ is the vehicle mass, kg; $\alpha$ is the road slope, (°); $f$ is the vehicle rolling resistance coefficient; $\delta$ is the conversion factor of vehicle rotation mass, as shown in (21); and $a_j$ is the vehicle acceleration, m/s².

$$\delta (i_k) = 1 + \frac{I_w}{m \cdot R^2} \cdot \frac{i^2_k \cdot i^2_0 \cdot \eta_0}{m \cdot R^2}$$ \hspace{1cm} (21)$$

Here, $I_w$ is the inertia moment of the wheel, kg·m²; and $I_f$ is the inertia moment of the flywheel, kg·m².

Based on the bench test data of the vehicle engine, combined with the model establishment method discussed in Section II-A, the final torque fitting order of the engine external characteristics was found to be 5, and the universal characteristic fitting order was found to be 8. Fig. 3 shows the universal engine characteristic diagram.

B. CLASSIFICATION OF DRIVING CYCLES BASED ON CHARACTERISTIC PARAMETERS USING PRINCIPAL COMPONENT AND K-MEAN CLUSTERING

To analyze the influence of driving gear on vehicle performance under different driving conditions, this study divides the driving data into a new database by defining the micro-trip, extracts the common characteristic parameters; and adopts the principal component analysis and K-means clustering [21] to obtain three kinds of driving cycles, which represent the vehicle driving characteristics in different traffic conditions.

The idle state is defined as a state, velocity of which is less than 0.5 m/s, and the driving data is divided into 77 micro-trips. The 11 characteristic parameters of each micro-trip are calculated using the Matlab, including acceleration time ratio $p_a$, %; deceleration time ratio $p_d$, %; cruise time ratio $p_c$, %; idle time ratio $p_i$, %; maximum velocity $v_{max}$, m/s; average velocity $v_{av}$, m/s; maximum acceleration, $a_{max}$, m/s²; minimum acceleration, $a_{min}$, m/s²; average acceleration, $a_{ave}$, m/s²; and average speed, $v_{ave}$, m/s. The vehicle classification is based on the vehicle driving cycles. 

FIGURE 8. Proportional distribution of driving gear on three driving conditions. Notes: OD-original database; DC-designed cycle; C-congested; F-free-flow; H-highspeed.

FIGURE 9. Proportional distribution of VSP on three driving conditions.
\(a_{am}, \text{ m/s}^2\); average deceleration, \(a_{dm}, \text{ m/s}^2\); and average driving velocity \(v_{dm}, \text{ m/s}\). Thus, a matrix with characteristic parameters (rows) multiplied by the number of micro-trip samples (columns) is obtained, as shown in Table 1.
The principal component analysis can express more information with less variables, and the main components have no correlation. Thus, all the characteristic parameters of samples were analyzed by principal component analysis, and the first 10 principal components were obtained $M_i, i = 1$ to $10$. The contribution and cumulative contribution of each principal component are shown in Table 2.

$$
\sum_{k=1}^{m} \frac{\lambda_k}{\sum_{k=1}^{10} \lambda_k}
$$

is the cumulative contribution of the first $m$ principal components, and $\lambda_k$ is the $k$th eigenvalue of principal components. Cumulative contribution rate indicates the ability of $M_1$, $M_2$, ..., $M_m$ to synthesize all original variables. Generally, the $m$ is determined by the rule that makes the cumulative contribution rate more than 85% to represent all the original variables. It can be seen from Table 2 that the cumulative contribution rate of the first three principal component eigenvalues is 87.95%, so the first three principal components are selected for analysis. And, the scores of each micro-trip sample on the first three principal components can be obtained, as shown in Table 3.

And then the $K$-mean clustering is used to classify the micro-trips on the three principal components. The micro-trip samples were clearly divided into three categories, including 28, 37 and 12 micro-trips, respectively, as shown in Fig. 4. The velocity and time series of each class are shown in Fig. 5. The first class is the typical frequently start-and-stop driving condition in urban congested conditions, the second class is the typical mixed driving conditions in free-flow traffic environment, the third class is obviously typical high-speed driving conditions. The driving characteristics of three kinds of driving conditions are obviously different, which can be used to verify this study under different driving conditions.

The characteristics of the state transition matrix were analyzed using the driving data for the three different driving conditions. The relevant parameter settings were as follows: the $v_{\text{max}}$ was 35 m/s; the $a_{\text{min}}$ was $-2$ m/s$^2$; the $a_{\text{max}}$ was 2 m/s$^2$, the $g_{\text{min}}$ was $-0.1$, the $g_{\text{max}}$ was 0.1, and the $s_{\text{max}}$ was 12. The associated intervals were 0.5 m/s, 0.1 m/s$^2$, 0.01, and 1, respectively. The idle state corresponded to the intervals of 0-0.1 m/s, $-0.02-0.02$ m/s$^2$, -0.2-0.2 %, and 0 for velocity, acceleration, grade, and gear, respectively. The four-parameter state transition probability matrix for the different road types was then calculated using (13), as shown in Fig. 6. In the figure, the abscissa represents the current state; the ordinate is the next state; and the size of the solid circle indicates the probability of state transition.

The findings were as follows. First, the four-parameter TPM of the three driving condition types showed strong Markov characteristics; Secondly, compared to the congested and highspeed conditions, the driving states of the free-flow condition shows a higher diversity of driving situations.
related to the following conditions. The medium and high gear utilization rate of free-flow situation was higher compared to the congested condition; the driving situations are also complex. The high-speed driving conditions were generally uniform and had a relatively simple distribution, which is caused by the high utilization of high-gear and few speed changes.

Finally, the MCE framework with more constraints was used to design multi-parameter driving cycles with the gears. The environmental conditions were set as follows: the lengths of time of the driving cycles on the congested, free-flow, and high-speed conditions types were 600 s, 1200 s, and 1800 s, respectively. The threshold for the relative deviation of the evaluation indices was set at 10%. The population size and the number of iterations were set at 100 and 300, respectively. The elite probability and crossover probability values were 0.05 and 0.9, respectively; the remainder was mutated individuals. The design process was completed in the MATLAB R2017 offline environment until the desired driving cycles with an objective function value of 0.1 were generated. A set of results was randomly selected for the analysis.

**C. REPRESENTATIVENESS OF FOUR-PARAMETER DRIVING CYCLES**

Table 4 compares the evaluation indices between the multi-parameter driving cycles of the three driving conditions and
the original data. First, the absolute value of the relative deviation of all evaluation indices from 8 to 10 columns was within 10%. Second, the study obtained desired driving cycles using multiple tests, reflecting the feasibility and robustness of the MCE method to design multi-parameter driving cycles. The relative deviation of fuel consumption meets the constraint requirement, indicating that the designed driving cycles satisfies the fuel economy requirements.

Fig. 7 shows the time series associated with the four-parameter driving cycles, and indicates that the driving characteristics on different driving conditions were quite different. Driving cycles on the congested condition were characterized by frequent stop-and-go conditions, large acceleration amplitudes, low speeds, and the high usage of low gears. The free-flow condition had significantly fewer stop-and-go events, a larger use of the middle and high gears. The high-speed driving characteristics were most stable, with the largest use of the high gear. In short, the four-parameter time series were coordinated with each other to present the vehicle driving characteristics on different roads.
D. ANALYSIS OF GEAR UTILIZATION RATE AND VSP
To further verify the effectiveness of the designed driving cycles, the proportion of each gear utilization and VSP was calculated, and was compared with the actual collected data. Fig. 8 shows the proportional distribution of the driving gear, and the similarity is quite high.

VSP was defined as the instantaneous power demand of the vehicle, divided by its mass, with a unit of Kw/ton. The VSP was calculated based on both vehicle and driving parameters. The percentage of frequency in time was included in each VSP bin. The formula for each VSP bin is shown in (22). Fig. 9 compares the distribution of VSP histograms under different driving cycles.

\[
\forall: \quad N - 0.5 \leq \text{VSP} < N + 0.5 \\
\text{VSPBin} = N \\
N \in [-15, 15], \quad N \in \mathbb{Z} \quad (22)
\]

The VSP distribution correlation coefficient was used to quantify the correlation and similarity of VSP distribution. The correlation coefficients of the VSP distribution between the designed driving cycles and the actual collected data were 0.9991, 0.9863, and 0.9482 for the congested, free-flow, and highspeed conditions, respectively. The two distributions were highly correlated, indicating that the VSP distribution of the designed cycles was highly similar to the actual collected data. The results were consistent across many tests.

E. ANALYSIS OF ENGINE DISTRIBUTION CONSISTENCY
Using the correlation coefficient of the distributions as an evaluation index, the driving cycles of different road types were tested to assess the consistency of engine distribution. The engine torque was calculated using (3) based on vehicle dynamics. The interval of speed and torque was set at 100. The speed ranged from 600 to 2200, and the torque ranged from 0 to 2100. The speed and torque were subdivided into 16 and 21 intervals, respectively. Fig. 10 the calculated engine distribution. The speed \((n_e)\) and torque \((T_e)\) plane graph were within the external characteristic curve, indicating that driving cycles met the vehicle power performance. The correlation coefficients of engine distributions on the congested, free-flow, and highspeed conditions were 99.58\%, 97.38\%, and 94.60\%, respectively. The bubble maps of engine distributions show a high similarity between driving cycles and the actual data. The engine cycle determined by transforming the vehicle driving cycles effectively reflected the actual driving conditions. This, in turn, may represent the inherent characteristics of the engine to guide performance optimization and emission control.

F. COMPARISON WITH A CONVERSION METHOD BASED ON ECONOMIC SHIFT STRATEGY
To verify the effectiveness of this approach considering gear information, the results of the study is compared with a conversion method based on the economic shift strategy. Given the same driving data source, the original MCE framework is used to design three-parameter driving cycles without the gear, only considering common parameter constraints such as speed, dynamics, and slope. The gear is matched by the transmission system model based on the economic shift strategy, and vehicle driving cycles are transformed into engine transient test cycles, which are called the contrast cycles. The time series of a random result is shown in Fig. 11.

Fig. 12 shows the engine cycle point distribution of three road types. Compared with Fig. 10, the cycle point distribution of the contrast cycles deviates obviously from the actual engine running condition, which results in the contrast cycles weakly representing the actual engine running condition. Furthermore, the difference between the actual shift rule and the selected transmission model significantly influences the engine cycle point distribution, which verifies the necessity for considering the actual driving shift gear rule in this study.

To further analyze the influence of different shift strategies on engine performance, the transient fuel consumption rate distributions of different engine transient test cycles were analyzed, as shown in Fig. 13. Compared with a conversion method based on the economic shift strategy, the results of this study are closer to the distribution of the fuel consumption rate of the original driving data, and can more effectively reflect the engine running condition in the actual vehicle driving process. Because of the limitations of the experimental conditions, the emission level of heavy diesel engines was not analyzed in this study. Considering that the fuel consumption of diesel vehicles is linearly related to the emission of gaseous pollutants [22], it can be inferred that the method can more accurately evaluate engine emission characteristics than the traditional conversion method.

V. CONCLUSION
Using an extended MCE framework, in this study, four-parameter driving cycles that included the gear parameter of heavy-duty vehicles were designed, which reflected the actual driving shift law. Additionally, engine transient test cycles were transformed by vehicle driving cycles. Based on the collected driving data of a heavy vehicle on different driving conditions, the results were verified and analyzed.
The experimental results showed that the deviation of the driving characteristic parameters and fuel consumption between the designed driving cycles on different road types and the collected driving data met the threshold requirements; the distributions of the designed driving cycles were highly correlated with those of the original database in terms of gear utilization rate, engine distribution, and VSP distribution, which verified the effectiveness of the designed four-parameter driving cycles.

Compared with the results of the study, the engine running point distribution from a conversion method based on the economic shift strategy greatly deviated from the actual running conditions, which verified that this study can more accurately evaluate engine fuel consumption and emission characteristics than the traditional conversion method.

The limitation of this research is that when designing the driving cycle on highspeed condition, there will occasionally be individual points that extend beyond the engine’s external characteristics because of Markov chain decoding. Although post-processing is required to correct these abnormal cycle points, it does not affect the performance requirements of driving cycles.

Future research efforts will include two aspects. First, engine transient test cycles will be used directly to design engine steady-state cycles, and the analysis related to fuel consumption and emissions will supplement the verification of this study. Additionally, the study of optimally predictable strategy [23] to improve vehicle performance can be considered as research direction. Second, other parameter constraints will be increased to improve the design efficiency, which could refer to the real-time energy consumption calculation model [24] based on the VA distribution.

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WENDONG CHENG received the B.S. and M.S. degrees in vehicle engineering from Yanshan University, Qinhuangdao, China, in 2007, and the Ph.D. degree in vehicle engineering from Chang’an University in 2017.

From 2007 to 2015, he was a Lecturer with the School of Mechatronic Engineering, Xi’an Technological University. Since 2016, he has been an Assistant Professor with the School of Mechatronic Engineering, Xi’an Technological University. He is the author of two books, more than 20 articles, and eight inventions. His research interests include intelligent driving assistance technology and the research on driver behavior recognition.

YUNBO SHEN received the master’s degree in mechanical manufacturing and automation in 2004, and the D.Eng. degree in 2009. In 2011, he was appointed as an Associate Professor with the School of Mechanical and Electrical Engineering, Xi’an Technological University. In 2018, he was appointed as a Professor and master’s Tutor at Xi’an Technological University. Since he was appointed as an Associate Professor, he was mainly engaged in high-performance gear transmission theory, gear design, and processing technology, among others; has undertaken more than ten national and provincial-level projects; received two provincial and ministerial level scientific and technological achievements awards; and published more than 40 articles. More than ten of them have been included in SCI or EI such as "Mechanism and Machine Theory" and "Journal of Aerodynamics." He is currently a Reviewer for journals such as Mechanism and Machine Theory (MAMT), Transactions of the Canadian Society for Mechanical Engineering, Shock and Vibration, Advances in Mechanical Engineering, Journal of Xi’an Jiaotong University, and Journal of Xi’an Xi’an Technological University.