Development of an Optimal Power-Distribution-Management Algorithm for Four-Wheel-Drive Electric Vehicles

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This work was supported by the Korea Institute of Industrial Technology as “Development of Core Technologies for a Working Partner Robot in the Manufacturing Field” under Grant KITECH EO-21-0004.

ABSTRACT In this paper, output power distribution algorithm is proposed for the front- and rear-motors through the power distribution system of four-wheel-drive (4WD) electric vehicles. Through the power distribution system, optimal control of the power distribution is obtained by applying a power distribution rate that increases battery range by improving the battery efficiency. Optimization of the power distribution according to the vehicle driving conditions reduces unnecessary power-loss and improves its driving energy efficiency through high-efficiency operation control to increase the range of the vehicle. Driving simulations are performed in a simulation environment developed using CarSim along with MATLAB/Simulink, and the performance of the proposed algorithm is verified. It was confirmed that with the proposed algorithm 4WD electric vehicles use less power based on the driving simulations and increased vehicle battery efficiency, depending on algorithm applicability.

INDEX TERMS Energy management system, four-wheel-drive electric vehicle, power distribution rate, power-distribution-management optimization algorithm, vehicle battery power optimization.

I. INTRODUCTION

The long-standing indifference to environmental issues has accelerated global warming. Environmental changes, which have significant impact on daily life, are rapidly progressing, threatening the global ecosystem. As a result, consumers are increasingly interested in low-pollution ecofriendly cars such as pure electric and hybrid electric vehicles. Accordingly, domestic and foreign automakers are actively conducting research and developing ecofriendly cars, and governments are promoting the supply of ecofriendly cars through various support policies [1]–[3]. In the case of pure electric vehicles, the only way to increase the battery capacity is to extend the range; however, it is impossible to increase the battery capacity indefinitely due to constraints such as cost and weight. In the case of hybrid electric vehicles, although there is relatively less concern regarding the range compared to pure electric vehicles, the interior space of the vehicle is reduced, in addition to weight increase, due to the increased number of complex structures and parts. Hence, technology that efficiently utilizes energy is recognized as a critical research area in the development of ecofriendly vehicles [4]–[6].

The power distribution system applied in the four-wheel-drive (4WD) electric vehicles considered in this study is a key component that controls the vehicle power system through motor control. Its functions are similar to the electronic control unit (ECU) and transmission control unit (TCU) of existing internal-combustion-engine vehicles. Therefore, the power distribution system plays a role in increasing the energy efficiency of electric vehicles by controlling the motors mounted on the front and rear wheels and distributing the motor power energy with optimal efficiency [7].

To overcome the limited battery capacity, this study discusses the methods for increasing the drag range of a vehicle by equipping the front and rear wheels of pure electric vehicles with drive motors and distributing the required power from the front and rear motors to maximize the battery efficiency through an optimal power distribution system.
The methods for increasing the range of navigation implemented in previous studies are mainly with respect to hybrid electric vehicles, and most are efficient in dividing the power demand between the engine and motor in hybrid vehicles. Martinez et al. [1] found that energy management is limited to power/torque division choices, and that the power/torque provided by each power source improved the overall vehicle energy efficiency, while meeting the driver demand. Keiser et al. [8] proposed a power distribution and energy management system for optimal charge and discharge time control of the expected proportion of renewable energy in the grid with electric vehicle batteries that can be integrated into virtual power plants. In addition, the control conditions can be set according to the mobility requirements. Tie and Tan [9] compiled the latest energy source, storage device, and power converter technologies, low-level controlled energy management strategies, and higher supervisor control algorithms used in electric vehicles. Moreover, they outlined the standards and patterns of the drive cycles for electric vehicles. Peng et al. [10] adopted dynamic programming (DP) to determine the optimal performance of engines and motors in PHEVs, and proposed recalibration methods to improve the performance of rule-based power management through the results calculated using DP algorithms.

Optimization of control systems capable of predicting vehicle state according to driving conditions and vehicle parameters is an active research field. Jin et al. [11] proposed a dual unscented Kalman filter (DUKF) approach, where two UKFs run in parallel to simultaneously estimate vehicle states and parameters such as vehicle velocity, vehicle sideslip angle, and inertial parameters. Cuma and Koroglu [12] presented a comprehensive review of the various estimation strategies used in hybrid and battery electric vehicles and developed strategies to increase classification and refinement with existing estimation strategies. Jin et al. [13] proposed a constrained robust H controller design of active suspension systems for in-wheel-independent-drive electric vehicles considering control constraint and parameter variation. Rath et al. [14] proposed a robust constrained output feedback approach employing sliding mode controllers for nonlinear active suspension systems equipped with hydraulic actuators.

Unlike previous research, this study focuses on the development of power distribution control optimization measures to improve the battery efficiency and increase the range using the energy management system of 4WD electric vehicles equipped with drive motors on the front and rear wheels, respectively. The remainder of this paper is organized as follows. Chapter 2 presents an overview and theory of the 4WD power distribution system. Chapter 3 details the dynamic models of 4WD electric vehicle driving parts such as motors and batteries for the calculating power distribution rates. An electric power system model is constructed using the dynamic equation of the driving element parts of a motor vehicle. In Chapter 4, the efficiency maps for the front and rear wheels are derived based on the values of $l_q$ and $l_d$ obtained through electromagnetic field analysis of the drive motors used for verification of the performance results. Chapter 5 explains the composition of the optimal power distribution algorithm, which applies the dynamic planning method and Pontryagin’s maximum principle to derive the optimal power distribution rate and derives the power distribution rate at the maximum efficiency point of the battery and motor. Chapter 6 addresses the simulation configuration in which the optimal power distribution algorithm is to be applied, constructs the simulation environment using CarSim along with MATLAB/Simulink, and verifies the results by comparing the road conditions with commercial vehicle reference models through driving simulations and EPA-based driving cycles. Finally, the conclusions are presented in Chapter 7.

II. 4WD POWER DISTRIBUTION SYSTEM

4WD electric vehicles can be driven using a single motor, as shown in Fig. 1a, or equipped with front-wheel and rear-wheel motors (Fig. 1b). A single-motor drive requires power transfer devices such as transfer cases, propeller shafts, and differential gears to transfer power from the front-wheel to rear wheel motor. Conversely, a separate power transfer device is not required, if the front and rear wheels are fitted with motors. Therefore, it is structurally concise and spacious. Electric vehicles are both equipped with batteries fitted in the lower half of the vehicle, which can provide wider battery space. In addition, when two motors are used instead of a single motor, the motors can be easily miniaturized and lightened, allowing them to be equipped with additional electrical or self-driving parts because of space availability.
Through optimal control of the power distribution system, this study proposes to increase the drag range for improving the energy efficiency and power performance by efficiently distributing the drive power to the front and rear motors. Using a power distribution system to drive the front and rear-wheel motors can solve the limitations of driving with a single motor. A high-speed motor used in a vehicle, with less impact of the inductance, has linear characteristics, as indicated by curve A in Fig. 2 [15].

The required torque (curve B) of the vehicle needs to be high during initial maneuvering, and when a constant speed area is reached, the nonlinear characteristic necessitates greater speed than torque [16]–[18]. Therefore, the designers of drive motors for vehicles are forced to design motors with characteristics such as curve A to generate maximum torque and maximum speed, while still enabling maneuver and generation of maximum vehicle speed. Area “C” (Fig. 2), caused by the nonlinear nature of the required vehicle torque, can be considered “over-torque” with more torque than necessary.

The proposed power distribution system aims to effectively reduce this excess. As it uses two motors instead of one, its structure can enable the optimization of the nonlinearity in existing vehicles. One of the motors is designed to be driven as high-torque motor (curve D), whereas the other is designed as a high-speed motor (curve E) to follow the nonlinear torque of the vehicle.

In 4WD vehicles driven by two motors, the motor driving area shall be controlled to achieve maximum efficiency. The basic driving algorithm of the EMS controls each motor to realize optimal efficiency. The two motors have high efficiency in areas a and b (Fig. 2); therefore, they are mainly driven in these areas. Specifically, if the required torque can be obtained from a motor driven in area a, then one motor alone is driven instead of two; if the torque of a motor is very high, it becomes less efficient; hence, the other motor is driven to produce optimal efficiency [19]–[22]. Thereby, the two motors should be driven in efficient areas as much as possible. Thus, the motors are driven in each speed area with maximum efficiency, while satisfying the nonlinear torque characteristics of the vehicle.

III. ELECTRIC-VEHICLE POWERTRAIN DYNAMIC MODELING

The electric vehicle powertrain includes a power generator that generates power, an electric power control unit (EPCU) that controls the electricity characteristics, and a battery pack that stores electrical energy. The fuel tank of the internal combustion engine that stores and discharges fuel is not included in the powertrain, but the battery pack of the electric vehicle is included because it also serves as storage for efficient energy management.

In this paper, an algorithm is proposed to distribute power to the front-wheel and rear-wheel drive motors when 4WD electric vehicles are driven. Additionally, a power distribution system for optimal vehicle control is proposed by inputting a power distribution rate that can improve the battery efficiency to increase the range. The main goal is to reduce unnecessary driving and improve driving energy efficiency through optimal power distribution according to vehicle driving conditions.

Fig. 3 shows the mechanical and electronic parts of a 4WD electric vehicle drive system schematized with respect to the direction of power transfer. The electric power system includes a battery, central instrument, power distribution system, inverter, and drive motor. The output power of the motor is transferred to the driveshaft, which is the connection to the mechanical system to transfer the motor output to the driving wheel [23], [24].

The electric vehicle drive motor generates drive power using electricity. It connects the decelerator to the motor shaft and transmits the appropriate torque to the wheels for driving the vehicle. The output of the motor is expressed in terms of the torque and angular velocity as follows:

$$P_m = \frac{2\pi \omega T}{60}$$  \hspace{1cm} (1)
The output command value determined by the main controller is introduced to the drive motor through the motor drive. The dynamic model of the three-phase permanent magnet synchronous motor in the reference coordinate system is expressed by the following nonlinear equations:

\[
\begin{align*}
V_d &= R_iq + L_d \frac{di_d}{dt} - \omega_r L_q i_q, \\
V_q &= R_iq + L_q \frac{di_q}{dt} - \omega_r (L_d i_d + \lambda_f), \\
T_m &= \frac{3P}{4} [\lambda_f i_q + (L_d - L_q) i_d i_q] \\
&= J_m \left( \frac{2}{P} \right) \dot{\theta}_r + B_m \left( \frac{2}{P} \right) \omega_r + T_L,
\end{align*}
\]

where \( L \) is the magnetic inductance, \( R \) is the resistance, \( \omega_r \) is the electric angular velocity, \( \lambda_f \) is the clasher speed, \( P \) is the number of poles, \( i \) is the current, and \( T_L \) is the load torque. Equations (2)–(4) represent the \( d \)-axis electrical model, \( q \)-axis electrical model, and the current equation and mechanical equation of the motor torque in the coordinate transformation state, respectively [25]. The formula for converting the motor-current component \( d \) and \( q \) axes from the rotary coordinate system to a \( u-v-w \) three-phase stationary coordinate system with 120° phase difference is as follows:

\[
\begin{bmatrix}
i_d \\
i_q \\
i_u \\
i_v \\
i_w
\end{bmatrix} = \frac{2}{3} \begin{bmatrix}
cos \theta_e & cos \left( \theta_e - \frac{2}{3}\pi \right) & cos \left( \theta_e + \frac{2}{3}\pi \right) \\
-sin \theta_e & -sin \left( \theta_e - \frac{2}{3}\pi \right) & -sin \left( \theta_e + \frac{2}{3}\pi \right) \\
1 & 1 & 1
\end{bmatrix} \begin{bmatrix}
i_u \\
i_v \\
i_w
\end{bmatrix}.
\]

Here, when the mechanical displacement of the motor rotor is \( \theta_m \), the electric angle displacement of the rotor \( \theta_e \) is defined as follows:

\[
\theta_e = \frac{P}{2} \theta_m = \int \omega_e dt.
\]

When equations (5) and (6) are applied to equation (4), the output torque of the motor is expressed as a function of \( i_u \) and \( i_v \):

\[
T_m = \frac{P \lambda_f}{2} \left[ \left( \frac{3}{2} \sin \theta_e - \frac{\sqrt{3}}{2} \cos \theta_e \right) i_u - \sqrt{3} \cos \theta_e i_v \right],
\]

where \( i_u + i_v + i_w = 0 \) is established under three-phase equilibrium. Therefore, by obtaining the input current of the motor and each displacement, the output torque of the current motor can be obtained [26].

When equation (1) is substituted in equation (7), the output \( P_{fo}, P_{ro} \) of the front and rear motors can be defined as follows by integrating the dynamic equations of the electrical and mechanical power systems for the front and rear motor, each:

\[
P_{fo} = \frac{1}{60} \left\{ \pi \omega P \lambda_{f}\frac{3}{2} \left[ \frac{\sin \theta_e - \sqrt{3}}{2} \cos \theta_e \right] i_u - \sqrt{3} \cos \theta_e i_v \right\}
\]

\[
P_{fo} = \frac{1}{60} \left\{ \pi \omega P \lambda_{f}\frac{3}{2} \left[ \frac{\sin \theta_e - \sqrt{3}}{2} \cos \theta_e \right] i_u - \sqrt{3} \cos \theta_e i_v \right\}
\]

**IV. ELECTROMAGNETIC ANALYSIS AND DESIGN OF THE DRIVE MOTOR**

The drive motor is a key component of the electric-vehicle powertrain system; hence, a high-power, high-efficiency motor is used. In recent years, DC motors, induction motors, or SPM motors have been gradually replaced by IPM motors because the motor speed has been increased, in general, to obtain small-sized, high-power, high-efficiency motors.

In this study, the motors were designed using JMAG, an electromagnetic field analysis software, and their performances were verified through no-load and load simulations. JMAG incorporates simulation technology to accurately analyze a wide range of physical phenomena including complicated geometries, various material properties, and the heat and structure at the center of electromagnetic fields.

The design of the IPM motor is carried out in the direction of solving magnetic phenomena based on the Maxwell equations and using them to satisfy the desired characteristics.

The motors were designed for mounting on the front and rear wheels of 4WD electric vehicles. High-efficiency motors in the low-speed and high-speed sections were designed to verify the power distribution performance through EMS. The front- and rear-wheel motors were designed with maximum torque specifications of 100 and 150 Nm, respectively. The detailed design specifications of the front- and rear-wheel motors are listed in Table 1.

For simulation, motor performance data such as the current, voltage, torque, and efficiency of the motor were obtained according to the rotational speed, through no-load and load simulations. In this study, the front and rear-wheel motors designed using electromagnetic field analysis programs were applied to the driving simulation model to verify the battery performance and driving performance, depending on the optimization of the power distribution.

In the electromagnetic field analysis, a constant current was entered according to the speed with the current source to proceed the analysis. The analysis was performed in the 1,000–10,000 rpm range, considering the reverse voltage. Initial analysis was performed with the magnet torque alone, which did not control the phase angle. If the phase angle is controlled, the maximum torque generally appears at a current phase angle ranging from 35 – 45°; hence a current phase of 40° was compared and analyzed in the maximum torque characteristic analysis.
To analyze the influence of the $d$ and $q$ axes in Fig. 4, the characteristics of the $d$-axis were analyzed by setting the $q$-axis current to zero. This method was applied because it has linear characteristics and analysis is straightforward.

Fig. 5 depicts the efficiency of the torque-specific motor according to the RPM; Figs. 5 (a) and (b) represent the front- and rear-wheel drive motors, respectively. The motor performance data obtained through the electromagnetic field analysis were applied to the dynamic equation to verify the results of the optimal power distribution algorithm.

V. CONFIGURATION AND RESULTS OF THE POWER DISTRIBUTION ALGORITHM OPTIMIZATION

The vehicle model employed in this study outputs power because there is a motor on the front and rear wheels, respectively. The required torque at the front and rear motors varies depending on the torque required when the vehicle is driven. The efficiency map of each motor shows that the efficiency varies, and that the battery power consumed varies according to the torque. Therefore, to increase the vehicle range, a distribution rate of the front- and rear-wheel motors is required that uses less total battery power.

Guarisco et al. [27] proposed a control strategy for a dual-wheel-drive electric bicycle by taking the human-bicycle coupling into consideration. Based on the drive conditions, the torque on each motor can be controlled separately to achieve better efficiency and performance. The efficiency maps are then implemented in the controller to dynamically calculate the optimal operation point of each motor under different drive conditions. Hu et al. [28] proposed a combined power source sizing and energy management optimization for multi-motor-driven electric powertrains. Through convex programming, a quick and effective co-optimization of the energy management strategy, battery dimension, and motor dimension for a dual-motor-driven electric bus powertrain was innovatively enabled. Zhang et al. [29] proposed a predictive power management for a dual-motor propulsion system, in which adaptive speed predictors are proposed to improve the predictive power management performance and parameters can be updated according to the driving pattern in which the coefficients of the proposed predictors are identified. According to the dynamic programming optimization results, a radial-basis-function neural network is trained to implement the driving condition prediction. Whereas previous studies used fuzzy logic and DP to optimize the drive control, in this study PMP was used to implement the optimization. The solution for the vehicle condition in PMP has an algebraic expression associated with the vehicular velocity and can be implemented more efficiently in the control algorithm. PMP is more sophisticated and computationally less expensive than other methods.

| TABLE 1. Electric-vehicle drive motor specification. |
|-----------------------------------------------|
| Front-wheel Motor                              |
| Parameters                                  | Unit | Value |
| Outside Diameter                             | mm   | 200   |
| Number of Slots                              | Slot | 48    |
| Number of Poles                               | Pole | 8     |
| Maximum Torque                               | Nm   | 102   |
| Maximum Speed                                | rpm  | 10,000|
| Air Gap                                      | mm   | 0.7   |
| Number of Turns                              | turn | 8     |
| Number of Strands                            | turn | 9     |

| Rear-wheel Motor                             |
|-----------------------------------------------|
| Parameters                                  | Unit | Value |
| Outside Diameter                             | mm   | 200   |
| Number of Slots                              | Slot | 48    |
| Number of Poles                               | Pole | 8     |
| Maximum Torque                               | Nm   | 151   |
| Maximum Speed                                | rpm  | 10,000|
| Air Gap                                      | mm   | 0.7   |
| Number of Turns                              | turn | 10    |
| Number of Strands                            | turn | 8     |
Fig. 7 presents the concept diagram of the power distribution system proposed in this study. Total output torque for the front- and rear-wheel motors, $T$, to drive at target speed, $n$, respectively; $x_n$ and $y_n$ indicates the torque efficiency at speed, $n$. The sum of $x$ and $y$ represents the torque required for the vehicle to drive at the target speed, and the power consumption for the drive also varies because $x_n$ and $y_n$ depend on the distribution rate.

The input power to the motors is expressed as follows:

$$P_{fi} = \frac{\eta_f}{60} \left\{ \pi \omega P_{\lambda f} \left[ \left( \frac{3}{2} \sin \theta_{fe} - \frac{\sqrt{3}}{2} \cos \theta_{fe} \right) i_{fa} - \sqrt{3} \cos \theta_{fe} i_{fb} \right] \right\}$$

$$P_{ri} = \frac{\eta_f}{60} \left\{ \pi \omega P_{\lambda r} \left[ \left( \frac{3}{2} \sin \theta_{re} - \frac{\sqrt{3}}{2} \cos \theta_{re} \right) i_{ra} - \sqrt{3} \cos \theta_{re} i_{rb} \right] \right\}$$

The total power consumption of the vehicle combined with the required power for each motor obtained in Equation (5) is required to drive the vehicle at the target speed, and at the minimum value, the battery efficiency is maximum.

To find this maximum value, it is necessary to calculate the efficiency at various torques of the front and rear wheels at the same speed and perform calculations using the vehicle dynamic equation for comparing the various resultant values. However, this is difficult because of the considerable calculation time. Thus, the calculation time was shortened using the dynamic programming method to simplify the calculation and reduce the calculation time.

The development of a power distribution algorithm is problem, even if the vehicle driving data are entirely available. To solve this problem, power distribution rate data based on computational simplification theory, such as the dynamic programming method, were derived. Based on the power distribution rate data obtained earlier, this study shows that the applied power distribution system using Pontrygin’s minimum principle is a good alternative to optimal power distribution, while maintaining the optimum [30], [31]. In the proposed power distribution system, Pontryagin’s minimum principle-based control implements optimality through the torque, and the efficiency based on the distribution rate is obtained using the dynamic programming method, assuming that battery efficiency optimization and range increase are the objectives.

Pontrygin’s minimum principle is an optimal control theory that defines what is intended to be minimized as the
purpose function. It combines the system’s equations of state using the Lagrange coefficient and minimizes it. In this study, the motor input power is defined as the function of purpose, and the state equation for the power and SOC of the vehicle battery are used to derive the following expression:

\[
P_k = \text{arg} H
\]

\[
H = P_{in}P_{bat}(\eta_{dis}\eta_{chg})^{-xgm(P_{bat})} - \lambda \eta_{bat}I_{bat} Q_{bat}
\]

\[
\dot{\lambda} = \frac{\lambda I_{bat} Q_{bat}}{Q_{bat}} \left( \frac{\delta I_{bat}}{\delta V_{OC}} + \frac{\delta I_{bat}}{\delta R_{bat}} \right). \tag{10}
\]

In general, the following two approaches are effective in guaranteeing that extreme solutions are sufficient for optimality: (1) The PMP-obtained optimal trajectory is a unique trajectory that meets the required boundary conditions. (2) As the optimal field is convex, its geometric properties provide the same optimality verification possibilities. In practical applications, PMP can be used to find candidate solutions and obtain extreme control through Hamiltonian computation and minimization for all \( t \in [t_0, t_f] \). As the SOC variation depends only on \( P_{bat} \), the assumption that the co-state \( P_1(t) \) corresponding to SOC is a constant is valid, which tremendously simplifies the computation [32).

The two-point boundary value problem can only be solved numerically using an iterative procedure because one boundary condition is defined at the end time, even though it is fully defined. This procedure is known as the shooting method and consists of replacing the two-point boundary value problem with the existing initial condition problem [33].

An optimal power distribution algorithm is proposed utilizing the above equation for the torque and the raw efficiency data according to the distribution rate calculated using the dynamic programming method. The distribution rate with maximum efficiency is calculating using Pontrygin’s minimum principle. Figure 9 displays the efficiency map, when the front and rear-wheel motors are driven by the optimal power distribution algorithm.

With the distribution rate derived using the optimal power distribution algorithm, it is confirmed that power is generated from the front- and rear-wheel motors according to the power distribution ratio shown in Fig. 10. Figs. 10 (a) and (b) show the distribution rate for the front- and rear-wheel motors, respectively. In the high-torque and high-speed sections, it is confirmed that the distribution rate of the rear-wheel motor with large maximum torque is greater than that of the front-wheel motor. In addition, the distribution rate of the front-wheel motor is higher in the low-torque and low-speed sections.
VI. COMPARATIVE ANALYSIS AND RESULTS

A. DRIVE SIMULATION ENVIRONMENT CONFIGURATION

Using CarSim, a simulation program that considering the vehicle dynamic characteristics, the command for speed control was obtained from an external port, and simulation was performed by receiving the command from MATLAB/Simulink, instead of CarSim. Driving simulation was performed by entering the speed information of each driving cycle at the speed required to drive the patterns used for measuring the authorized range of actual mass-produced vehicles. The driving cycles were selected based on the environmental protection agency (EPA) criteria. EPA’s EV driving experiments are also called multicycle tests (MCTs). The EPA urban cycle is driven along the speed curve shown in [34].

In this study, the distribution rate of the comparison model was selected by analyzing the 4WD systems of major car manufacturers and compared with the model to which the optimal power distribution algorithm was applied.

Therefore, this study selected the distribution rate of the comparison model as the average value, according to the power distribution standard of existing commercial vehicles. The standard distribution ratio of the front and rear motors was selected as 40:60 for comparison simulation with the proposed model. The driving simulations were performed based on the EPA standards to confirm the increase in the vehicle range increase.

B. EPA DRIVING SIMULATION

To analyze the driving performance of the target 4WD electric vehicle in an environment similar to road driving, a drive cycle was applied as per EPA standards. The electric vehicle efficiency depends considerably on several variables including various types of driving patterns and environmental conditions. In particular, the range, battery power consumption, and SOC vary depending on the driving conditions. Therefore, for electric vehicles, the performance measurement under various driving modes and environmental conditions is used as an indicator of the energy management or the effect of technology development.

C. EPA URBAN CYCLE DRIVING SIMULATION

Urban driving simulation was performed by simulating the driving characteristics in an urban area and included a simulated driving course with a total mileage of 7.45 km, average driving speed of 19.58 km/h, maximum speed of 56.7 m/h, 17 stops, and a total test time of 1,369 s. Fig. 12 shows the vehicle speed with respect to the driving time in the EPA urban cycle.

The results were compared by performing urban driving simulation with a comparison model for the same time as that of conventional driving simulation. The performance of the optimal power algorithm was compared in terms of the battery efficiency and battery power consumption for the same mileage and time.

Fig. 13 depicts the battery efficiency with respect to the driving time. The battery efficiency increases by 1.9% on an average than the comparison model, resulting in a 1.1-kW reduction in the battery power consumption on an average. It is observed that the efficiency and battery power consumption deviate more in the areas where the vehicle accelerates compared to the other areas because the model with the optimum power algorithm has greater power train efficiency than the comparison model in the lower and higher torque segments.

Fig. 14 (a) shows the cumulative battery power consumption when the vehicle is driven. The model to which the EPA urban cycle reference algorithm is applied consumes...
141.58 kW power and the comparison model consumes 144.19 kW; the power consumption difference is 2.61 kW. This is the power consumption of the algorithm-applicated model when driving a distance of 0.13 km at 20 km/h, indicating that the driving range is increased compared to the comparison model.

Fig. 14 (b) displays a graph comparing the SOC changes in the urban driving simulations. At the completion of the entire 1,369 s of the run, the model to which the proposed algorithm is applied records 91.413% SOC, and the model without the algorithm records 91.236%. Therefore, if the same distance was driven at the same speed, the model with the optimal power distribution algorithm was driven with less power consumption, and the driving range increased until discharge.

D. EPA HIGHWAY CYCLE DRIVING SIMULATION

Highway driving simulation was performed by simulating the characteristics of a highway in which vehicles generally travel at high speed, with a total mileage of 16.39 km, average driving speed of 77.13 km/h, maximum speed of 95.84 m/h, zero stop count, and total test time of 765 s. Fig. 15 shows the vehicle speed with respect to the road time for the EPA highway cycle.

The results were compared by performing highway driving simulation with a comparison model for the same time as that of conventional driving simulation. The performance was compared at the same mileage, time reference, battery efficiency, and battery power consumption, with and without the optimal power algorithm.

Fig. 16 shows the battery efficiency with respect to the driving time. The battery efficiency increases by 4.5% on an average than the comparison model, resulting in a 5.7-kW reduction in the battery power consumption on an average. The need for more torque to drive the vehicle in areas where the vehicle accelerates, and the high-speed driving areas result in more deviations than the other areas, and more deviations compared to the urban driving simulations.

Fig. 17 (a) shows the cumulative battery power consumption when the vehicle is driven. The model to which the EPA highway cycle reference algorithm is applied consumes 278.22 kW power, the comparison model consumes 320.89 kW, and the power consumption difference is 42.87 kW. This is the power consumption of the algorithm-applicated model when driving a distance of 2.51 km at 80 km/h, indicating that the driving range is increased compared to the comparison model.

Fig. 17 (b) displays a graph comparing the SOC changes in the urban driving simulations. The model to which the...
proposed algorithm is applied records 82.975% SOC volume at the completion of the entire 765 s of the run, and the model without the algorithm records 80.455%. Therefore, it is confirmed that the highway driving simulations show a tendency similar to the urban driving simulations when driving the same section at the same speed, and the deviation increases at high speed.

VII. CONCLUSION

In this study, a power distribution system control plan was proposed considering the optimal power distribution applicable to 4WD electric vehicles. The power distribution ratio with maximum efficiency for the front and rear batteries and power trains was determined, and distributed to increase the battery efficiency, reduce power consumption, and increase the range of 4WD electric vehicles for improving the driving performance.

To optimize the power distribution rate, the efficiency and power distribution rate of the power train were optimized by inputting the data obtained using the dynamic programming method and the performance data of each drive motor into an algorithm that applies Pontrygin’s minimum principle. Using MATLAB/Simulink, the vehicle was modeled based on the dynamic characteristics of the major components of a 4WD electric vehicle, and a performance simulator was organized to verify the performance.

The power distribution control optimization algorithm developed in this study reduced the power consumption by 1.81% in the urban driving simulation and 13.36% in the highway driving simulation. In addition, as the power consumption improved, the remaining SOC was reduced. Regarding the remaining SOCs at the same driving simulation conditions, it was determined that the vehicle model with the proposed power distribution control optimization algorithm improved the battery performance by 0.2% in the urban driving simulation and 2.52% in the highway driving simulation when compared with the comparison model. Moreover, it was confirmed that a high-speed and high-torque operation range increased the driving efficiency and performance with higher deviation from the low-speed and low-torque operating range, depending on the application of the power distribution control optimization algorithm.

In future, we intend to improve the battery efficiency by improving the optimal power distribution ratio for actual vehicle driving behavior and the environmental variables of 4WD electric vehicles, and study the application of the power distribution control optimization algorithm for improving the range and performance of 4WD electric vehicles.

ACKNOWLEDGMENT

The authors would like to thank Editage (www.editage.co.kr) for English language editing.

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VOLUME 9, 2021