

Research Article

Multiobjective Optimization of a Traction Motor in Driving Cycles Using a Coupled Electromagnetic–Thermal 1D Simulation

Sungho Ahn,^{1,2} Wonseok Song,³ and Seungjae Min ^{1,3}

¹Department of Automotive Engineering (Automotive-Software Convergence), Hanyang University, Seoul, Republic of Korea

²LG Magna, Incheon, Republic of Korea

³Department of Automotive Engineering, Hanyang University, Seoul, Republic of Korea

Correspondence should be addressed to Seungjae Min; seungjae@hanyang.ac.kr

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This paper proposes an electric propulsion system model for computationally efficient multiobjective optimization considering overall driving cycles using coupled electromagnetic–thermal 1D simulation. The proposed system model uses equivalent circuit networks rather than finite element method to obtain high computational efficiency because considering both driving cycles and motor temperature change during optimization requires considerable computational cost. The magnetic saturation effect and temperature change of traction motor during operation are examined by constructing look-up tables. This study first integrated the lumped parameter thermal network into the system model to consider the motor temperature change without any iterative process. The 1D simulation results over urban and highway driving cycles indicate that the changes in the induced current, efficiency, and motor temperature could be predicted while driving. The Pareto optimal solution of traction motor cross-sectional geometry including reduction ratio is successfully obtained by multiobjective optimization with the maximum output torque constraint. Constructing the proposed system model once, optimal design for multiple target driving cycles can be obtained without any driving cycle analysis. In addition, high computational efficiency indicates that the proposed system model is practical in the early design stage of various electric propulsions.

1. Introduction

As the EVs operate under various torque and speed conditions, the entire driving cycle should be considered in traction motor optimization instead of only a few operating points. In addition, the varying performance depending on the temperature should be reflected during optimization to prevent thermal demagnetization of the permanent magnet. Previous research has struggled to consider the driving cycle and temperature change in motor optimization, as listed in Table 1.

In previous studies, representative operating points were utilized to consider the driving cycle, and the FEM was generally used for analysis and optimization. Carraro et al. [1] improved the torque characteristics and reduced the losses of a PMA-SynRM while considering the driving cycle. The optimization was conducted for six operating points representing the driving cycle; the optimal design had a better

objective function than the design obtained by considering only the rated point. Parasiliti et al. [2] optimized the IPMSM considering the wide operating range of the motor by maximizing the torque at rated and maximum speeds and minimizing the weight. Fetemi et al. [3] introduced a clustering method for IPMSM optimization over a target driving cycle and selected seven representative operating points. The clustering method has been consistently used to efficiently consider the driving cycle during motor design [10]. Diao et al. [4] classified common driving cycles into five operating points and selected important objective functions, such as torque and the efficiency, at each point to design SRM. Sarigiannidis et al. [5] clustered the new European drive cycle into four operating points based on energy consumption and optimized the IPMSM and surface-mounted permanent magnet synchronous motor for the selected points. Sun et al. [6] designed a PMSHM while considering four representative operating points. Lopez-Torres

TABLE 1: Motor optimizations considering driving cycles and temperature change.

Motor type	Operating points	Temperature	Model	Reference
PMa-SynRM	6	x	FEM	Carraro et al. [1]
IPMSM	2		FEM	Parasiliti et al. [2]
IPMSM	7	Indirectly considered	FEM	Fatemi et al. [3]
SRM	5		FEM	Diao et al. [4]
PMSMs	4		FEM	Sarigiannidis et al. [5]
PMSHM	4	o	EMCN, LPTN	Sun et al. [6]
PMa-SynRM	418	o	FEM, LPTN	López-Torres et al. [7]
PMSM	8	x	FEM	Pastellides et al. [8]
PMa-SynRM	Overall	x	FEM	Shao et al. [9]

TABLE 2: Similarity between electric circuit and EMCN.

Electric circuit	EMCN
Resistance $R_e [\Omega]$	Reluctance $R_m [A/Wb]$
Voltage $V [V]$	Magnetomotive force $V_m [A]$
Current $I [A]$	Magnetic flux $\phi [Wb]$
$V = IR_e$	$V_m = \phi R_m$

TABLE 3: Similarity between electric circuit and LPTN.

Electric circuit	LPTN
Resistance $R_e [\Omega]$	Thermal resistance $R_T [^\circ C/W]$
Voltage $V [V]$	Temperature $T [^\circ C]$
Current $I [A]$	Heat flux $q [W]$
$V = IR_e$	$T = qR_T$

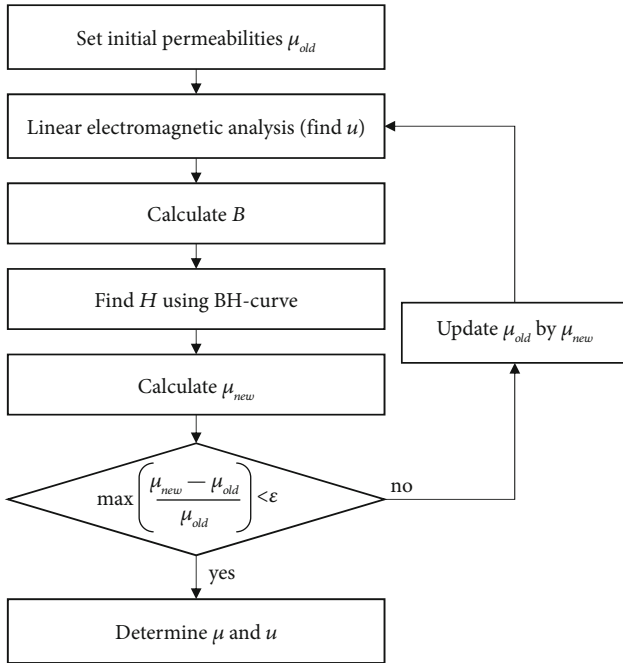


FIGURE 1: Nonlinear electromagnetic analysis procedure.

et al. [7] chose 418 operating points to precisely reflect the target driving cycle for the PMa-SynRM design and utilized equivalent circuit networks to reduce the computational resources. Although utilizing the EMCN and LPTN could save computing time, the discrete 418 points were still not sufficient to entirely reflect the driving cycle in the design process. Design methods focusing on representative operating points are reasonable, however, additional electromagnetic analyses are required to determine the optimal

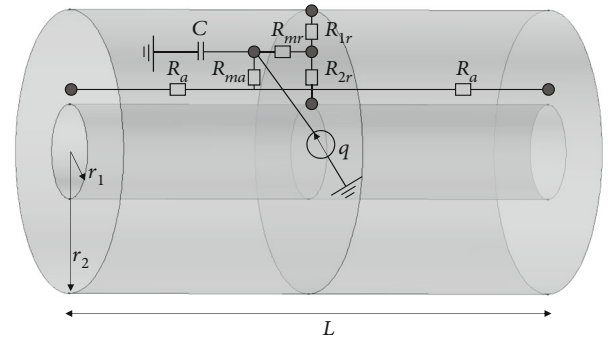


FIGURE 2: Equivalent hollow cylinder and thermal elements.

current that rotates the motor at the exact operating points. Pastellides et al. [8] introduced a strategy on how to efficiently determine representative operating points in PMSM optimization according to design purpose. Considering the operating point on the flux map saved time for finding the current vector for each point; however, it is clearly shown that optimal design depends on the number of representative operating points. Increasing the number of representative operating points to accurately reflect the driving cycle makes the design process more time-consuming. Moreover, new points must be determined when the driving cycle changes. Although Shao et al. [9] minimized the loss of PMa-SynRM efficiently considering overall driving cycles using a system model, temperature change while driving was ignored. The varying electromagnetic characteristics depending on the motor temperature were considered in some optimizations by limiting the current density with constraints [2–5]. As a result, excessive temperature increases could be avoided; however, the temperature rise while

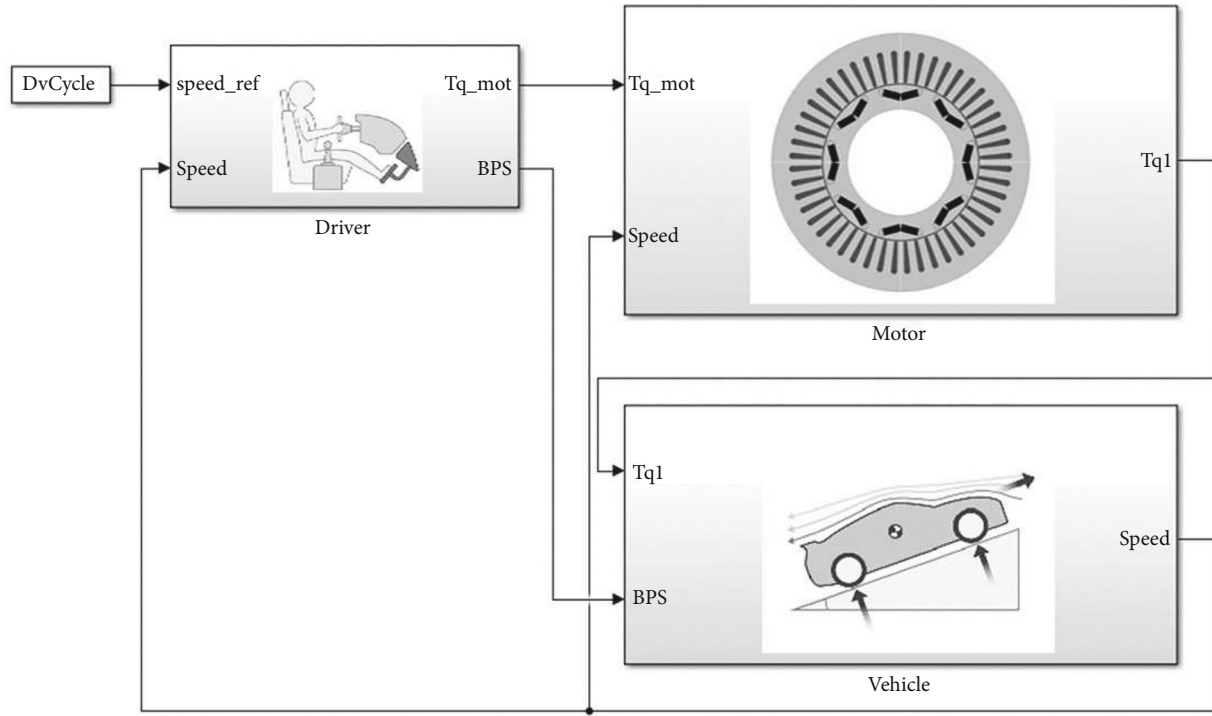


FIGURE 3: Electric vehicle propulsion system configuration.

driving was hard to predict. Therefore, conservative conditions for safety were reflected in the constraints that could weaken the design improvement. Other optimizations have constrained the maximum temperature after predetermined periods at a fixed operating point because it is not feasible to consider the thermal demagnetization effect of permanent magnets during operation [6, 7]. However, this consideration does not include temperature and characteristic changes over the target driving cycle.

This study proposed an electric propulsion system model to efficiently consider both overall driving cycle and temperature change while driving. The proposed system model overcomes the trade-off relationship between accurate reflection of the driving cycle and computational efficiency in optimization. The system model includes the driver, motor, and vehicle subsystems and considers magnetic saturation through LUTs developed using the EMCN in advance. In addition, this study first integrates the LPTN into the system model to calculate motor temperature change during operation. This integration makes coupled electromagnetic–thermal analysis possible without any iterative process. After validating the proposed system model, a multiobjective optimization of IPMSM cross-section and reduction ratio is conducted with four objective functions and one constraint. The computationally efficient coupled electromagnetic–thermal analysis using the proposed system model can be adopted in an early design stage of other electric propulsion systems.

The remainder of this paper is organized as follows. In Section 2, the characteristics of the equivalent circuit networks and the proposed system model are introduced. In Section 3, a 1D simulation is performed over urban and

highway driving cycles, confirming that the proposed system model successfully reflects the magnetic saturation and temperature change during operation. In Section 4, using the 1D simulation, five geometric parameters and one system parameter are optimized considering four objective functions such as average efficiencies over the UDDS and HWFET, maximum motor torque, and magnet volume. The results show that the different optimal designs depending on objectives can be obtained using the proposed simulation model. Finally, Section 5 summarizes this paper concluding that the proposed 1D simulation is effective at the concept development stage of an electric propulsion system due to its superior computational efficiency.

2. EV System Modeling for 1D Simulation

2.1. EMCN for Efficiency Calculation. The EMCN is a model for electromagnetic analysis that uses the similarity between the electrical and magnetic circuits, listed in Table 2. Because the EMCN can perform analysis with significantly fewer DOF than the FEM [11], it has been utilized for motor optimization due to its computational efficiency [12, 13].

To accurately calculate the performance of the motor such as torque and losses, the magnetic saturation should be considered, as illustrated in Figure 1. The vectors μ , B , and H , corresponding to the domain for considering magnetic saturation, are calculated and updated until the change rate of the relative permeability becomes smaller than ϵ using the following equation:

$$B = \mu H. \quad (1)$$

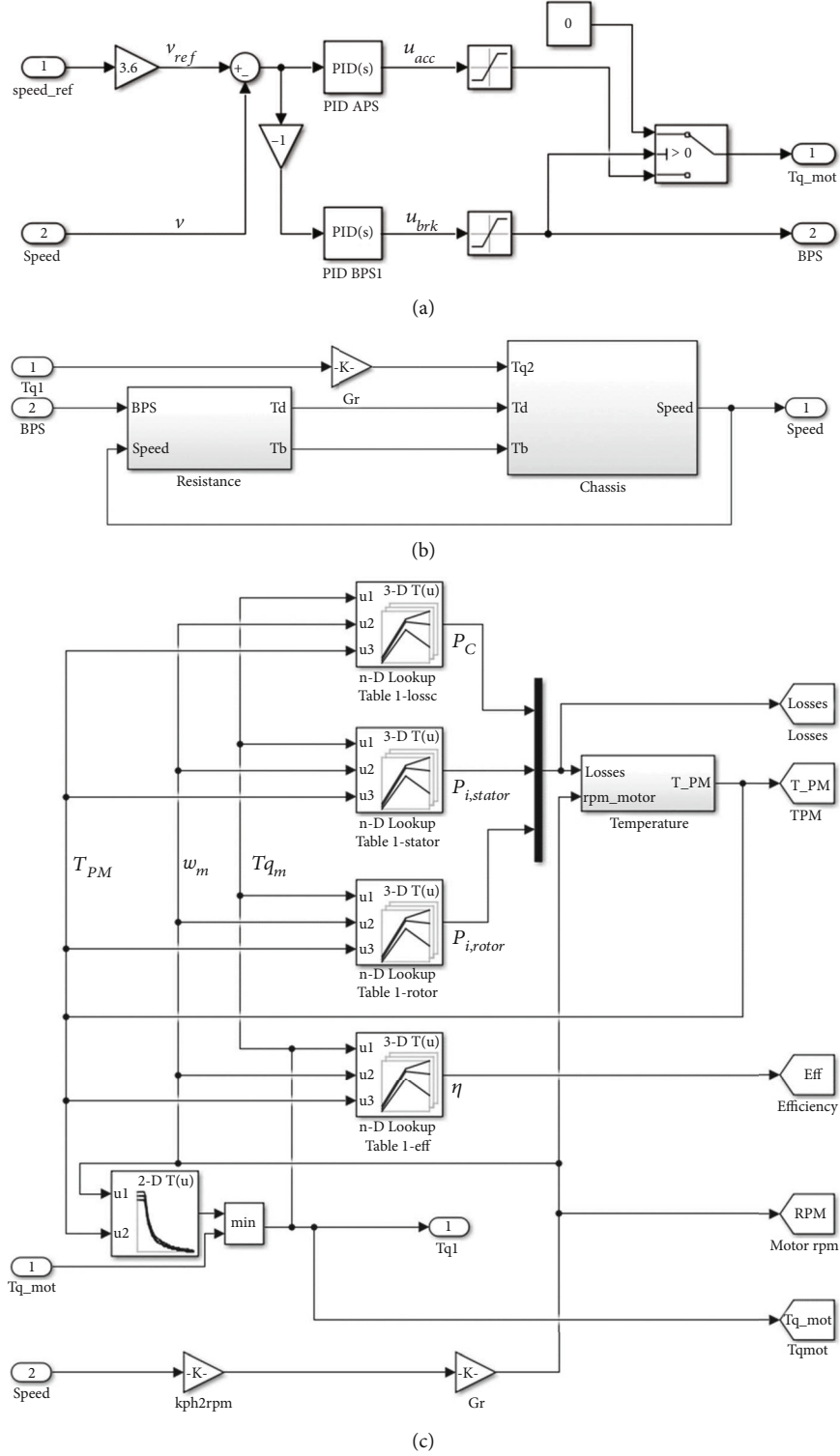


FIGURE 4: Subsystems in electric propulsion system: (a) driver, (b) vehicle, and (c) motor.

Motor loss occurs at the copper, iron, and mechanical shaft, and its configuration depends on the operating condition. The copper loss P_c caused by the current is calculated using the following analytic equation:

$$P_c = I_{c,rms}^2 R_c, \quad (2)$$

where $I_{c,rms}$ is assumed to be pure sinusoidal. The iron loss P_i , considered at both the stator and rotor, is calculated as the sum of the hysteresis loss and eddy current loss, shown in the following equations [14]:

$$P_i = P_h + P_e, \quad (3)$$

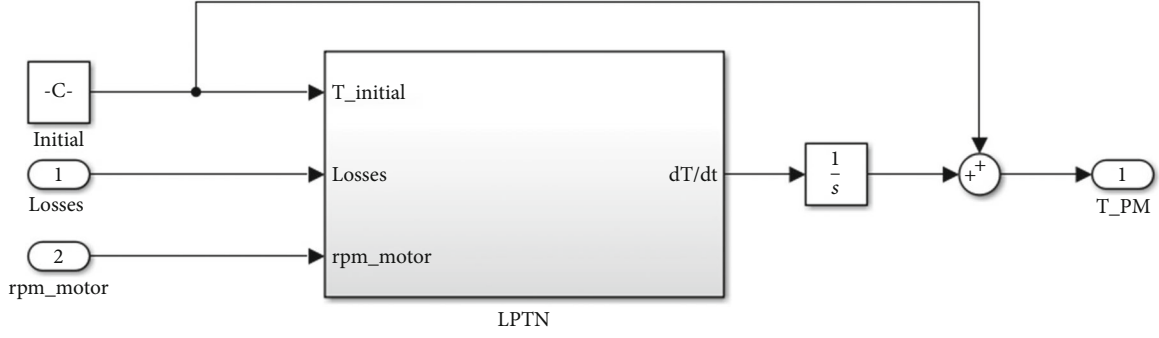


FIGURE 5: Temperature block configuration in motor subsystem.

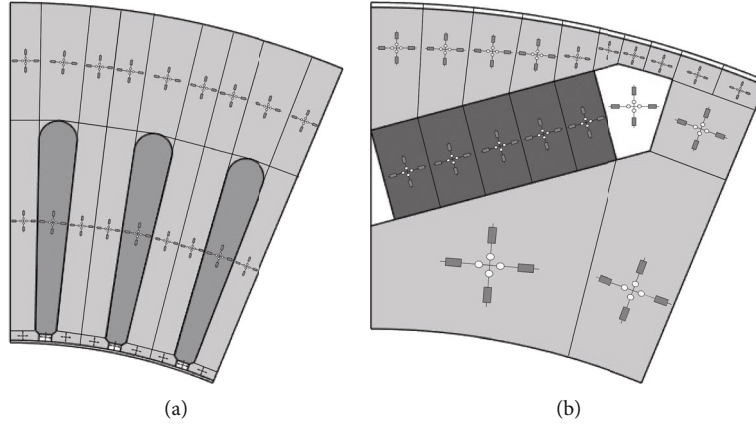


FIGURE 6: EMCN configuration corresponding to half pole: (a) stator and (b) rotor.

$$P_h = k_h B^{\alpha_h} f^{\beta_h}, \quad (4)$$

$$P_e = k_e (Bf)^{\alpha_e}, \quad (5)$$

where the coefficients k_h , α_h , β_h , and k_e are given by material experiments and fixed at the reference values presented in the document [15]. In (4)–(5), B and f represent the frequency domain value converted using the fast Fourier transform of the corresponding frequency, respectively. Using the reference loss and speed, the mechanical loss P_m is calculated by the following equation:

$$P_m = P_{m,ref} (\omega_m / \omega_{m,ref})^{k_m}, \quad (6)$$

where k_m is empirical value referred by document [15] in this study. The motor efficiency η is then calculated using all the losses, as shown in the following equations:

$$\eta = 100 \times \frac{P_{out}}{P_{in}} = 100 \times \frac{Tq_m \cdot \omega_m}{Tq_m \cdot \omega_m + P_c + P_i + P_m}. \quad (7)$$

2.2. LPTN for considering Motor Temperature Change. Motor losses generate heat and increase the temperature across the stator and rotor. Therefore, coupled electromagnetic–thermal analysis is required because the high temperature at the winding and permanent magnet changes the electromagnetic characteristics. The LPTN is adopted for

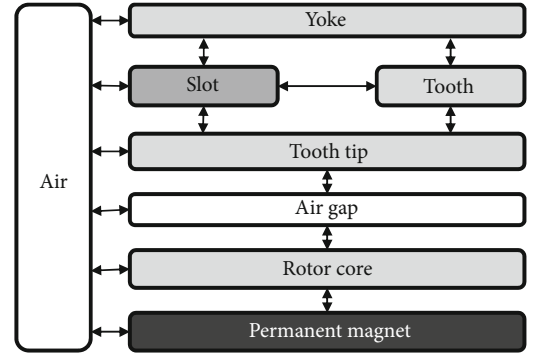


FIGURE 7: Heat transfer path considered in LPTN.

TABLE 4: Three operating points in overall motor operating region.

Operating point	Current (A)	Control angle (°)	Motor speed (rpm)
1	150	50	1300
2	50	45	1000
3	50	60	5000

efficient coupled electromagnetic–thermal analysis and optimization, instead of the FEM [16]. The LPTN based on the hollow cylindrical shape of the motor follows the similarity listed in Table 3.

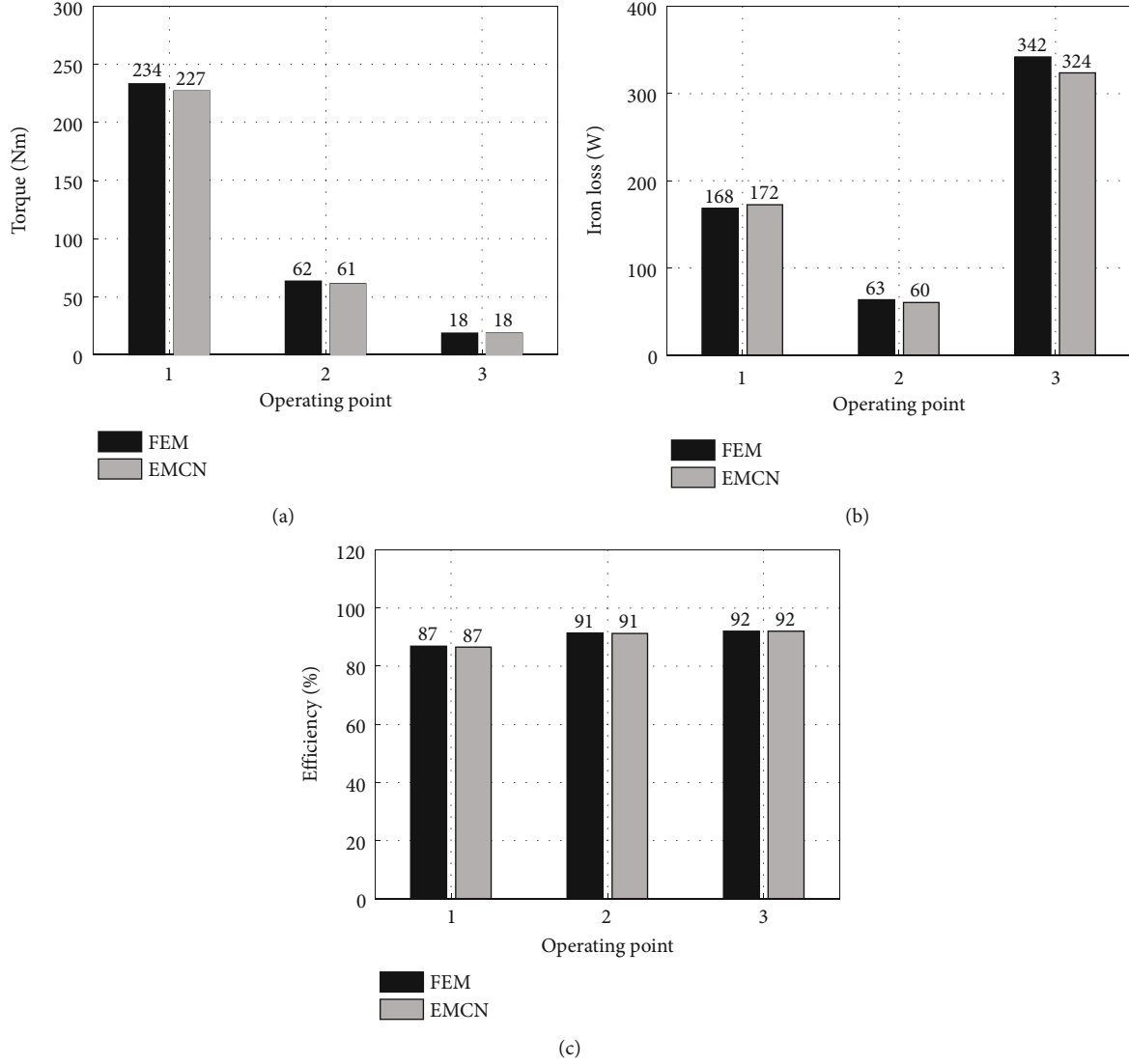


FIGURE 8: Result of electromagnetic analysis at three operating points: (a) average motor torque, (b) iron loss, and (c) efficiency.

The LPTN was constructed by dividing the motor parts into equivalent hollow cylinders and by determining the thermal resistances (R_{1r} , R_{2r} , R_{mr} , R_{ma} , and R_a) and heat capacitance C [17] as illustrated in Figure 2. In the cylinder, r_1 , r_2 , L , k , c , ρ , and q represent the inner radius, outer radius, axial length, thermal conductivity, heat capacity, density, and heat source, respectively. Because copper, air, impregnation, and insulation are included in the winding, the equivalent thermal conductivity of the winding is calculated and used for an efficient analysis [18]. The contact resistance is considered by assuming that a thin layer filled with air is located at the boundary of the adjacent materials [18]. At the air gap, forced convection should be considered using the convection coefficient determined by the rotor speed and material properties [19].

2.3. Electric Propulsion System Model. Because the mathematical expression-based system model provides fast simulation, the system model is an efficient method in

considering driving cycles [20]. Using the system model, previous research has conducted 1D simulation considering varying electromagnetic parameters and motor temperature [21]. An electric propulsion system model—including the driver, motor, and vehicle subsystems—proposed in this study, as illustrated in Figure 3, fully considers the driving cycle, unlike previous optimizations that used representative operating points. In addition, mathematical modeling helps integrate subsystems based on different physics and adjust fidelity according to purpose [22]. Because this study considers varying nonlinear electromagnetic motor parameters according to temperature change, motor subsystem is modeled as higher fidelity than other subsystems.

In the driver subsystem, a PID controller is included to control vehicle speed, as shown in Figure 4(a). The input signals of the driver are v_{ref} and v . The acceleration signal u_{acc} and braking signal u_{brk} are calculated by the following equations:

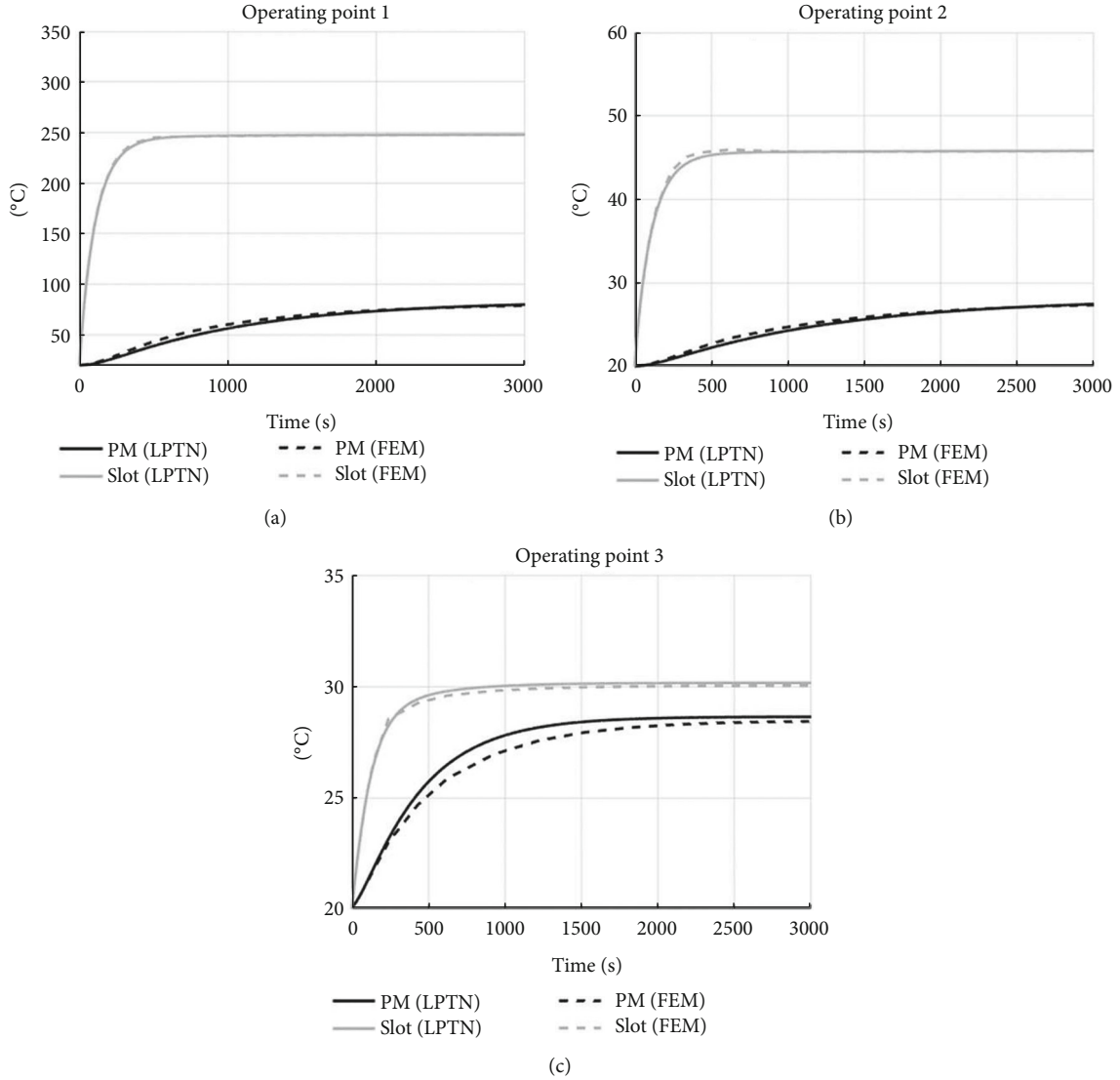


FIGURE 9: Temperature of slot and magnet at operating points (a) 1, (b) 2, and (c) 3.

$$u_{acc} = K_p e + K_I \int_0^t e \, dt + K_D \frac{de}{dt}, \quad (8)$$

$$e = v_{ref} - v.$$

The vehicle subsystem consists of a resistance, reducer, and chassis, as shown in Figure 4(b). In the resistance block, the aerodynamic drag force F_{air} and rolling force F_{roll} are calculated using the following equations:

$$\begin{aligned} F_{air} &= 0.5 C_d A_f \rho_{air} v^2, \\ F_{roll} &= \mu_{roll} mg, \\ T_d &= r_t \times (F_{air} + F_{roll}), \\ T_b &= T_{q_b} \cdot \tanh(v). \end{aligned} \quad (9)$$

The braking torque T_b is derived from the T_{q_b} and $\tanh(v)$ to prevent excessive deceleration. The torque

and speed are distributed to the motor and chassis based on the reduction ratio Gr , as given by the following equation:

$$Gr = \frac{T_{q_2}}{T_{q_1}} = \frac{\omega_1}{\omega_2}, \quad (10)$$

where subscripts 1 and 2 represent the motor and chassis, respectively. The chassis is modeled using the following equations:

$$\begin{aligned} T_{q_2} - (T_d + T_b) &= J_{eq} \frac{d\omega_2}{dt}, \\ J_{eq} &= m r_t^2. \end{aligned} \quad (11)$$

The motor subsystem considers the varying electromagnetic characteristics depending on temperature, as

shown in Figure 4(c). One 2D LUT and four 3D LUTs are contained in the motor subsystem to quickly perform simulations over the target driving cycles. A 2D LUT with two inputs (ω_m and T_{PM}) restricts the motor torque when the torque is larger than the maximum limit. The 3D LUTs have Tq_m as an additional input, and the outputs are copper loss, stator iron loss, rotor iron loss, and motor efficiency—used to calculate the motor temperature.

An assumption regarding the control strategy should be considered before configuring all LUTs in the motor subsystem. In this study, the MTPA control strategy is adopted under the rated motor speed, and flux weakening is performed until the voltage reaches its limit. The LUTs are built by implementing the control strategy through the following optimizations:

$$\begin{aligned} \underset{i_d, i_q}{\text{minimize}} \quad & f_1 = -\frac{2}{3}p(\phi_d i_d - \phi_q i_q), \\ \text{subject to} \quad & g_1 = i_d^2 + i_q^2 - I_{\max}^2 \leq 0, \end{aligned} \quad (12)$$

$$\begin{aligned} & g_2 = p\omega_m \sqrt{\phi_d^2 + \phi_q^2} - V_{\max} \leq 0, \\ \underset{i_d, i_q}{\text{minimize}} \quad & f_2 = i_d^2 + i_q^2, \\ \text{subject to} \quad & g_1 = i_d^2 + i_q^2 - I_{\max}^2 \leq 0, \\ & g_2 = p\omega_m \sqrt{\phi_d^2 + \phi_q^2} - V_{\max} \leq 0, \\ & g_3 = Tq_m - \frac{2}{3}p(\phi_d i_d - \phi_q i_q) \leq 0, \end{aligned} \quad (13)$$

where the subscripts d and q represent the orthogonal axes for control. The formulation (12) is used to determine the maximum torque limit at given motor speed and temperature. After determining the optimal current vector (i_d, i_q) using (12), the objective function value is used for the data in 2D LUT. The current and voltage limits are reflected by the constraints g_1 and g_2 , respectively. As g_1 or g_2 becomes active constraint according to the motor speed, the MTPA or MTPV control strategy is realized. The current amplitude is minimized in (13), and the torque at the desired operating point is guaranteed using the constraint g_3 .

In (12)–(13), the flux linkages (ϕ_d, ϕ_q) show significant nonlinear variations with current [23]. In addition, the thermal demagnetization of the permanent magnet lowers the remanent flux density B_r , as given by the following:

$$B_r = B_{r0}(1 - \alpha_d(T_{PM} - T_{PM,ref})). \quad (14)$$

Thus, flux linkage maps according to i_d, i_q , and T_{PM} should be prepared to construct LUTs considering nonlinear flux linkage in a reasonable time. Preparing flux linkage maps requires electromagnetic analyses corresponding to the following:

$$N_{\text{eval}} = N_{i_d} \times N_{i_q} \times N_{T_{PM}}, \quad (15)$$

TABLE 5: Main parameters and working conditions of IPMSM.

Description	Unit	Value
Poles/slots	—	8/48
Stator outer radius	mm	132
Rotor outer radius	mm	80
Rotor inner radius	mm	55
Airgap length	mm	0.75
Stack length	mm	84
Lamination factor	—	0.95
Magnet length	mm	17.9
Magnet thickness	mm	7.2
Magnet angle	deg	150
Remanent flux density of magnet (25°C)	T	1.03
Maximum current	A_{rms}	216
Maximum voltage	V_{rms}	170
Thermal conductivity of steel	W/(m•K)	51.9
Thermal conductivity of magnet	W/(m•K)	47.3
Thermal conductivity of coil	W/(m•K)	400
Thermal conductivity of coil insulation	W/(m•K)	0.26
Slot fill factor	—	0.45
Density of steel	kg/m ³	7650
Density of magnet	kg/m ³	7500
Density of coil	kg/m ³	8940
Thermal capacitance of steel	J/(kg•K)	460
Thermal capacitance of magnet	J/(kg•K)	502
Thermal capacitance of coil	J/(kg•K)	385
Maximum torque (25°C)	Nm	360
Rated speed at maximum torque (25°C)	rpm	1250

TABLE 6: Parameters of EV propulsion system model.

Description	Unit	Value
Control gains for acceleration (P, I, D)	—	(100, 1, 0)
Control gains for braking (P, I, D)	—	(10, 0.1, 0)
Vehicle weight	kg	1375
Wheel radius	in	16
Front area of vehicle	m ²	2.57
Drag coefficient	—	0.26
Rolling friction coefficient	—	0.01
Reduction ratio	—	8

where N_{i_d} , N_{i_q} , and $N_{T_{PM}}$ refer to the number of points that divide each coordinate (i_d , i_q , and T_{PM}) equally. From the N_{eval} electromagnetic analyses, iron loss maps and flux linkage maps are constructed simultaneously. Although iron loss also depends on ω_m , additional analyses are not needed because the iron loss is calculated by postprocessing using (3)–(5). Therefore, the total number of electromagnetic analyses for constructing all LUTs is N_{eval} ; this process accounts for the majority of the computing time in the 1D simulation. As electromagnetic analyses are performed by the EMCN,

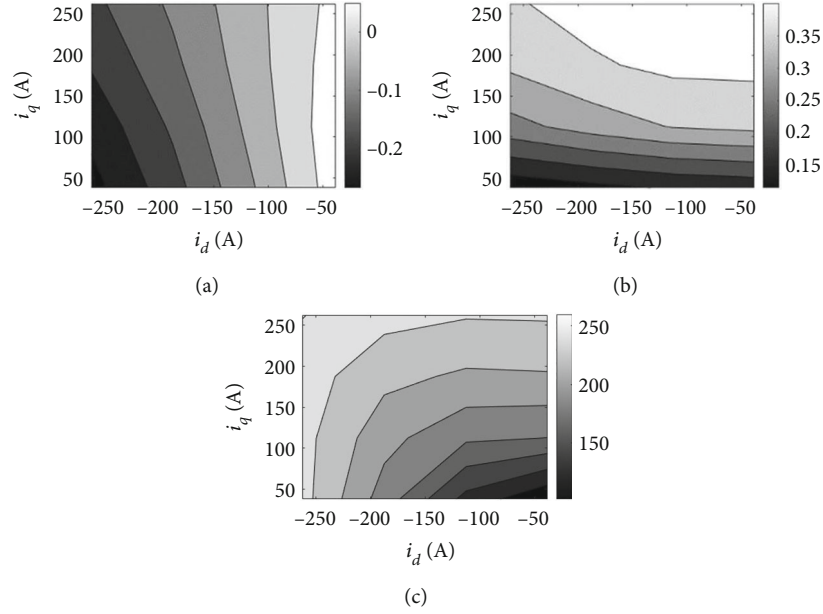


FIGURE 10: Maps used for constructing LUTs at 90°C: (a) flux linkage along d -axis (Wb), (b) flux linkage along q -axis (Wb), and (c) iron loss at 1300 rpm (W).

considerable computing time is saved compared with the FEM. In addition, N_{eval} can be modulated according with which the designer considers the magnetic saturation effect of the motor.

The temperature change is reflected using the initial temperature, losses, and speed as inputs, as illustrated in Figure 5. The change rate of the motor temperature dT/dt at n^{th} time step is calculated by the finite difference method using the following approximation:

$$\frac{dT}{dt} \approx \frac{\Delta T}{\Delta t} = \frac{T^{(n+1)} - T^{(n)}}{\Delta t}, \quad (16)$$

where $T^{(n+1)}$ is obtained by transient thermal analysis. The current motor temperature is calculated by integrating dT/dt as given by the following equation:

$$T = T_0 + \int \frac{dT}{dt} dt. \quad (17)$$

3. One-Dimensional Simulation over Target Driving Cycles

To validate the analysis accuracy of equivalent circuit models used in the proposed system model, the EMCN and LPTN are modeled as shown in Figures 6 and 7, respectively. The validations are conducted at three operating points distributed in the overall operating region, as listed in Table 4.

In Figure 8, motor torque, iron loss, and efficiency, evaluated by EMCN and FEM, are compared to each other. The difference between the electromagnetic analysis results is less than 3.5%, 5.6% 0.5%, respectively, in motor torque, iron

loss, and efficiency. From the results, it is confirmed that the EMCN can substitute the FEM in electromagnetic analyses required in the 1D simulation over driving cycles.

The transient thermal analyses are conducted using the LPTN and FEM at the same operating points as electromagnetic analyses. The initial motor temperature and time step are set to 20°C and 1 s, respectively, and the slot and magnet temperatures, evaluated by LPTN and FEM, are compared in Figure 9. In transient and steady state, the error between two models is less than 5% and 1%, respectively. Therefore, the analysis error between LPTN and FEM can be negligible while driving.

For system model validation, the geometric and material parameters of the IPMSM and its working conditions are used as listed in Table 5 based on the PRIUS 2004 hybrid EV traction motor [24]. The 1D simulations are performed to calculate the motor efficiency over UDDS and HWFET, and the parameters of the electric propulsion system are listed in Table 6. Total $N_{\text{eval}} = 75$ ($N_{i_d} = N_{i_q} = 5$, $N_{T_{\text{PM}}} = 3$) times of electromagnetic analyses are conducted in configuring all maps and LUTs. The temperature range of the permanent magnet used in the maps (shown in Figure 10) is defined by 0 and 180°C, sufficiently large for covering various driving conditions. The maps are utilized to treat nonlinear parameters in the optimizations (12)–(13) and calculate the motor efficiency. Furthermore, the LUTs used in the motor subsystem are constructed, as shown in Figure 11.

The simulation results show that the system model follows the driving cycles with a speed error of less than 1 km/h, which is sufficiently small, as shown in Figure 12. In addition, the system model reflects the temperature change in the permanent magnet while driving. The results show that the temperature increases by 13°C

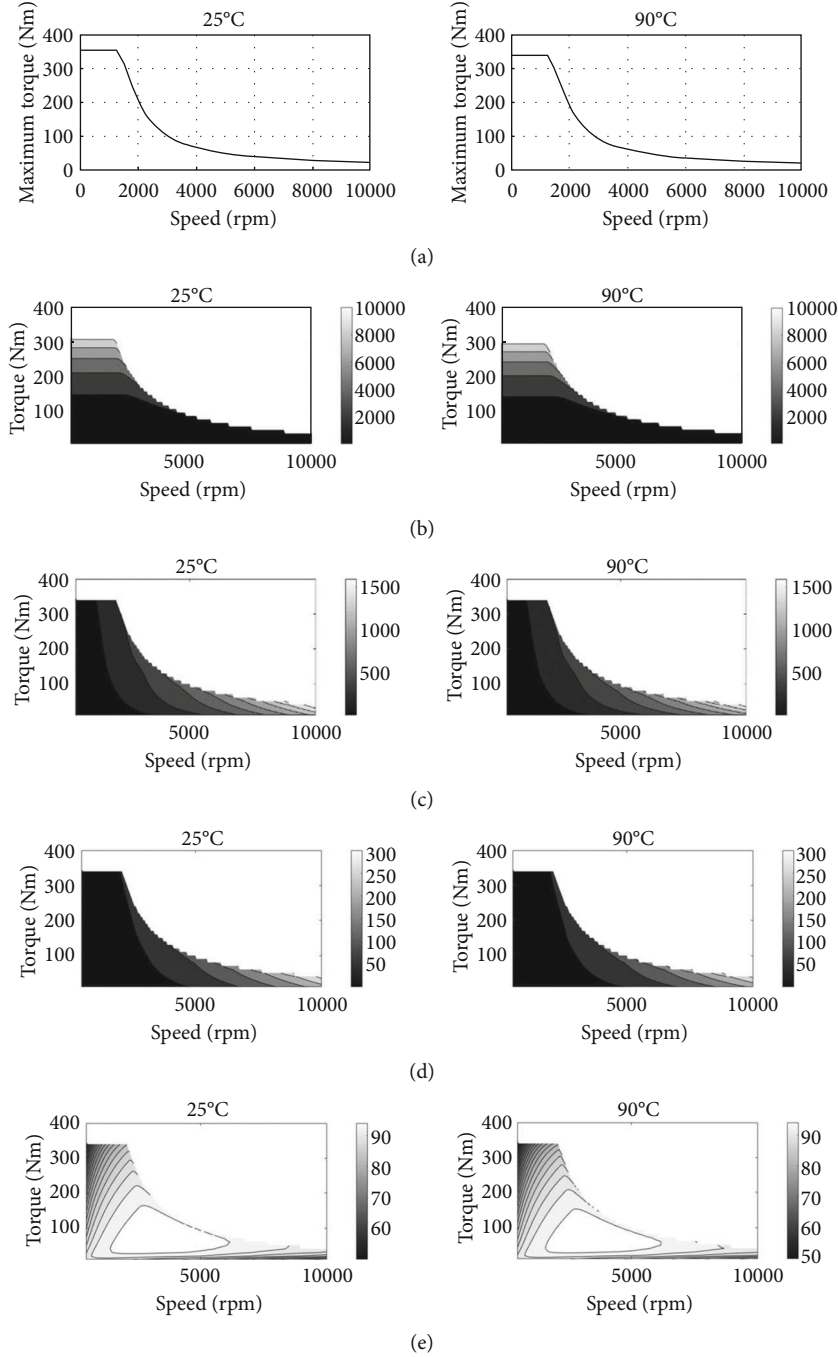


FIGURE 11: LUTs in motor subsystem: (a) maximum torque, (b) copper loss (W), (c) stator iron loss (W), (d) rotor iron loss (W), and (e) efficiency (%).

and 24°C in UDDS and HWFET, respectively, and that the permanent magnet temperature can considerably depend on the driving cycle.

To clearly show that the efficiencies over driving cycles are calculated successfully while considering the dependency on temperature, the results are compared to cases in which the motor temperature is fixed to 20°C and 60°C, respectively, as shown in Figure 13. The calculated efficiency is close to the 20°C fixed case at the beginning of the cycles; however, the efficiency becomes closer to the 60°C fixed case

as the temperature increases. Therefore, it is confirmed that the proposed system model can effectively consider the varying motor characteristics and temperature.

A simulation is performed over five repeated cycles to investigate the varying motor characteristics and temperature in detail. The temperatures at the winding and permanent magnet reached a steady state after three or four cycles, as shown in Figure 14.

In addition, the electromagnetic motor characteristics depend on the driving cycle, as shown in Figure 15.

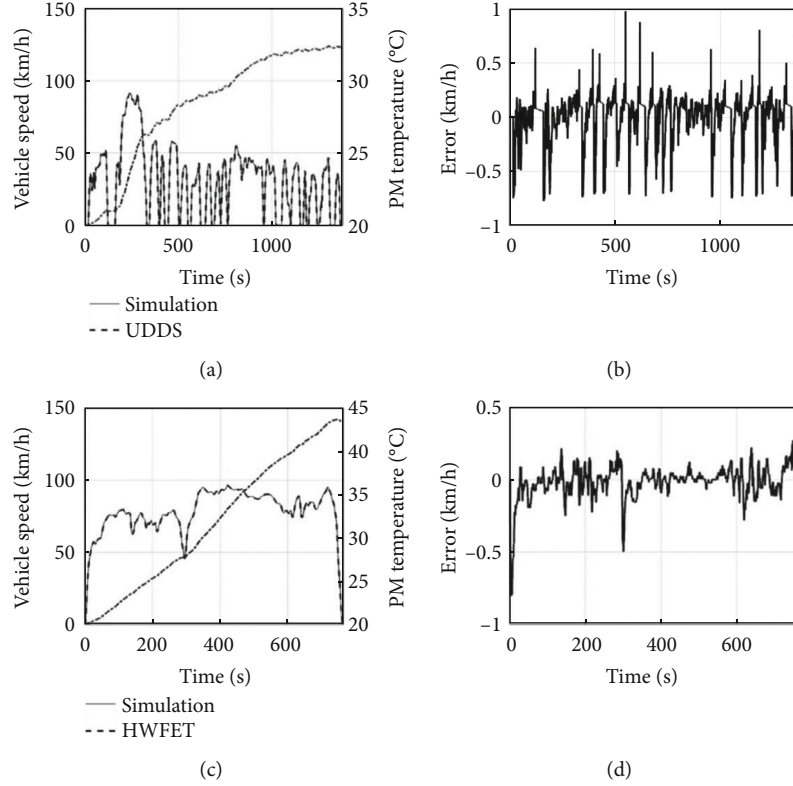


FIGURE 12: Simulation results: (a) permanent magnet temperature during UDDS, (b) speed error during UDDS, (c) permanent magnet temperature during HWFET, and (d) speed error during HWFET.

The average efficiency η_{avg} is evaluated using the following equation:

$$\eta_{\text{avg}} = \frac{1}{t_{\text{end}}} \int_0^{t_{\text{end}}} \eta \, dt, \quad (18)$$

where t_{end} denotes the end of the simulation. The maximum current increases in both driving cycles, whereas the tendency of the average motor efficiency is the opposite for each cycle. In the low-speed operating region, more current is required because thermal demagnetization reduces the output torque. Because both cycles required the maximum current in low-speed operation, the corresponding results are obtained. However, in the high-speed operating region where the field-weakening control is needed, thermal demagnetization reduces the current required to relieve the influence of the permanent magnet. Because the operating point distribution in the HWFET is more concentrated in the high-speed region than that in the UDDS, thermal demagnetization helps the field weaken and increases the average efficiency. Thus, 1D simulation using the proposed system model can consider motor characteristics that are difficult to predict empirically over driving cycles.

The total computing time required for the 1D simulation is 17.1 min, as shown in Table 7. The construction of maps and LUTs is included in the total time consumed; 75% of

the computing time is spent on 75 electromagnetic analyses. Since all electromagnetic analyses are performed by the EMCN, 92% of the computing time is saved compared with the case that uses the FEM, which requires 169.6 min. Moreover, simulations over various driving cycles require the construction of maps and LUTs only once, with approximately 0.3 min added for other driving cycles. Therefore, the 1D simulation using the proposed system model has the advantage of computational efficiency and can be included in the optimization.

4. Multiobjective Optimization of IPMSM

Using the proposed system model, the IPMSM geometry and system parameters are optimized to maximize motor performances, such as efficiency over the target driving cycles and maximum torque, and to minimize magnet volume. The design variables consist of the five geometric parameters shown in Figure 16 and the reduction ratio. The geometric parameters are selected based on [25], showing the global sensitivity of the variables to torque, iron loss, and efficiency.

The boundaries of the design variables are determined so as not to interfere with the different material domains, as listed in Table 8. In addition, the upper limit of the magnet width is the same as the initial value to prevent the magnet volume from increasing. Four objective functions were formulated to consider the motor performance and magnet volume, and the maximum output torque transferred to

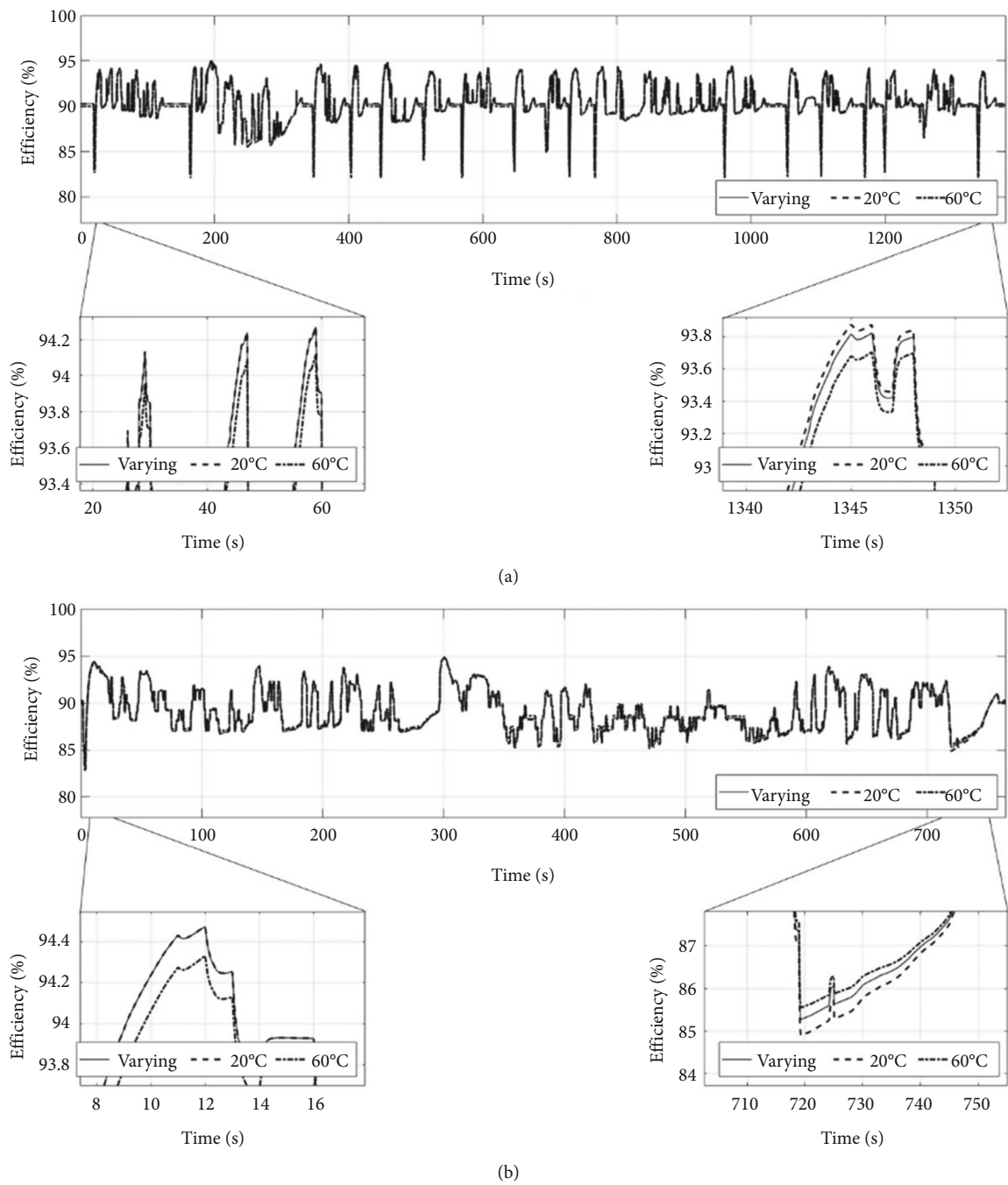


FIGURE 13: Motor efficiency at (a) UDDS and (b) HWFET compared with fixed temperature cases.

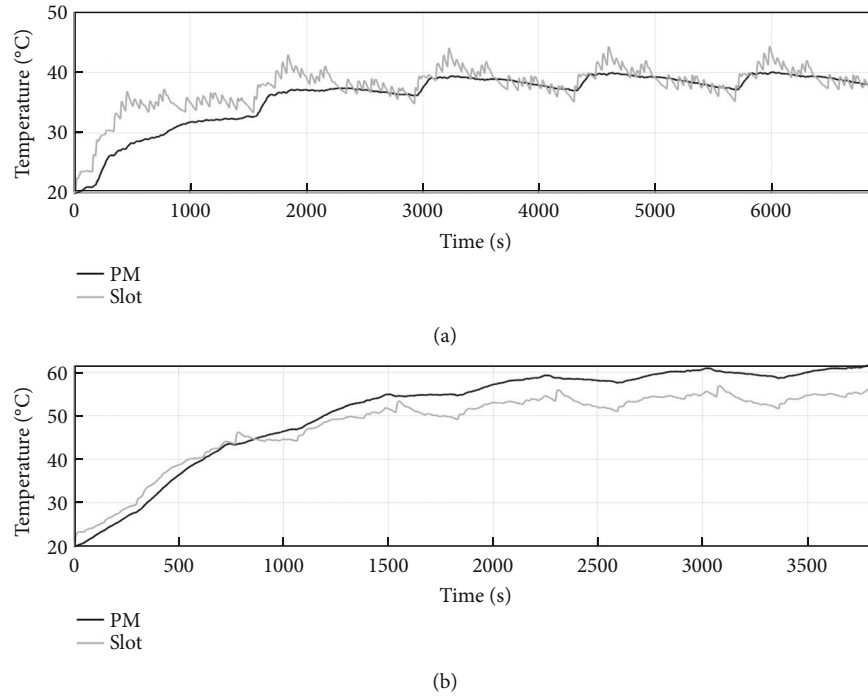


FIGURE 14: Temperature change at driving cycles repeated 5 times: (a) UDDS and (b) HWFET.

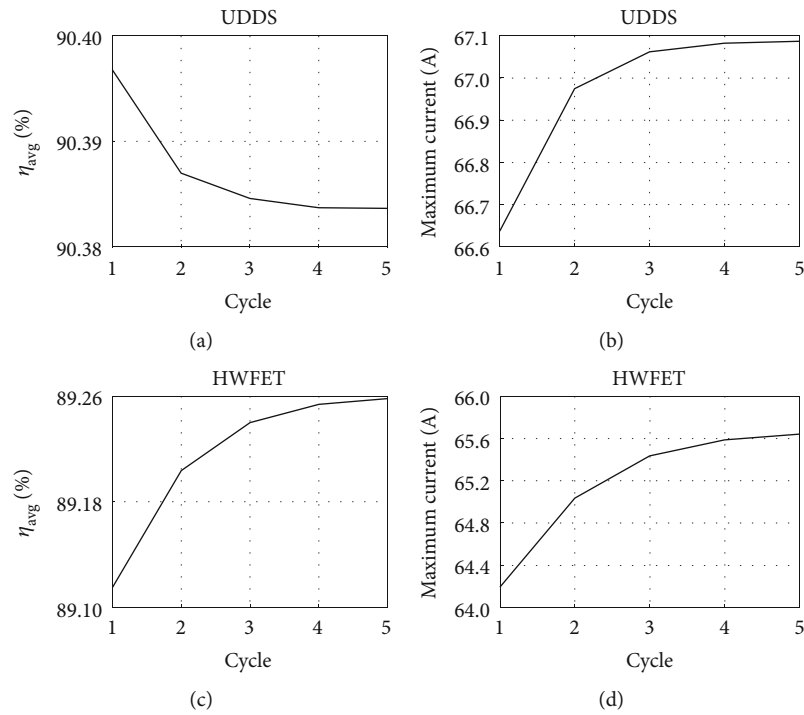


FIGURE 15: (a) Efficiency and (b) maximum current over repeated UDDS and (c) efficiency and (d) maximum current over repeated HWFET.

TABLE 7: Computing time required for 1D simulation.

Process	Time (min)	Normalized	Note
Maps in d - q axes	12.9	0.75	75 evaluations
LUTs	3.9	0.23	9915 data
1D simulation	0.3	0.02	1 cycle
Total	17.1	1.00	—

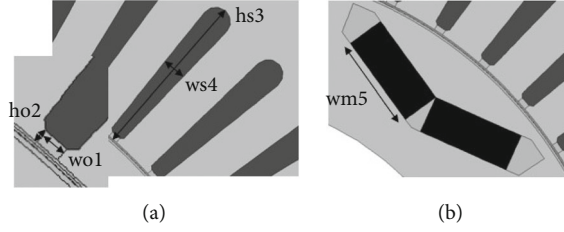


FIGURE 16: Design variables for motor geometry: (a) stator and (b) rotor.

TABLE 8: Initial values and boundaries of design variables.

Description	Variable	Unit	Initial value	Boundary
Slot opening width	wo1		1.9	(1.0, 2.3)
Slot opening height	ho2		1.0	(0.8, 1.2)
Slot height	hs3	mm	33.5	(30, 35)
Slot width	ws4		4.5	(4.0, 5.5)
Magnet length	wm5		17.9	(15.9, 17.9)
Reduction ratio	gr6	—	8.0	(7.5, 9.5)

the wheels is constrained to guarantee the acceleration performance, as shown in the following equation:

$$\begin{aligned}
 &\underset{x}{\text{minimize}} \quad \begin{cases} f_{\text{obj}(1)} = -\eta_{\text{UDDS}}(x)/100, \\ f_{\text{obj}(2)} = -\eta_{\text{HWFET}}(x)/100, \\ f_{\text{obj}(3)} = -T_{q_{\text{max}}}(x)/T_{q_0}, \\ f_{\text{obj}(4)} = wm5/wm0, \end{cases} \\
 &\text{subject to} \quad g = T_{q_0} gr_0 - T_{q_{\text{max}}}(x) gr6 \leq 0, \\
 &\quad lb \leq x \leq ub, \quad x = [wo1 \ ho2 \ hs3 \ ws4 \ wm5 \ gr6]^T,
 \end{aligned} \tag{19}$$

where $T_{q_0} = 420 \text{ Nm}$, $gr_0 = 8$, and $wm0$ is the initial value of the magnet length.

To conduct the multiobjective optimization according to the procedure in Figure 17, the equivalent circuit networks (EMCN/LPTN) and electric propulsion system are modeled first. Thereafter, η_{avg} on UDDS and HWFET and $T_{q_{\text{max}}}$ are evaluated at the design of experimental points obtained by OLHD, which distributes the points

evenly by maximizing the distance between all points [26]. This study uses the Kriging surrogate model to construct each response; this model is generally used in electromagnetic device designs [27]. The quadratic polynomial regression model and Gaussian correlation function are adopted as the regression model and random process model, respectively. In this study, 28 experimental points, the minimum number, are selected for constructing the kriging surrogate model. The surrogate models are validated at ten points selected by the new OLHD, and the maximum absolute errors in each response are 0.18%, 0.34%, and 3.54%. Thus, the average efficiencies over two driving cycles and maximum torque are evaluated using the surrogate model during optimization.

The Pareto optimal solutions are obtained using the NSGA-II, which performs an efficient multiobjective optimization with constraints [28]. The population and generation of the NSGA-II are fixed at 500 and 600, respectively. In Figure 18, the Pareto optimal solutions are projected onto six criterion surfaces that include all combinations of the four objective functions. Here, D1, D2, D3, and D4 represent designs superior to others in terms of the UDDS efficiency, HWFET efficiency, maximum torque, and magnet volume,

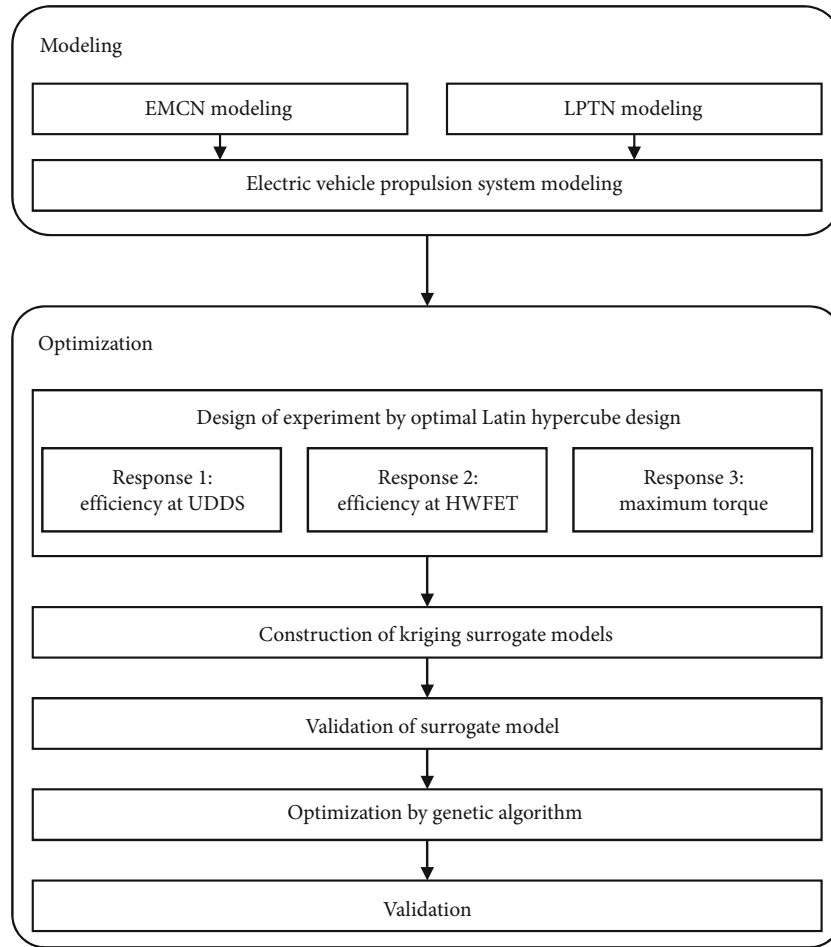


FIGURE 17: Optimization procedure.

respectively. The designer can select appropriate design according to performance priority, for example, a proper design for small magnet usage is one of D2 and D4. Additionally, when the efficiency over specific driving cycle is important, one of D1 or D2 becomes the best solution.

At operating point 1 listed in Table 4, the magnetic flux distributions of the optimal designs are evaluated using the FEM and compared in Figure 19. Owing to the wider magnet, D1 and D3 are more highly saturated than others. In Figure 19, although the maximum flux density is higher than 3.0 T, this value results from the limited data for the BH-curve, which is linearly extrapolated at a high magnetic field strength area.

All designs and the performance validated using the FEM are listed in Table 9. The results indicate that the slot opening width (ws1) and slot height (hs3) converge to upper and lower bounds, respectively, regardless of the objective function. The slot opening width converges to the upper bound to reduce the magnetic saturation on the teeth tip because it is helpful in increasing both the efficiency and torque. A large slot height implies a smaller core volume of the stator yoke region, which reduces the iron loss produced in the stator yoke region. Additionally, a wide slot area decreases the slot fill factor

and shortens the heat transfer path between the copper and stator outer diameters. Such a design presents the advantage of a cooling motor.

In Table 9, the underlined numbers imply that the corresponding design produces the best response compared to the others, and the numbers in round braces denote the validation results obtained using the FEM. From the validation results, we can observe that the maximum torque of D1 is superior to that of D3, which is a different aspect from the surrogate model, owing to the difference between the EMCN and FEM. However, the maximum torque difference is less than 1.2%, which is negligible in the early design process. Because the optimization is performed using a surrogate model and an equivalent circuit network, their effects on feasibility are investigated. The maximum torque constraint g is active for designs D1, D2, and D4; however, there exists a maximum margin of 10% according to the FEM validation. Because the margin originates from the accuracy difference between the EMCN and FEM, additional optimization with a modulated constraint is required to overcome this margin. However, because the optimization is performed using a surrogate model, the additional computing time is sufficiently small and can be ignored.

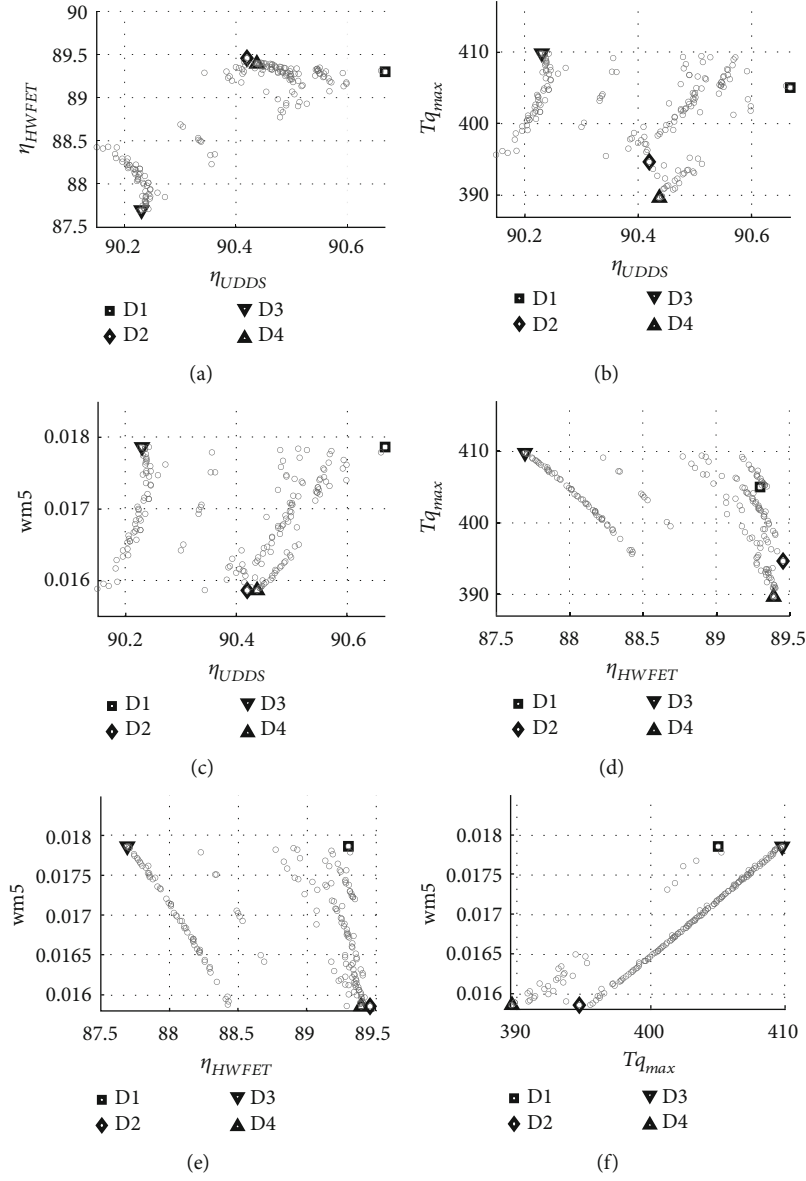


FIGURE 18: Pareto optimal solution projected to criterion surfaces: (a) UDDS efficiency and HWFET efficiency, (b) UDDS efficiency and maximum torque, (c) UDDS efficiency and magnet width, (d) HWFET efficiency and maximum torque, (e) HWFET efficiency and magnet width, and (f) maximum torque and magnet width.

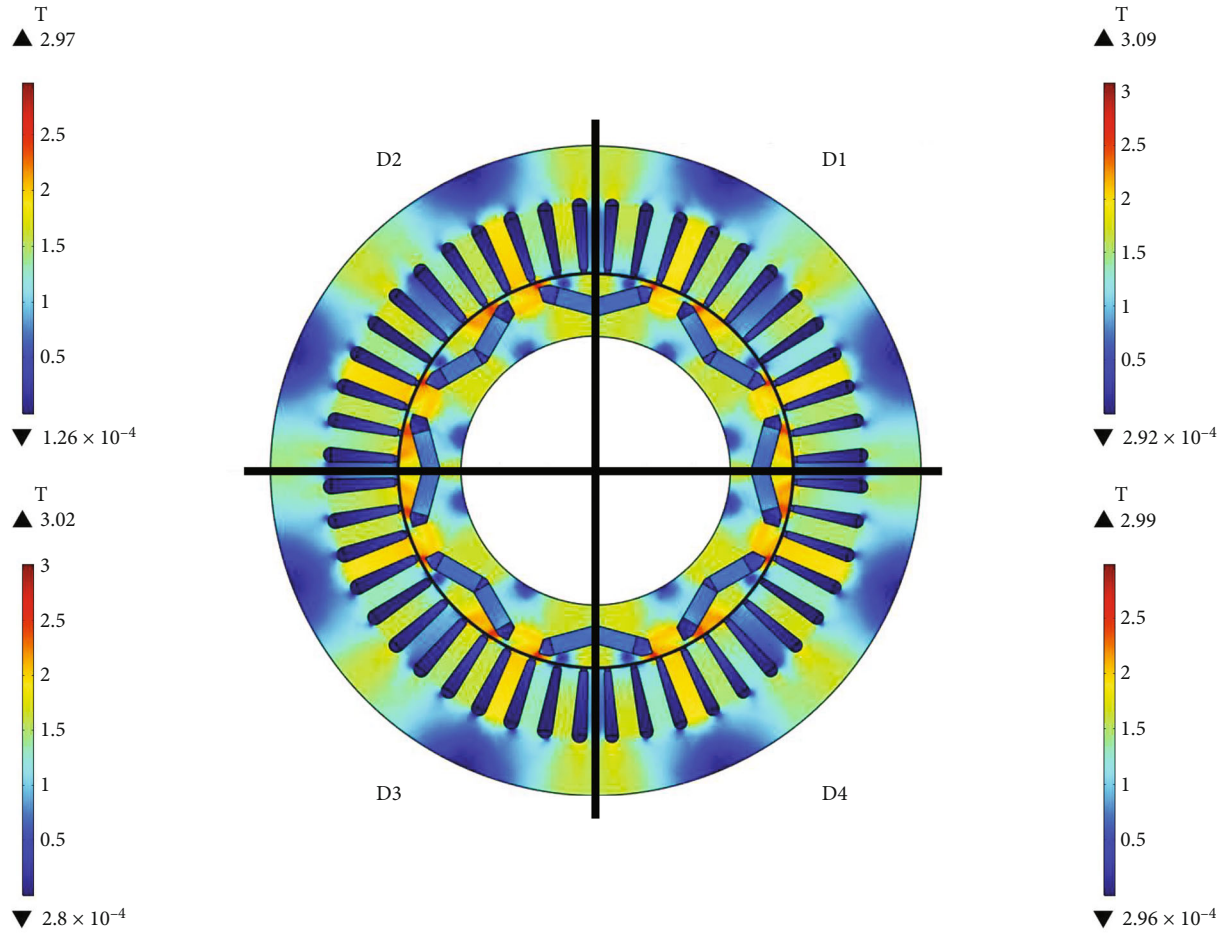


FIGURE 19: Magnetic flux distribution of optimal designs at operating point 1.

TABLE 9: Multiobjective optimization result.

Result	D1	D2	D3	D4
wo1 (mm)	2.3	2.3	2.3	2.3
ho2 (mm)	1.2	1.2	0.9	1.2
hs3 (mm)	30.0	30.0	30.0	30.0
ws4 (mm)	4.1	4.5	4.7	4.0
gr6	8.3	5.5	9.5	8.6
η_{UDDS} (FEM) (%)	<u>90.69</u> (90.91)	90.42 (90.75)	90.23 (90.47)	90.44 (90.76)
η_{HWFET} (FEM) (%)	89.30 (89.17)	<u>89.46</u> (89.62)	87.70 (87.16)	89.39 (89.56)
Tq_{max} (FEM) (Nm)	405.0 (<u>449.0</u>)	394.7 (419.1)	<u>409.8</u> (444.1)	389.6 (422.2)
wm5 (mm)	17.9	<u>15.9</u>	17.9	<u>15.9</u>
Tq_{max} gr6 (FEM) (Nm)	3360 (3725)	3360 (3568)	3894 (4219)	3361 (3642)

5. Conclusion

In this study, the system model, computationally efficient and capable of coupled electromagnetic–thermal 1D simulation, was proposed. The proposed system model was validated by 1D simulation over UDDS and HWFET driving cycles. From the simulation results, the proposed system model successfully reflected the varying motor characteris-

tics and temperature while driving. Because it is difficult to intuitively predict how the temperature change affects the efficiency and current usage for individual operating points, 1D simulation using the proposed system model is effective for motor design considering driving cycles. All electromagnetic analyses required for constructing the LUTs in the system model were performed by the EMCN rather than the FEM; the computational efficiency was improved by

more than 13 times. The total time required for one simulation was approximately 17 min, of which 75% was spent constructing maps and LUTs. In addition, to consider an additional driving cycle, only negligible computing time is required without any process of clustering the driving cycle like previous research. Accordingly, it was shown that the proposed system model had sufficient computational efficiency to be included in the optimization. Multiobjective optimizations of the motor cross-section and reduction ratio were performed to maximize motor efficiency over two driving cycles and maximum torque and to minimize magnet volume. Four optimal designs were obtained from the Pareto front, and the results demonstrate that the proposed system model is effective for optimization at an early design stage.

In the optimization process, the system model provides two main advantages in terms of flexibility and integration: first, the model accuracy and computing time can be adjusted according to the designer's intention because subsystems are flexible and can be changed or added; second, the motor geometry and system parameters can be optimized simultaneously. This integrative optimization is important because it facilitates designing subsystems with different physics simultaneously. For example, in this study, the geometric motor parameters adopted to maximize efficiency were closely related to the efficiency distribution in the operating region according to the torque, speed, and temperature. Consequently, the optimal motor geometry offered the best efficiency distribution for the target driving cycle. In addition, changing the reduction ratio was the same as tuning the operating points of the driving cycle from the perspective of the motor. Therefore, the integrative optimization increases design freedom and improves the system performance, which is difficult to obtain from component-level optimization.

Although normal driving cycles were considered in this study, any cycle can be utilized in the 1D simulation and optimization to reflect extreme conditions where the temperature and performance are difficult to predict in the design process. Thus, the system modeling, simulation, and optimization performed in this study can be applied to various electric propulsion systems including EVs. In particular, the superior computational efficiency of optimization using the proposed system model represents the practicality of the concept development stage of a new electric propulsion system.

Abbreviations

EV:	Electric vehicle
Pma-SynRM:	Permanent magnet-assisted synchronous motor
IPMSM:	Interior permanent magnet synchronous motor
SRM:	Switched reluctance motor
PMSHM:	Permanent magnet synchronous hub motor
FEM:	Finite element model
EMCN:	Equivalent magnetic circuit network
LPTN:	Lumped parameter thermal network
LUT:	Look-up table

UDDS:	Urban dynamometer driving schedule
HWFET:	Highway fuel economy test
DOF:	Degree of freedom
PID:	Proportional-integral-derivative
MPTA:	Maximum torque per ampere
MPTV:	Maximum torque per voltage
OLHD:	Optimal Latin hypercube design
NSGA:	Nondominated sorting genetic algorithm.

Symbols

μ :	Relative permeability vector (-)
B :	Flux density (T)
H :	Magnetic field intensity (A/m)
ε :	Tolerance value (-)
$I_{c,rms}$:	Root mean square value of the current (A)
R_c :	Phase resistance of the winding (Ω)
P_h :	Hysteresis loss (W)
P_e :	Eddy current loss (W)
$P_{m,ref}$:	Reference loss for motor mechanical loss (W)
$\omega_{m,ref}$:	Reference motor speed for motor mechanical loss (W)
ω_m :	Motor speed (rpm)
Tq_m :	Motor torque (Nm)
P_{in} :	Input power of motor (W)
P_{out} :	Output power of motor (W)
K_p :	Proportional gain parameter for PID control (-)
K_i :	Integral gain parameter for PID control (-)
K_D :	Derivative gain parameter for PID control (-)
C_d :	Drag coefficient (-)
A_f :	Front area (m^2)
μ_{roll} :	Rolling friction coefficient (-)
m :	Vehicle mass (kg)
T_d :	Drag torque (Nm)
r_t :	Wheel radius (m)
Tq_b :	Maximum braking torque (Nm)
J_{eq} :	Equivalent moment of inertia ($kg \cdot m^2$)
T_{PM} :	Magnet temperature ($^{\circ}C$)
p :	Pole pairs (-)
I_{max} :	Current limit (A)
V_{max} :	Voltage limit (V)
α_d :	Demagnetization coefficient at reference temperature (-)
B_{r0} :	Remanent flux density at reference temperature (T)
T_0 :	Initial motor temperature ($^{\circ}C$).

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Additional Points

Replication of Results. All important parameters used for the proposed model, 1D simulation, and optimization are provided in the manuscript. Because stochastic methods such as the Kriging and genetic algorithms are adopted, the authors confirm that the optimization result is not affected by repeating the optimization. Therefore, all results shown in figures and tables are replicable with the provided information provided in this paper.

Conflicts of Interest

The authors declare that they have no conflicts of interests.

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