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Rule-Based Alternator Control Using Predicted Velocity for Energy Management Strategy

The market concern of improvement of vehicle safety and its convenience to drive a vehicle has resulted in the growth of the demand for vehicular electronic equipment. This trend requires additional power in the vehicle and thus makes prone to the increase of fuel consumption for vehicles equipped with internal combustion engines. To minimize this fuel consumption, an efficient energy management (EM) strategy for the electrical system of alternator and battery is required. This paper proposes a successful EM strategy based on the rule-based alternator control using predictive information. The proposed strategy reduces fuel consumption by charging batteries using the residual kinetic energy during deceleration. In particular, we predict electrical energy that is recovered by the residual energy using a Markov chain-based velocity prediction algorithm. The accommodation of predicted electrical energy and current vehicle information determines one of the three predefined control modes, such as charge, hold, and discharge, depending on vehicle driving states. This control mode determines the power generation from the alternator and controls the amount of torque to the vehicle electrical system. The proposed strategy is verified through simulation and experiment. The simulation with the new EM strategy is validated as comparing the operation difference with a conventional proportional-integral (PI) control algorithm under the same driver behaviors. Further validation in real vehicle driving experiment shows that fuel consumption was reduced by 2.1% compared to the conventional PI control algorithm.
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Keywords: energy management system, alternator control, internal combustion engine vehicles, vehicle speed prediction, rule-based control, fuel economy

1 Introduction

Growing consumer demands for safer and more convenient driving have promoted an increase in the number of electrically driven units in internal combustion engine (ICE) vehicles. Such added auxiliary devices consume more electrical energy of the vehicle [1–3]. Thus, additional alternator operation of the engine is required to compensate for more required energy use, which causes additional fuel consumption. Therefore, strategic energy management (EM) of the electrical system should be addressed to minimize any fuel consumption caused by more burden to the ICE from electrically driven devices [4].

As a means of cranking the ICE and storing electrical energy, an alternator and a lead-acid battery are generally combined. The alternator generates electrical energy, connected to the engine by a pulley belt and controlled by a regulator. The battery provides energy to start the engine and stores extra electrical energy. This stored energy is used when the power from the alternator is below the power demand from the electrical load [5,6]. The EM strategy should control the alternator to meet the load requirements of electrically driven units while minimizing fuel consumption.

Therefore, to minimize fuel consumption and meet electrical power requirements, several optimization techniques based on the knowledge of future driving information have been proposed. Optimal off-line strategies and causal strategies were proposed and solved dynamic programming and quadratic programming based optimization problems in the model predictive control framework [5,7]. The model predictive control framework required the engine information (power, rotational speed) of the future driving. In recent years, another approach using a Pontryagin's minimum principle (PMP)-based strategy has been widely used to improve computational efficiency. Waldman et al. proposed a supervisory EM strategy by formulating a constrained optimization problem based on PMP [6]. Nguyen et al. also provided a PMP-based strategy to optimally control the power system of a vehicle equipped with an electric supercharger [8]. These proposed PMP-based strategies commanded alternator duty cycle with full knowledge of the future driving cycle.

However, these optimization techniques are challenging to guarantee performance when implemented in real driving situations. The prediction of future driving information is nondeterministic and affected by various driving environments. These properties make it difficult to guarantee the consistent performance of the optimization techniques [9–12]. Also, most of the introduced techniques do not contain how to handle system robustness. The robustness of these techniques is the resistance of model uncertainties, system noise, and disturbances. Negligence of this factor can cause performance degradation when implemented in a target process. Time-varying parameters can reduce the model accuracy and degrade performance as well. For example, in the case of city buses or garbage trucks, the vehicle mass

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varies from unloaded to the fully loaded situations [13,14]. In addition, battery aging may increase the modeling error of the electrical system [15].

To overcome the difficulty of implementation in real driving situations, Lakshminarasimhan and Athani proposed a rule-based control algorithm [16]. This algorithm is designed based on a state machine and determines the voltage set point of the conventional regulator. Combining with the regulator ensures the robustness of system noise, disturbance, and eliminates model inaccuracy. This algorithm focused on reducing fuel consumption by two control strategies. The first strategy is to recycle the residual energy that appears during deceleration or coasting condition of the vehicles. In these conditions, the energy is usually wasted as friction by brakes or drive shafts. However, the strategy charges a battery using this wasted energy by increasing electrical generation of the alternator. Using this recuperated energy as an electrical load can increase the fuel efficiency of the ICE. The technology that recycles waste energy to improve fuel efficiency is called energy recovery systems [17,18]. The second strategy is to shut down the alternator when the stored energy is sufficient [16]. This strategy can undoubtedly reduce the fuel consumption of the electrical system but limits its usage only to when the state of charge is high. These control strategies were implemented to a demonstrator vehicle, presenting fuel savings under various driving conditions.

For more aggressive recuperation of the residual energy and shutting off the alternator engagement at sufficient energy storage level, we propose an EM strategy based on a rule-based alternator control, which employs a predictive velocity. The proposed control strategy uses the predictive velocity to estimate the amount of electrical energy recuperated by the residual energy. If the battery energy is discharged as much as the amount of the predictive electrical energy, the future recuperation of the residual energy maintains sufficient energy storage level. The model to predict the vehicle speed consists of a Markov chain based on stochastic reasoning and a constraint model designed in the form of an intuitive matrix. Using the predicted electrical energy and vehicle information, three control modes such as charge, discharge, and hold are predefined. This control model determines the alternator required torque, which becomes a set-point of the conventional regulator.

This paper is structured as follows: The environments of the strategy are described in Sec. 2. Section 3 presents the vehicle speed prediction algorithm in three parts. Section 4 explains the predictive alternator control (PAC). The proposed strategy is verified through vehicle simulations and experiments. Finally, conclusions and future work are provided in Sec. 5.

2 Environments

The vehicle used for the model and control algorithm verification was the 2014 2WD KIA Sorrento SUV with 2.2 L diesel engine. A 2 kW belt-driven alternator, which is originally installed in the Sorrento SUV, was used. The alternator is controlled by the built-in regulator. An intelligent battery sensor attached to the 12 V 66 Ah lead-acid battery transmits the battery status (temperature, voltage, current) through a local interconnect network. Additional configuration details are shown in Table 1.

We selected a 4.2 km route (Fig. 1) without traffic lights and surrounding vehicles as a test site for the algorithm performance validations. This environment reduces fuel economy disturbance caused by rapid acceleration/deceleration. Furthermore, this provides uniform conditions for the validation test by minimizing unintended speed changes of the ego-vehicles owing to uncontrolled traffic light timings and the movement of nearby vehicles.

Table 1 Specifications of the validation vehicle

Component	Specification
Engine	147 kW 2.2 L diesel
Transmission	Sixth automatic transmission
Alternator	2 kW
Battery	12 V 66Ah lead-acid battery

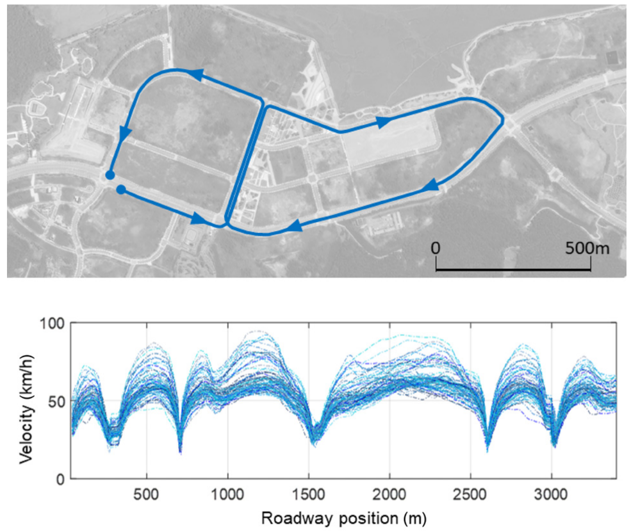

Fig. 1 Test site: Midan City, Incheon, South Korea

The proposed EM strategy consists of two parts, i.e., vehicle speed prediction and predictive alternator control as shown in Fig. 2. The prediction algorithm is constructed based on a Markov model with a constraint model to produce predictive velocity, which is utilized for the estimation of the residual energy. This residual energy is converted to the form of electrical energy. The alternator control section presents a rule-based control algorithm on three predefined modes such as charge, discharge, and hold mode. The three control modes are interchangeable according to the real-time measurements and the level of residual energy, which determines the amount of alternator energy generation as well.

3 Vehicle Speed Prediction

3.1 Markov Chain. A Markov chain was employed as a base model to predict vehicle speed using the measured dataset. At each discrete time (s), the state ($\bar{x}$) of the chain belongs to a finite set of possible states, called the state space (X). This chain model estimates future values within the state space based on probabilistic state transition. This state transition is expressed as Eq. (1). For the modeling of the vehicle speed prediction by a Markov chain, we should admit a key assumption that the future state is independent of given past states and only depends on a current state,

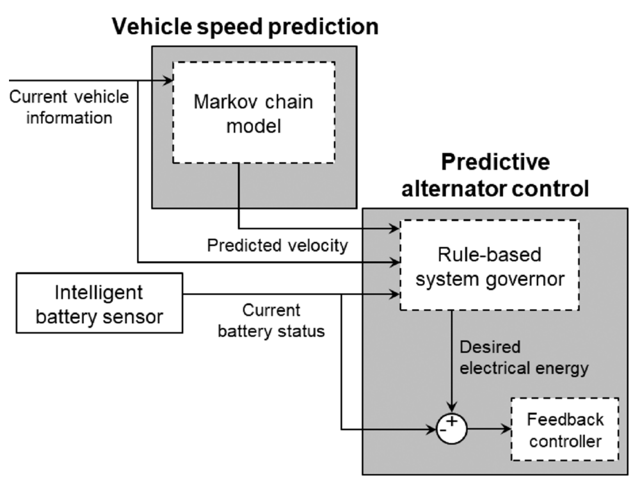

Fig. 2 System architecture of the EM strategy

which means that if you know the current state, then knowing past states does not give additional knowledge about next state (or any future state) (memoryless property) [19–21]

$$\Pr(x(s+1)=\bar{x}_j|x(s)=\bar{x}_i, x(s-1)=\bar{x}_{i-1}, \ldots, x(0)=\bar{x}_0) = \Pr(x(s+1)=\bar{x}_j|x(s)=\bar{x}_i) \tag{1}$$

$$\pi_{ij}^{+k} = \Pr\big(x(s+k)=\bar{x}_j|x(s)=\bar{x}_i\big) = \frac{N_{ij}(n)}{N_{oi}(n)} \tag{2}$$

$$N_{ij}(n) = \sum_{r=1}^{n} f_{ij}(r)\,,\; N_{oi}(n) = \sum_{r=1}^{n} f_i(r) \tag{3}$$

The transition probability to further future time-step (k) can be estimated using Eq. (2) [22–25]. The π_{ij}^{+k} means the k steps forward transition probability from the current i state to the future j state, which is the ratio of the number of transition events ($N_{ij}(n)$) to the total amount of i state's data ($N_{oi}(n)$) as described in Eq. (3). $f_{ij}(r)$ is transition event from i state to j state at r, expressed as true (1) or false (0). $f_i(r)$ is triggered when an event initiated from i state.

Each state is defined as using the interval encoding method. This method divides the state space (X) into a finite set of disjunct intervals and then discretizes the continuous data by matching each interval to a single state ($x_j \in I_i$).

The finite set of the disjunct interval is expressed by the following equation:

$$\mathrm{I_j},\, I_i \cap I_j = \phi,\; i \neq j; \quad \bigcup_j I_j = X; \quad i,j = 1,\ldots,M \tag{4}$$

The representative value of the state is defined as the median of each interval. Using the transition probabilities (2) and the representative value of the states, the predicted value for k-step ahead can be calculated using Eq. (5). By generalizing this expression, the predicted trajectory up to the k-step can be expressed as Eq. (6), which is used as the base model of the prediction algorithm

$$\hat{x}(s+k) = \sum_{j=1}^{M} \pi_{ij}^{+k}\bar{x}_j, \quad \text{if } x(n) \in I_i \tag{5}$$

$$\hat{X}(s+k|n) = [x(s), \hat{x}(s+1), \ldots, \hat{x}(s+k-1), \hat{x}(s+k)] \tag{6}$$

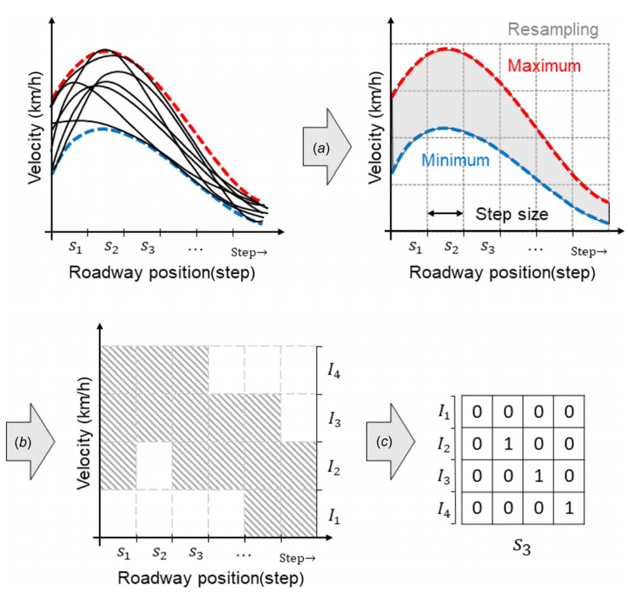

Fig. 3 Design process for the speed constraint model

In this study, the vehicle speed (v) and acceleration (a) were used as inputs, and the step variable of the model was selected as the roadway position of the ego-vehicle. A model that uses multiple inputs is called a multivariate Markov chain [23,24].

$$\pi_{(ij)(uv)}^{+k} = \Pr(v(s+k)=\bar{v}_j, a(s+k)=\bar{a}_v|v(s)=\bar{v}_i, a(s)=\bar{a}_u) \tag{7}$$

3.2 Speed Constraint Model. A constraint model is designed to improve prediction performance using an existing driving dataset. The range of constraint is encoded to the state through an interval encoding method. This constraint model, combined with the Markov chain, limits the predictable range to the empirical area, extracted from the existing dataset.

The constraint model generation process is represented in Fig. 3, which consists of constraint searching (a), state encoding (b), and matrix designing (c). In the constraint searching stage (a), the collected vehicle speed data resample size is the same as the prediction step size of the Markov chain. Based on the resampling of previous driving data, the constraint (from maximum to minimum value) for each step is carefully chosen. If input data (currently measured velocity) is beyond the constraint, the boundary value of the constraint is generated as the output of the constraint model. The large deviation of the actual measured velocity from the boundary value may degrade the accuracy of the velocity prediction algorithm. Then, the constraint value is converted to a state according to the interval encoding. The continuous values of the constraints are discretized based on the steps and state sizes as shown in (b). The discretized information is expressed as a diagonal matrix set (c), where the inner region of the constraint is represented by 1, and the outer region is represented by 0. Through a transformation of the diagonal matrix, the velocity constraint model can be combined with the Markov chain.

3.3 Validation. Total 86 driving datasets collected by a single driver were utilized to design the model. The driver collected data after having enough experience on the test site. An experienced driver can eliminate any confusion that may occur on unfamiliar roads. Also, the speed limit was set to 100 km/h. The experimental data logged by time base was resampled in 10 m increments for the model design. The Markov chain for validation consisted of 30 vehicle speed states and 20 acceleration states. The prediction trajectory was generated using 15 transition probability matrices with a step size of 10 m; that is, a future velocity up to 150 m ahead is predicted.

As a result, the Markov model was designed with a transition probability matrix of $15 \times 600 \times 600$. It combines with the constraint model. The constraint model uses the parameters selected from the Markov chain. A diagonal matrix of the same size as the number of velocity states was designed with a 10 m resolution, and the model size was defined as $30 \times 30 \times 340$ to cover the total test route. Table 2 shows the results of the prediction algorithm. It was verified using off-line simulation and was conducted on five selected validation sets. These sets were randomly selected from the driving dataset within the velocity constraint, which had been excluded from the model design. The performance of the algorithm was evaluated by comparing the predicted velocity and the actual velocity for the entire route, expressed by the determination factor (R^2) and the root-mean-square error (RMSE). In this table, an average performance of the algorithm showed R^2 of 0.8409 and RMSE of 3.9341 km/h. The largest deviation among the sets was 0.0127 of R^2 and 0.6134 of RMSE. Similar results were observed regardless of the test sets.

Figure 4 shows the results of the prediction algorithm in the first test case. The red dashed line represents the actual driving data, and the green lines indicate the prediction trajectory. The prediction results were spread within the velocity constraint represented by the blue colored area. In particular, this algorithm can improve the prediction performance in the section where the

Table 2 Performance analysis of the prediction algorithm with different test cases

Test case	R^2	RMSE (km/h)
1	0.8211	4.7311
2	0.8337	3.7068
3	0.8562	3.1613
4	0.8414	3.4989
5	0.8520	4.5726
Average	0.8409	3.9341

vehicle decelerates when entering the curved road. The size of the speed constraint varies with position along the roadway, and the size of this area at corners is smaller than in straightaways. This makes a decisive contribution to improving the performance of the algorithm.

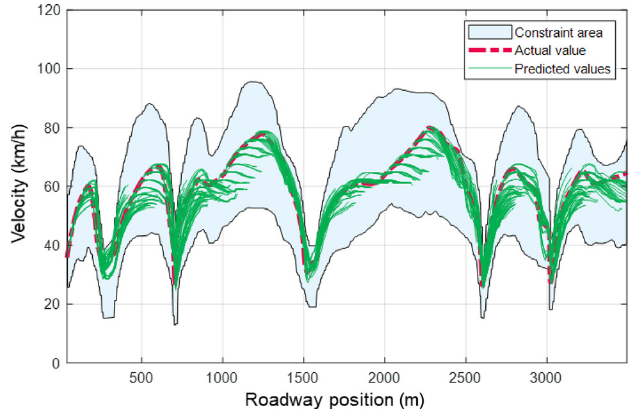

Fig. 4 Velocity prediction algorithm simulation results

4 Predictive Alternator Control

4.1 System Overview. The PAC utilizes both current and predicted information to improve fuel economy. The current information for the vehicle is measured by a battery sensor. Predicted information is estimated by the prediction algorithm, which is explained in Sec. 3. The controller consists of a rule-based system governor and feedback controller, as shown in Fig. 5. The rule-based system governor determines a control mode according to electrical energy, fuel-cut activation signal, and the predicted velocity. Then, the desired electrical energy set-point is switched along with the control mode. The alternator is controlled to track the electrical energy set-point by the feedback controller.

The proposed EM system supplements the electrical energy of the battery using energy recovery. The alternator of ICE vehicles usually uses fuel as its energy source for electrical power generation. However, in energy recovery systems with an alternator, the fuel can be replaced by residual kinetic energy. Therefore, an efficient EM strategy can be designed in a manner of recycling the residual energy. Implementation of prediction algorithm makes use of predicted information to estimate and utilize future electrical energy which is converted from residual energy. Sections 4.2 and 4.3 describe the details of the PAC.

4.2 Feedback Control. The feedback controller for the proposed algorithm controls the alternator to manage vehicle electrical system. The controller receives an error between desired electrical energy and the net electrical energy (E_{net}) as an input. To minimize this error, a proportional-integral (PI) controller is adopted for the feedback controller. E_{net} is calculated as the cumulative net power over the driving time as

$$E_{\text{net}} = \int_0^t P_{\text{net}} dt \tag{8}$$

The net electrical power (P_{net}) is expressed as follows:

$$P_{\text{net}} = P_{\text{gen}} - P_{\text{load}} \tag{9}$$

where P_{gen} is the electrical power generated by the alternator, and P_{load} is the power consumed by the electrical loads in the vehicle. The positive net power means that the power generated by the alternator is more than the power consumed by the load so that the battery stores the remained power. Conversely, the battery supplies the power consumed by the load.

4.3 Rule-Based System Governor. The rule-based system governor determines the desired electrical energy, a reference input to the feedback controller. The desired electrical energy set-point is changed according to the control mode, which is decided by the predefined rules of the system governor: charge, hold, and discharge. Three control modes are shown as Fig. 6 depending on the energy flow. In the charge mode, the generated energy from the alternator flows to the electrical load, and the remained energy to the battery for the charging. In the hold mode, the alternator solely supplies the energy required for electrical load. On the other hand, in the discharge mode, the only battery discharges the energy to the electrical load.

The system governor determines the control mode according to the rules shown in Fig. 7. First, when fuel-cut activates, this governor switches to the charge mode. One of the two remained modes are determined when the fuel-cut deactivates. Predicted energy generation (E_{pred}) is estimated using predicted velocity and E_{net} is calculated using the information (current, voltage) measured by the battery sensor. The sum of these two data is used as the future electrical energy. Depending on the value of the future electrical energy, the governor determines one of the two modes (discharge mode, hold mode).

4.3.1 Charge Mode. The charge mode recuperates residual energy into electrical energy without additional fuel consumption. This mode is mostly activated in decelerating or coasting situations to absorb kinetic energy as the engine management system (EMS) cuts off fuel injection from the engine. At this mode, the fuel injection is cut off and the alternator does not consume any fuel for electrical energy generation. Instead, the remnant of energy to overcome engine and vehicle driveline friction is recovered to the battery. Using this characteristic, the proposed rule-based governor switches to the charge mode at the onset of the fuel-cut signal of the EMS and sets the set-point of the desired electrical energy to the upper limit value to maximize the generation power of the alternator.

4.3.2 Discharge Mode. The discharge mode shuts down the alternator and uses solely the power of the battery. This mode is

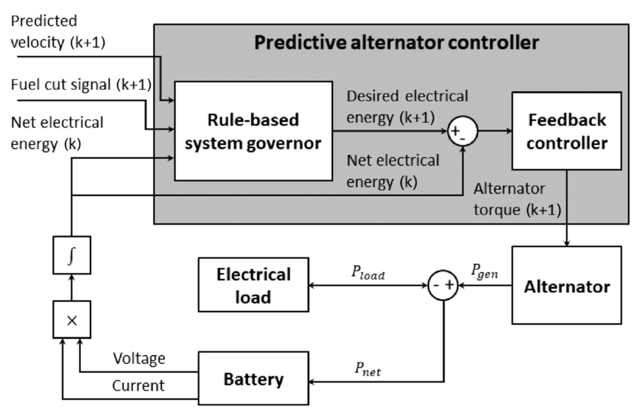

Fig. 5 System architecture of the PAC

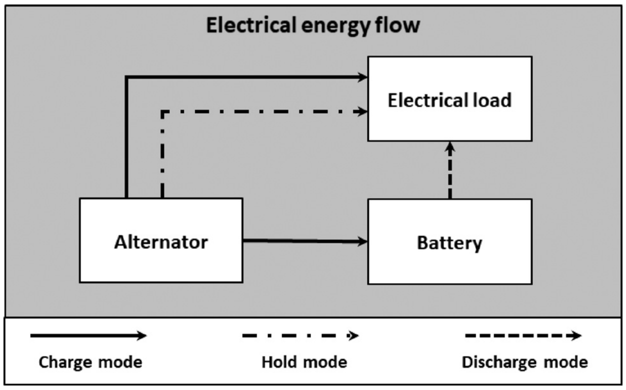

Fig. 6 Electrical energy flow for each control mode

activated right before entering into the charge mode to maximize the benefit of fuel economy. In the charge mode, the electrical system can recuperate energy without fuel consumption as mentioned earlier. However, when the stored energy of the battery is fully charged, the battery is exposed to the overcharge and has no room for the energy recovery. Thus, the discharge mode predicts the amount of electrical energy generation and consumes battery energy by shutting off the generator. The energy content in the battery becomes reduced and makes room for the energy recovery at the next charge mode.

The predictive energy generation is related to the duration time of the fuel-cut signal. The fuel-cut signal is determined by the EMS based on the position of the accelerator pedal and the desired engine power. However, this information is difficult to predict directly. Therefore, this study indirectly estimates the duration time of the signal using the predicted vehicle acceleration. The predicted acceleration is calculated from the estimated velocity trajectory of the prediction algorithm, which is the first part of the EM strategy. Thresholding the predicted acceleration, the duration time of the fuel-cut signal (t_{RKE}) can be estimated. E_{pred} is calculated by using the duration time of the fuel-cut signal in a short-term future. E_{pred} is the amount of electrical energy, which is generated during the time of the t_{RKE} activation in a short-term future. Therefore, E_{pred} increases as the t_{RKE} time increases. At the same time, the generation power of the alternator is maximized. The maximized generation power is assumed to be a constant value. The tendency of E_{pred} according to the t_{RKE} time was analyzed by vehicle experimental data. As a result, the predicted energy is modeled by the following second polynomial equation:

$$E_{\mathrm{pred}} = c_2(t_{\mathrm{RKE}})^2 + c_1(t_{\mathrm{RKE}}) + c_0 \tag{10}$$

When the potential charge supplements the lack of current electrical energy, the discharge mode activates, whose condition is expressed by the following equation:

$$E_{\mathrm{pred}} + E_{\mathrm{net}} > 0 \tag{11}$$

When the discharge mode is activated, the desired electrical energy is switched to a lower limit value and thus the alternator is turned off.

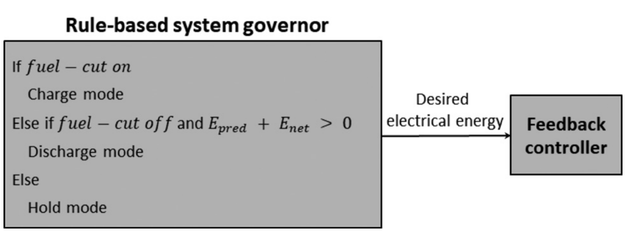

Fig. 7 Rules for the control mode determination

4.3.3 Hold Mode. Hold mode generates electrical energy as much as required by the electrical load. Setting the desired electrical energy to zero, this mode leads to maintaining the initial electrical energy. This mode is activated when the fuel-cut signal is turned off and the potential charge cannot compensate for the current lack of electrical energy.

4.4 Validation of the Control Algorithm. The PAC is compared with a conventional control algorithm. The conventional algorithm is the PI control scheme shown in Fig. 8. The control period is set to 0.1 s and the desired electrical energy is set to zero, which is the same as the desired value of the PAC hold mode. In addition, the velocity prediction model described in Sec. 3 has been combined for the input to this conventional PI control algorithm. This model was designed with the same specifications as described in the PAC. The predicted trajectory is generated 150 m ahead with 10 m resolution in every 0.3 s. This sampling time should be shorter than the duration that it takes for the vehicle to travel one step size (10 m). Therefore, the sampling time is determined based on the step size of the algorithm and the speed limit of the test site.

Validation of the proposed strategy based on vehicle experiment has difficulty in repeating the same conditions. The fuel consumption of the vehicle is sensitive to the driver's pedal operation. To compare the performance of two algorithms, a driver should repeat the same pedal inputs. However, it is difficult to repeat the same pedal inputs in real driving situations. Therefore, both simulation and experiment were conducted to verify the performance of the proposed control algorithm. The simulation evaluated the signal differences over the time domain because the same pedal input is possible. In the experiment, we confirmed the feasibility of the proposed algorithm and checked the performance by averaging five times running data on two cases.

4.4.1 Simulation for the Validation. As a virtual test driving software, CarMaker™ (IPG) was used for vehicle simulation and the test site emulation shown in Fig. 1. The vehicle model for the simulation was designed using the specifications shown in Table 1. The vehicle model was validated through the acquired data logged by the vehicle. A controller area network (CAN) based logger was installed to acquire the driving data and a GPS to generate the vehicle's route. The proposed algorithm was implemented in MATLAB™ and was fully integrated with the simulation environment.

Simulation results show the functional verification and fuel efficiency improvement of the proposed algorithm. The results for the entire route are shown in Fig. 9. The desired electrical energy is set to zero in order to keep the charge state of the battery at the initial value throughout the entire route. The PAC control mode is determined according to E_{pred} and fuel-cut operation. As a result, the alternator torque and the amount of electrical energy are controlled. The results of the PAC show dynamic charging or discharging behavior according to the control mode change. On the other hand, the PI controller is almost steady. Importantly, the alternator with the PAC consumes less fuel. To analyze the

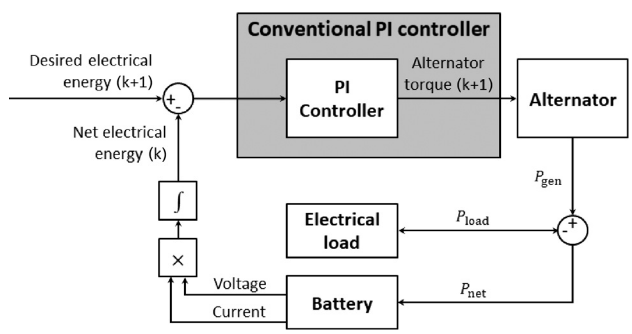

Fig. 8 Conventional PI controller system architecture

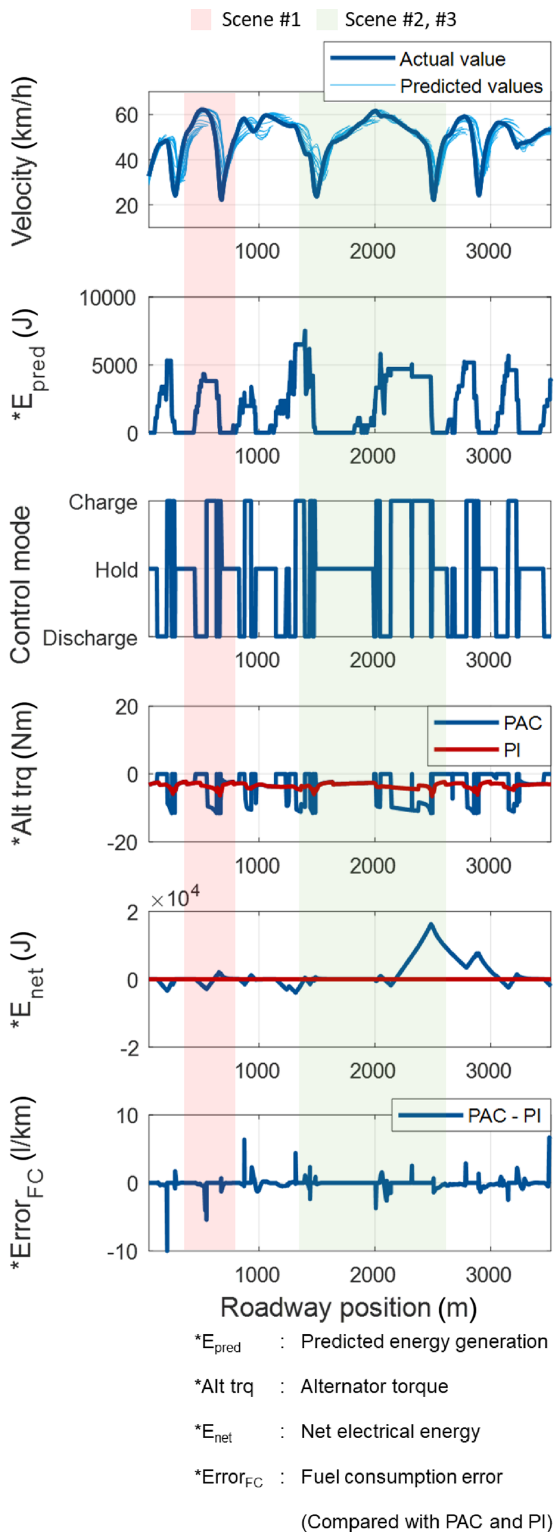

Fig. 9 Simulation results for the entire target route: velocity with predicted velocity profiles, predicted energy generation, control mode, alternator torque, net electrical energy, and fuel consumption error between PAC and PI

simulation results in detail, three sections of the target route were selected: a corner on a flat road (#1), a corner on an uphill road (#2), and a downhill road (#3). Each section shows the operation of the PAC for different situations.

In scene #1, the vehicle meets and turns the corner on a flat road. As shown in Figs. 10 and 11, all three control modes of the PAC are activated. Up to 450 m of roadway, the hold mode is turned on when the vehicle approaches the corner from a distance. At such condition, the fuel-cut is not activated and the predicted electrical energy is insufficient to switch on the discharge mode. Both conventional PI controller and PAC controller control the alternator equally and cause the same amount of fuel consumption. After 450 m of roadway, the discharge mode is activated by getting closer to the corner since the predicted kinetic energy recovery becomes positive. The amount of E_{pred} increases in this area. The PAC algorithm turns off the alternator and conserves fuel as compared to the conventional PI controller. Then, the charge mode is followed while the vehicle enters and turns around the corner. The vehicle decelerates to turn around the corner safely and activates engine fuel-cut. In the charge mode, the fuel consumption is zero due to the recovery of kinetic energy, even though the alternator's power generation increases. In scene #2, the vehicle meets and turns the corner on an uphill road. The first deceleration section in Fig. 12 shows scene #2. In the previous scene on the flat road, vehicle deceleration led to a fuel-cut. However, the deceleration and fuel-cut do not match exactly on the uphill road. This is because engine power is required to climb the hill even when the vehicle slows down. As a result, the duration of the charge mode that recovers the residual energy is reduced relative to the flat road (scene #1), thereby reducing the electrical energy generation. Furthermore, the discharge mode is visited more frequently to save fuel consumption.

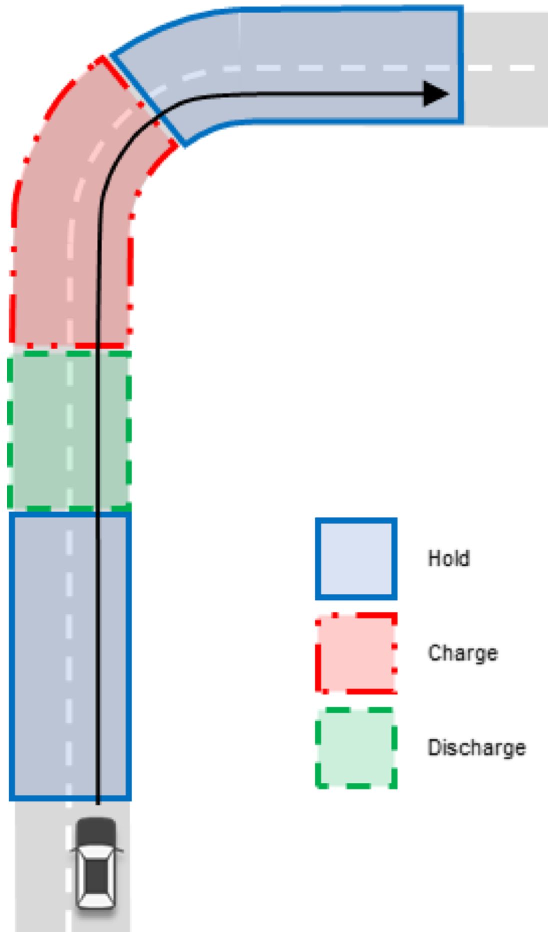

Fig. 10 Control mode distribution on a curved flat road

On the downhill road in scene #3, the proposed algorithm shows more effective EM. First, the discharge mode activates on the uphill road before entering the downhill. This is the result of the predicted energy recovery on the downhill. This battery discharging prevents the alternator from consuming additional fuel and thus improves fuel efficiency. Then, the charge mode is turned on entering the downhill, and the kinetic energy recovery begins. On the downhill road, the vehicle can drive under coasting conditions without engine power. Thus, in this case, the fuel-cut activates, and alternator energy generation maximizes. As a result, a large amount of electrical energy can be obtained without consuming fuel.

4.4.2 Experiment for the Validation. The system configuration for experimental validation is shown in Fig. 13. The proposed strategy is implemented in two parts, a laptop and a rapid prototyping device. First, the prediction algorithm was implemented in the laptop equipped with a 2.6 GHz Intel Core i7-6600 U CPU. The laptop receives driving information (acceleration, velocity) and vehicle position via the CAN network and transmits the generated predictive velocity. The PAC is embedded in the rapid prototyping device (VN8910A of Vector) to guarantee real-time performance for the alternator control. This prototype device uses CAN and local interconnect networks to receive EMS signal (fuel-cut) and battery sensor information (current, voltage). The target torque calculated in this system is converted to pulse width modulation signal and transmitted to the regulator.

The experiment was carried out on the defined route shown in Fig. 1. The test driver conducted five repetitions of the same route with the two driving styles (cases A and B), which are defined by velocity range. Figure 14 shows the comparison results between the PAC and the conventional PI controller for case A. As shown in the figure, it is difficult for the driver to maneuver the vehicle consistently in the same driving route. Therefore, the test driver tried to maneuver as consistently as possible with the same driving style.

Table 3 summarizes the experimental results. The amount of fuel consumed by the alternator is calculated as the difference between the overall data and the data collected when the vehicle drove with the alternator turned off. The generated electrical energy, which affects fuel consumption, is the cumulative amount of net electrical power measured by the battery sensor. Experimental results show that the proposed algorithm reduces overall fuel consumption by about 2.1% compared to the conventional PI controller. Out of fuel consumed by the alternator, the proposed algorithm achieves fuel saving of about 42.1%. This is because the amount of fuel consumed by the alternator is a small part of the total amount of fuel consumed by the engine. In addition, the PAC strategy shows an increase of the electrical energy generation compared to the conventional PI control algorithm despite the decrease in fuel consumption.

The proposed PAC shows additional engine braking effects on off-throttle response of the engine during charge mode as shown in Fig. 15. When the charge mode is activated, e.g., the vehicle is decelerating or coasting with fuel-cut activation, the requested alternator torque from the PAC controller as an output is increased. The increase of the requested alternator torque from the PAC controller as compared to the conventional PI controller acts as a source of additional braking of the vehicle to generate more electrical energy. Thus, the vehicle speed or the engine speed with a fixed gear position decreases even faster as described in Fig. 15.

The proposed EM strategy was designed to guarantee robustness of electrical system irrespective of velocity prediction accuracy. Figure 16 represents a situation in which the algorithm inaccurately predicted velocity when the vehicle turns around a corner. When the vehicle gets close to the corner up to 635 m of the roadway, the discharge mode is activated because E_{pred} can

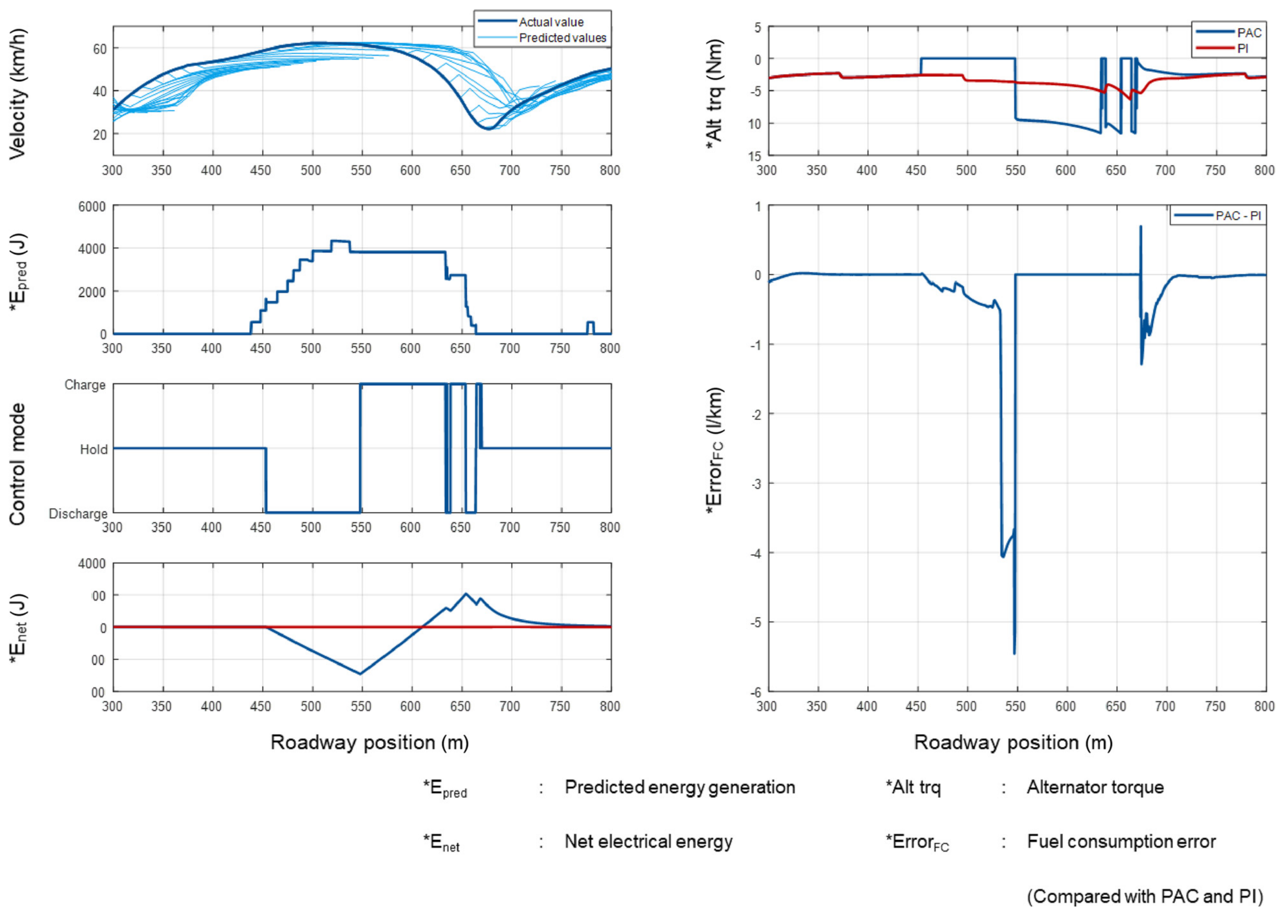

Fig. 11 Simulation results for scene #1, the red region in Fig. 9

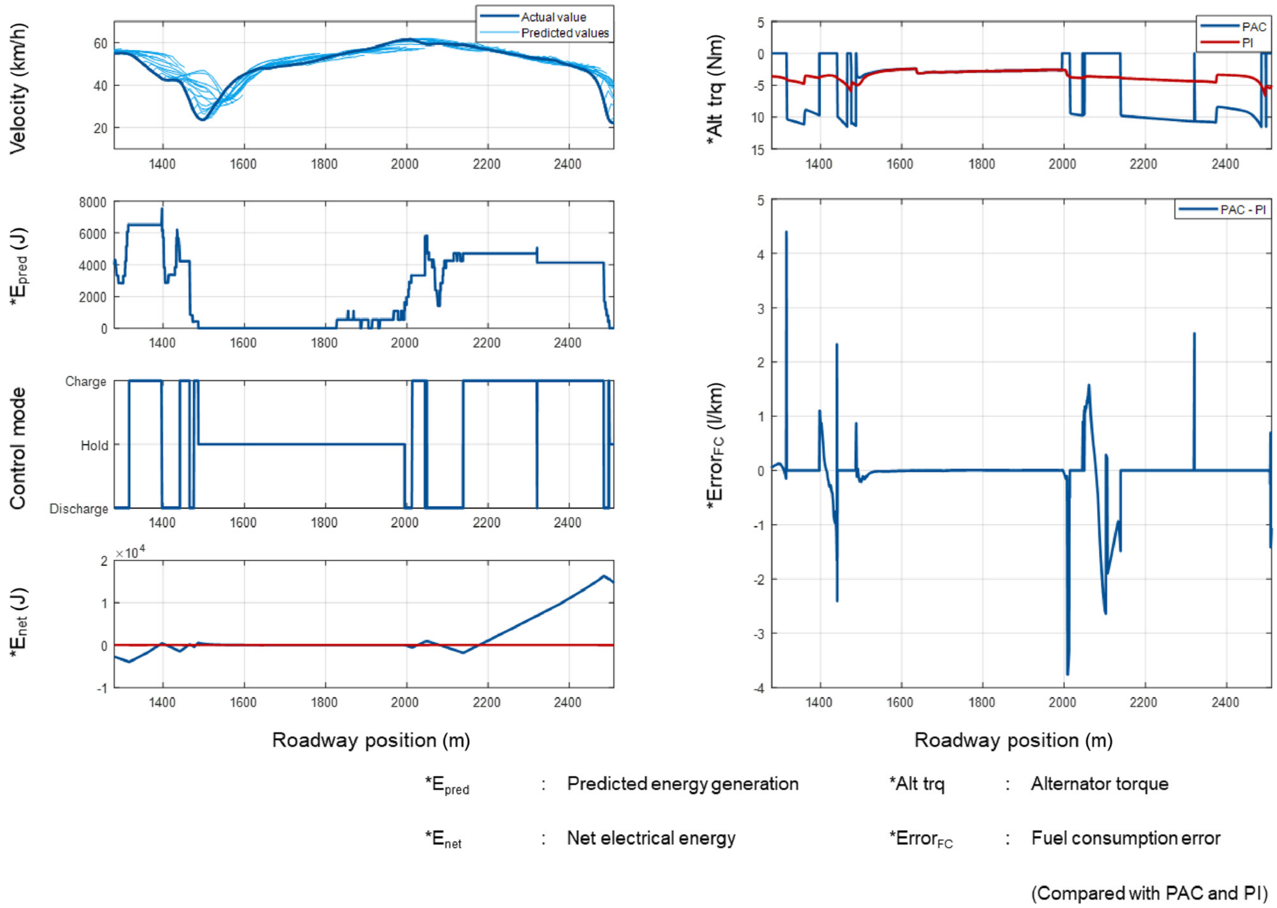

Fig. 12 Simulation results for scene #2 and scene #3, the blue area in Fig. 9

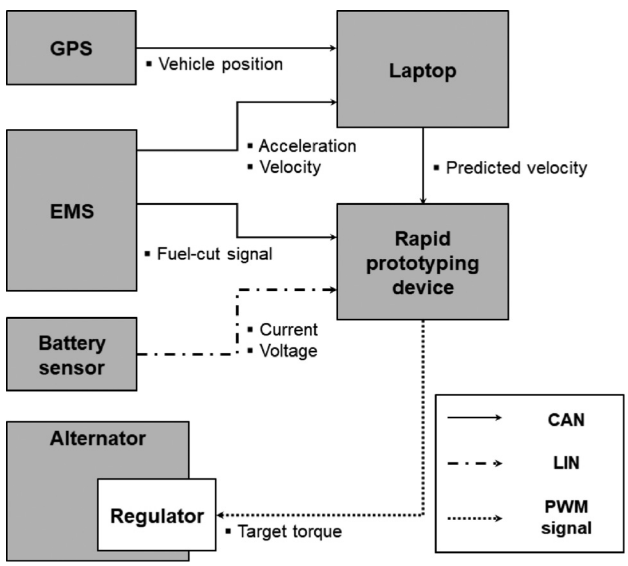

Fig. 13 Configuration of the experimental setup

compensate for E_{net}. Then, as the vehicle decelerates to turn around the corner, the charging mode is turned on by activating fuel-cut. In the case of accelerating out of the corner after 700 m, the hold mode is turned on when the velocity is predicted accurately. However, the range from 710 m to 750 m shows incorrect prediction that the vehicle speed will decelerate. Therefore, E_{pred} becomes positive, which is one of the conditions that the discharge mode is activated as shown in Fig. 7. Invalid activation of the discharge mode causes excessive battery drain. However, since the net electrical energy is a factor to determine the control mode as (11), the hold mode is activated before the battery is excessively drained to ensure the system robustness.

Conversely, if the proposed algorithm incorrectly predicts that the vehicle speed is accelerating, the hold mode is activated instead of the discharge mode. Since this mode tries to maintain initial electrical energy through feedback control, the system can be robust regardless of the prediction accuracy.

5 Conclusion

This paper proposed an EM strategy based on rule-based alternator control using predictive information. The following results are summarized:

- The prediction algorithm was designed by combining the Markov chain and the velocity constraint model. This algorithm estimated the future velocity up to 150 m and showed an RMSE of 3.9341 km/h in the simulations.
- In the PAC, the predicted velocity was used to estimate the amount of future residual energy. This estimated energy together with the sensor data (fuel-cut, current, voltage) determined the PAC control modes such as charge, discharge, and hold.
- The proposed PAC strategy was validated through simulation and experiment. The simulation compared the operational difference with the conventional PI control. In the experiment, as compared with the conventional PI controller, this proposed PAC strategy showed a total fuel consumption reduction by 2.1%, and out of total fuel consumption reduction, the alternator control contributes to the reduction by 42.1%.

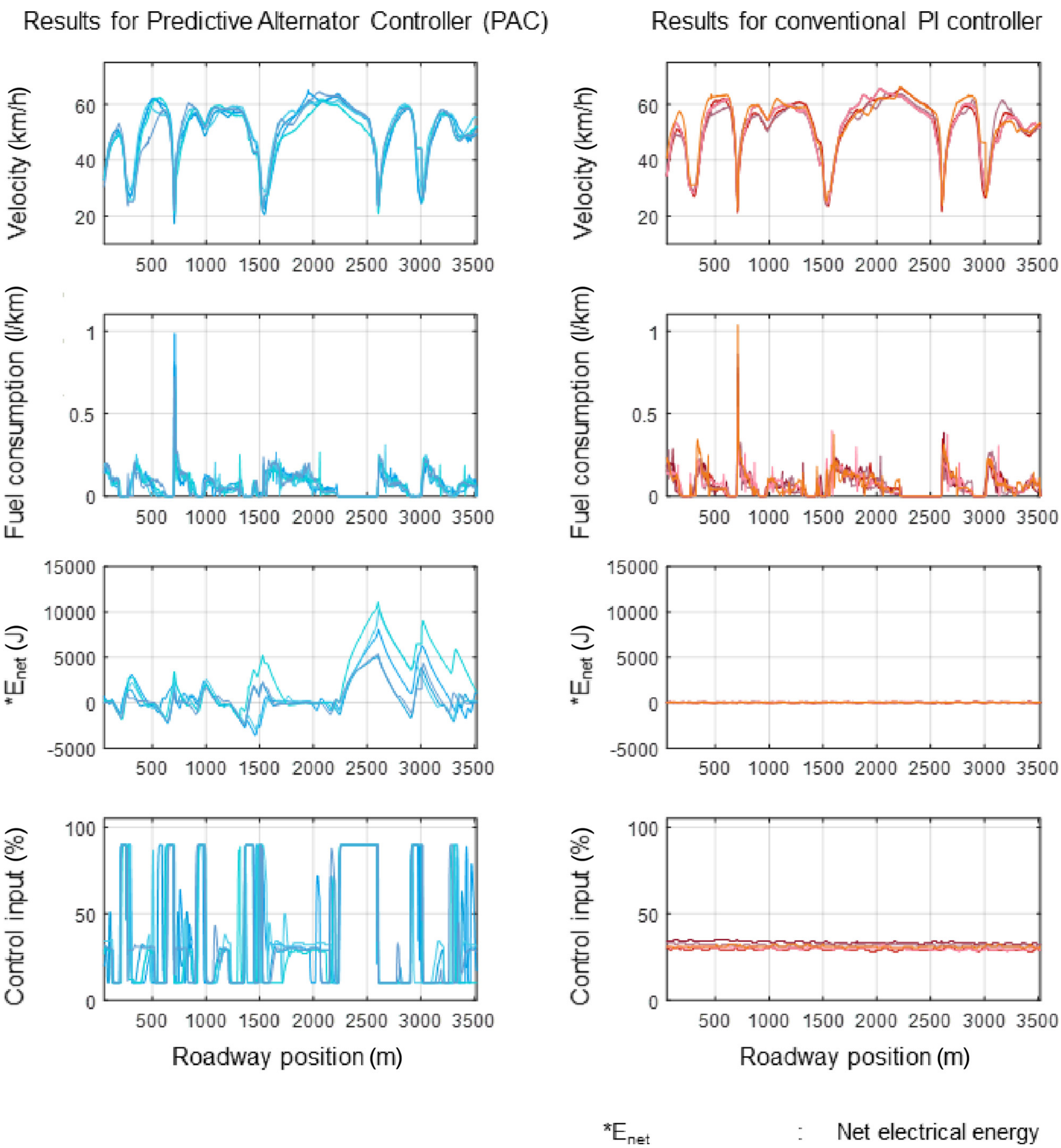

Fig. 14 Experimental results of case A for entire target route

Table 3 Summary of the experimental results

Case	Strategy	PI	PAC (Fuel saving (%))
	Distance (km)	17.60	17.60
	Total time (s)	1290.62	1338.64
A	Fuel consumption (ml)	1110.65	1095.37 (1.376)
	Fuel consumption (by alternator) (ml)	47.02	31.74 (31.915)
	Generated electric energy (J)	18.34	2437.16
	Distance (km)	17.60	17.60
	Total time (s)	1209.36	1239.42
B	Fuel consumption (ml)	1203.73	1169.87 (2.813)
	Fuel consumption (by alternator) (ml)	65.58	31.72 (51.631)
	Generated electric energy (J)	−10.74	1784.42

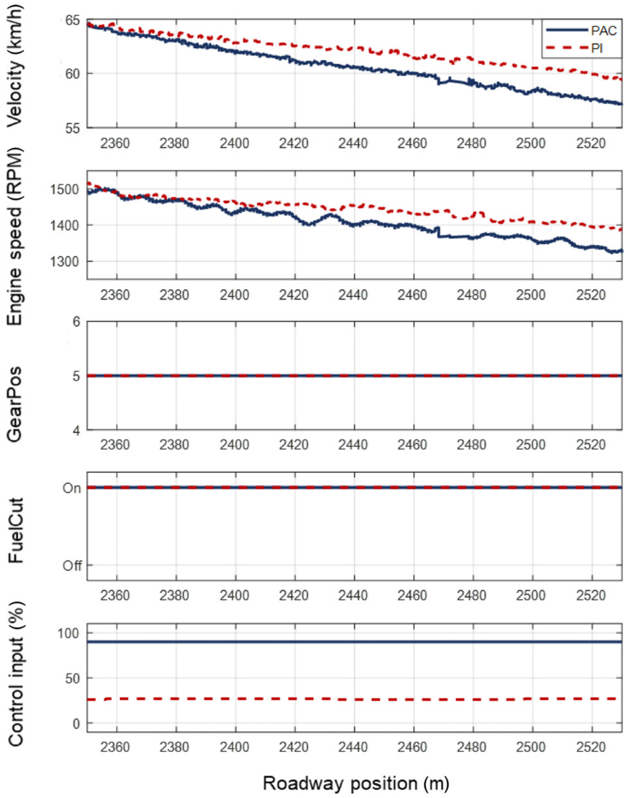

Fig. 15 Increase of engine braking effect during the charge mode

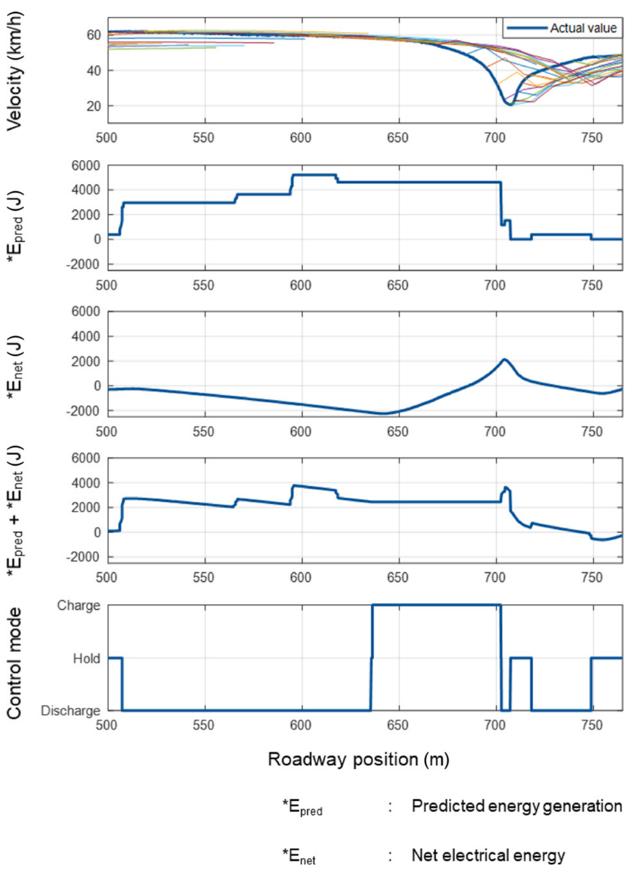

Fig. 16 Experimental results for inaccurately predicted velocity at a corner

This proposed strategy can be applied without modifying the hardware of the electrical system if the vehicle position is measurable. However, this method can be applied only to vehicles that travel on the same route repeatedly since the predictive information can only be estimated from fixed routes. Because the proposed prediction algorithm is designed with only velocity and acceleration, the future work to extend this algorithm to more versatile application should take into account diverse traffic situations (surrounding vehicles, traffic flows, traffic signs) by accommodating driving data from various routes and utilizing various intelligent transportation system information as inputs to the velocity prediction model.

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Nomenclature

a = vehicle longitudinal acceleration (m/s^2)
c = coefficient
E = electrical energy (J)
f = frequency rate of transition events
I = finite set of disjunct intervals
n = order of data
N = number of data points
P = electrical power (W)
Pr = probability distribution
s, r = order of step
t = duration time (s)
v = vehicle speed (km/h)
$\boldsymbol{x}$ = state of Markov chain
X = state space of Markov chain
$\hat{\boldsymbol{x}}$ = predictive state of Markov chain
$\hat{X}$ = predictive state space of Markov chain
$\boldsymbol{\pi}$ = transition probability
$\boldsymbol{\phi}$ = empty set

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