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Engine RPM and Battery SOC Activation Optimization in Hybrid Vehicle Energy Management System Utilizing BPNN - Genetic Algorithm and BPNN – Particle Swarm Optimization

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Abstract

The energy used in the hybrid vehicle needs to be regulated to gain further mileage and lower fuel consumption. It is achieved by selecting the correct levels of hybrid energy management system (EMS) parameters (i.e., vehicle speed, engine RPM, and activation State of Charge (SOC) of battery). This study focused on the modeling and optimization of Sepuluh Nopember Institute of Technology (ITS)'s series plug-in hybrid electric vehicle (PHEV) car mileage and fuel consumption by comparing the backpropagation neural network (BPNN) method – genetic algorithm (GA) and BPNN – particle swarm optimization (PSO). The BPNN was used to model the character of ITS's series PHEV EMS and predict mileage and fuel consumption. The BPNN's model obtained the best EMS parameters, most extended mileage, and minimum fuel consumption. The result of the validation experiment showed that both the integration of BPNN - GA and BPNN - PSO were able to predict and optimize the multi-objective characteristic with the same results.

Keywords: EMS, BPNN, genetic algorithm, particle swarm optimization, optimization

1. Introduction

According to a recent study by [1], around 1.2 billion vehicles are running around the globe, while 95% are light-duty vehicles, of which 99% still use internal combustion engines (diesel and gasoline-fueled). This condition contributes highly to global warming and the continuous reduction of global oil reserves. Electric vehicles (BEV) and hybrid vehicles (HEV) are alternative vehicles developed to face global warming and the reduction of petroleum reserves [2]. In Hybrid Electric Vehicles (HEV), the drive system and power source can be obtained by combining a conventional internal combustion engine with an electric motor system. The drive system and power source division can be divided into a series system, a series-parallel system, and a parallel system. The drive system is entirely driven by an electric motor in the series system used at ITS's PHEV. The combustion motor drives a generator that aims to charge the battery without directly assisting the drive system [3,4]. These power distributions need an EMS to enable the vehicle to reach the furthest mileage with the lowest fuel consumption possible.

The EMS works by a rule-based strategy, responding to predetermined parameters to execute some tasks. In ITS's PHEV, the parameters used as a rule-based strategy were SOC of battery and engine RPM. The SOC of the battery effect when the engine needs to be activated, while the engine RPM affects the power generated by the alternator. Both parameters affect the mileage of the car and its fuel consumption. These parameters deem possible to be optimized to suit better the character of the vehicle's main drivetrain components for further mileage and lower fuel consumption [5]. Currently, the rule-based EMS used in ITS's series PHEV produces a car with either a long-range mileage with high fuel consumption or a low-range mileage with low fuel consumption.

Determining the suitable parameters by experiments on each parameter with a long-range option is considered time-consuming and resource-intensive. Thus, researchers try to implement soft computing techniques to optimize the EMS rule-based parameters. The soft computing technique enabled the researcher to solve complicated problems, including multivariable and non–linear problems. These methods usually consist of some set of algorithms to find the possible best solutions for a general or specific problem.

In this study, two sets of algorithms were used to determine which one has the better solution to optimize the EMS of the ITS series PHEV car. These algorithms were BPNN-GA and BPNN-PSO. Each problem was unique and may have a different best optimization method. Hence this study's goals include finding the best optimization

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method to optimize EMS parameters of ITS's series PHEV by comparing BPNN-GA and BPNN-PSO. Various articles have used GA and PSO separately and showed a good result in EMS optimization [6–9]. There was no previous study regarding ITS's series PHEV EMS. Hence this study's goal is to find the optimum value of the parameters to gain the furthest mileage and the least fuel consumption to improve ITS's series PHEV EMS. To further validate the optimization process, vehicle efficiency at the optimum vehicle speed, engine RPM, and State of Charge (SOC) activation needed to be determined. The optimum efficiency is then compared with vehicle efficiency without optimization.

2. Method

2.1. Back Propagation Neural Network (BPNN)

An artificial neural network (ANN) was a digital model of the human brain. It simulated how the brain processed data or information by detecting patterns and connections between data. Therefore, it was suitable to optimize a complex problem [10]. In an artificial neural network, the processing occurred in neurons, signals were sent between neurons via links, and connectors between neurons had weights that amplified or weakened the signal. Each neuron used an activation function assigned to the received input in determining output. The magnitude of this output was compared with a threshold [11]. ANN also had two types of learning phases, which were feedforward and feedback. ANN also could be a single-layer neural network or a multilayer neural network. A multilayer neural network utilized the learning algorithm of a backpropagation neural network (BPNN), a supervised training algorithm that made BPNN able to modify the weight between input and output to minimize error [12,13]. To further enhance the optimization, BPNN could be coupled with a metaheuristic method [14], such as a genetic algorithm and particle swarm optimization.

The modeling of BPNN's architecture could be detailed in the following steps:

- Step 1: Normalized the study's input and output using the mapminmax function, so it had a similar range from -1 to 1.
- Step 2: Created the BPNN architecture by varying the value of hidden layers, number of neurons, and activation function.
- Step 3: Training, validation, and testing the BPNN architecture.
- Step 4: Saving the best BPNN architecture with the lowest mean square error (MSE).

2.2. Genetic Algorithm (GA)

A genetic algorithm was a metaheuristic method based on Darwin's Theory of Evolution [15]. The characteristic of the parent, called genes, were passed to its offspring. Each generation had a better characteristic or a smaller error. The first generation with random characteristics with the number of offspring could ultimately produce the perfect individual. The basic elements of GA were reproduction, crossover, and mutation. A study by Yin [16] used a hybrid backpropagation neural network and genetic algorithm to optimize the injection molding process resulting in a higher optimum value of the design parameter. Each GA parameter could alter the optimum value of the optimization. According to Zhang [17], the more the number of populations, the better the result. Although, after achieving convergence, the optimum value only slightly changed. The mutation rate, however, varied in every problem and needed to be adjusted.

2.3. Particle Swarm Optimization (PSO)

Particle swarm optimization was a metaheuristic method based on the social interaction of a swarm or school of fish or birds. As a swarm, each individual affected others. For example, when an individual found some food or objective function, another individual was affected and tended to head to the same spot as the one that found it first. This social trend was then modeled and became PSO. PSO had a faster processing time but could be trapped in an optimum local value [18].

2.4. Hybrid Vehicle Efficiency

The efficiency of the optimized parameter compared to the experiment parameter. This comparison validated the result of the optimization. Since the hybrid vehicle had three driving modes: full electric, hybrid, and charging, three different equations were used to determine the efficiency of each driving mode [2]. For full-electric driving mode, Equation 1 is used.

$$\eta_{tc} = \frac{P_{tc}}{V_b \cdot I_b} \times 100\% \tag{1}$$

η_{tc} was the test cycle efficiency, P_{tc} was the power of the test cycle or the power at the wheel hub, vb was the battery's voltage, and Ib was the battery current. For hybrid driving mode, the battery and alternator supplied the power. The equation was shown in Equation 2.

$$\eta_{tc} = \frac{P_{tc}}{V_b \cdot I_b} \times 100\% \tag{2}$$

Similar to Equation 1, Equation 2 now introduced $\dot{m}$ the fuel mass flow rate and LHV as the lower heating value of gasoline. The last driving mode was charging driving mode, where the power produced from the alternator was transmitted to the motor controller to run the vehicle and charge the battery. The equation of vehicle efficiency while the vehicle was running in charging mode, was shown in Equation 3.

$$\eta_{tc} = \frac{P_{tc} + (V_b \times I_b)}{\dot{m} \cdot LHV} \times 100\% \tag{3}$$

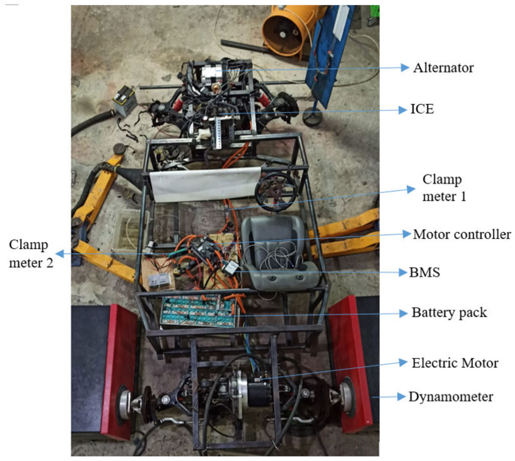

Figure 1. Prototype of series PHEV ITS.

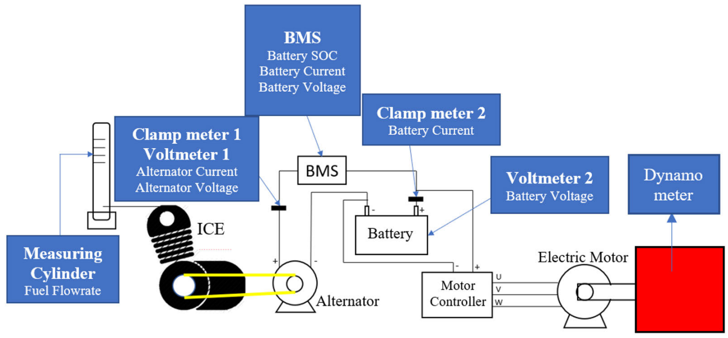

Figure 2. Schematic of SOC, voltage, current, and fuel flowrate measurement on PHEV prototype.

2.5. Experiment Method

This experiment used a prototype of ITS's series PHEV. Several of the main components used were a 12 kW 150 cc internal combustion engine (ICE) taken from a Honda CB150R motorcycle, 5 kW Werner alternator DC Model F60AD, 10 kW Golden BLDC electric motor, and 4.8 kWh $LiFePO_4$ GB System battery with 15 series and two parallel configurations. Dynapack dyno test kit measured the power at the wheel hub and the vehicle speed. Orion BMS Jr 2 was used as a battery management system (BMS) to collect data such as the battery's current, voltage, and SOC. The prototype of the series PHEV ITS showed in Figure 1. The schematic of the prototype and the data measurement showed in Figure 2.

The experimental design shown in Table 1 showed the variable level used in a Rule-Based energy management system. The researcher ran the experiment using a combination of parameters and its level. The prototype was placed at dyno test and loaded with a vehicle mass of 745 kg, as shown in Figure 1 and Figure 2. It ran from the battery SOC of 95% with the electric motor running at the various vehicle speed shown in Table 1. ICE turned on when the battery state of charge and RPMs reached a specific value. The electric motor ran until the battery SOC got 20%, and the fuel consumption was measured with a measuring cylinder. The procedure of this study showed in Figure 3.

As shown in Figure 3, this study started with a literature review. With predetermined input and output parameters, the researcher experimented with obtaining the experiment data. The data were normalized to alter the experiment value to a specific range. This study used a -1 to 1 range. The BPNN model was generated by finding the best BPNN parameter, which was the number of hidden layers, the number of neurons, and the activation function. The model with the lowest mean square error (MSE) was saved and used in GA and PSO optimization. The optimized value for engine RPM, battery SOC activation, mileage, and fuel consumption was found using GA and PSO. These values were denormalized and compared between GA and PSO. The best value was validated using the prototype and whether it was under 10% error. Finally, to further validated the optimized parameters, the researcher calculated the efficiency of the vehicle after optimization and compared it with the experiment value.

3. Results and Discussion

3.1. Objective Function

This study uses the objective function equation to express the combined output parameters of mileage and fuel consumption. Each of which is given a similar weight of 0.5. The objective function is formulated in the following equation [7].

$$Objective function = ((w_1 \times Obj_1) + (w_2 \times Obj_2)) \quad (4)$$

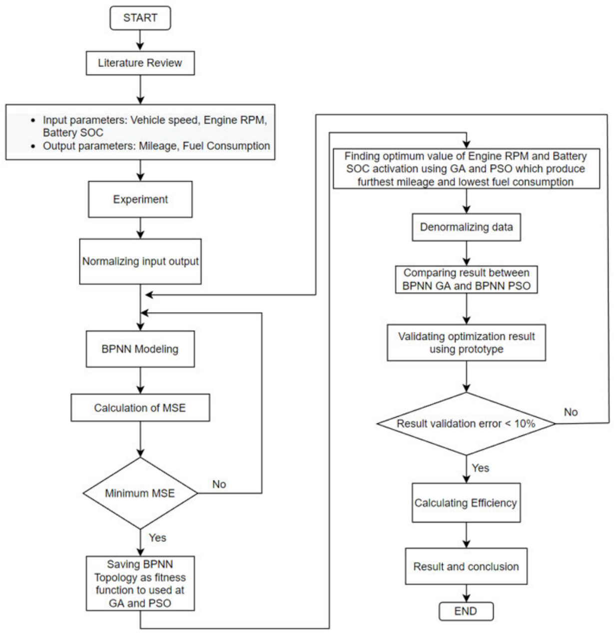

Figure 3. Experimental procedure

Table 1. Experimental design

Energy Management System Rule Parameter	Unit	Level 1	Level 2	Level 3
Vehicle Speed	km/hour	17	30	50
Engine RPM	RPM	7000	7500	-
Battery State of Charge (SOC)	%	40	60	-

The objective function expresses the target or combined output parameters. For example, Obj_1 represents the vehicle's total mileage, while Obj_2 represents the fuel consumption. The fuel consumption parameter is given a negative sign since it minimizes while the mileage maximizes.

The BPNN modeling consists of the number of hidden layers from 1 to 5, the number of neurons from 8 to 14, and the activation function of hardlim, hardlims, purelin, satlin, logsig, and tansig. The best parameters combination for one problem may differ from others. From each parameter combination, the best parameter combination with the lowest MSE value, shown by Figure 4, is a combination of the activation function of tansig, the number of hidden layers of 2, and the number of neurons of 12 with the value of MSE 0.0017. Figure 5 compares the real normalized target value and the BPNN predicted value. There was a slight different from target and the prediction seen from Figure 5 since there was an MSE though it was small. The BPNN modeling is used as the fitness function in the GA and PSO optimization phase.

3.2. GA and PSO Optimization

The GA and PSO optimization phase started with searching for the best parameters which produce the highest value of optimum value with the least iteration process. The optimum value of each parameter at GA and PSO is shown in Table 2.

From Table 2, the best GA parameter combination with the number of populations of 100 and a mutation rate of 0.01. While for PSO, the best parameter combination is with the number of populations of 100 and PSO inertia of 0.5. GA and PSO have a better value if the population size increases. The value needs to be adjusted for the mutation rate and the PSO inertia to produce the best optimum value with the least number of iterations. Figure 6 shows the graphic between GA and PSO results.

From Figure 5, GA and PSO have the same optimum value, but PSO needs less iteration to achieve the optimum value. Compared with PSO, GA commonly performs better because it can escape a local optimum trap by generating offspring through crossover and mutation processes [16]. Due to the narrow range of the experiment data and the small amount of experiment data, the optimum value from GA and PSO has the same value. On the other side, PSO needs less iteration since PSO derives from continuous equation optimization [17]. The optimized value can be seen in Table 3.

Table 2. GA and PSO best parameters

GA		PSO	
Number of populations	100	Number of populations	100
Mutation rate	0,01	PSO inertia	0,5

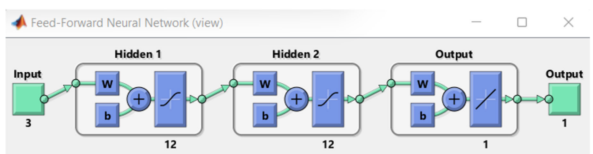

Figure 4. BPNN architecture

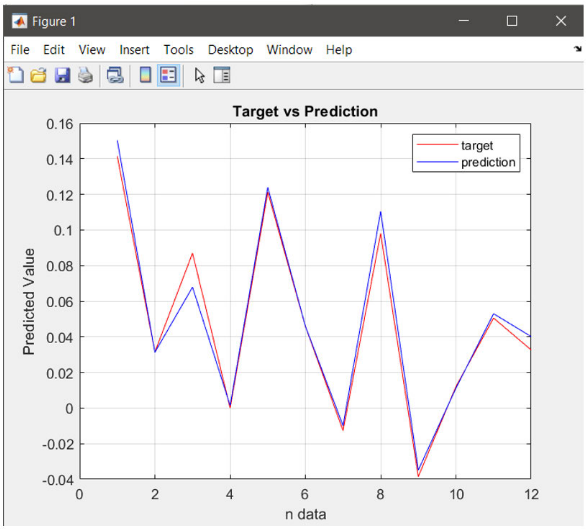

Figure 5. Comparison between the target value and BPNN prediction value

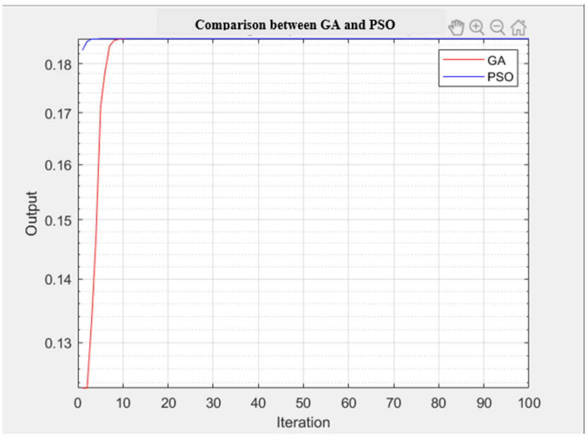

Figure 6. Comparison of optimum value and iteration between GA and PSO

Table 3. Optimization value of GA and PSO

	Vehicle Speed (km/hour)	SOC Activation Condition	RPM	Mileage (km)	Fuel Consumption (L)
GA	36.32	48.72	7500	83.1233	6.007857
PSO	36.33	48.73	7500	83.1233	6.00785

Table 4. Comparison between optimized parameters with experiment data

Vehicle Speed (km/hour)	SOC Activation Condition (%)	RPM	Mileage (km)	Fuel Consumption (L)	Difference in Mileage (km)	Difference in Fuel Consumption (L)
36.33161	**48.7361**	**7499.99**	**83.12334844**	**6.007857429**	-	-
17	40	7000	123.8	12	-40.677	-5.992
17	40	7500	135.71	12	-52.587	-5.992
17	60	7000	129.7	12	-46.577	-5.992
17	60	7500	137.23	12	-54.107	-5.992
30	40	7000	47	3.76	36.123	2.251
30	40	7500	128	11.88	-44.877	-5.872
30	60	7000	61.5	3.76	21.623	2.251
30	60	7500	128.5	12	-45.377	-5.992
50	40	7000	35	0.7	48.123	5.308
50	40	7500	35	1.27	48.123	4.737
50	60	7000	30.83	1.27	52.293	4.737
50	60	7500	49.167	2.98	33.956	3.026

Table 5. Comparison between optimization method (BPNN-GA and BPNN-PSO) with confirmation experiment.

	Speed (km/hour)	SOC Activation Condition	RPM	Mileage (km)	Fuel Consumption (L)
MATLAB	36.33	48.74	7500.0	83.12	6.008
Experimental validation	36	48	7500.0	81.57	6.380
Error (%)	0.9	1.54	0	1.90	5.83

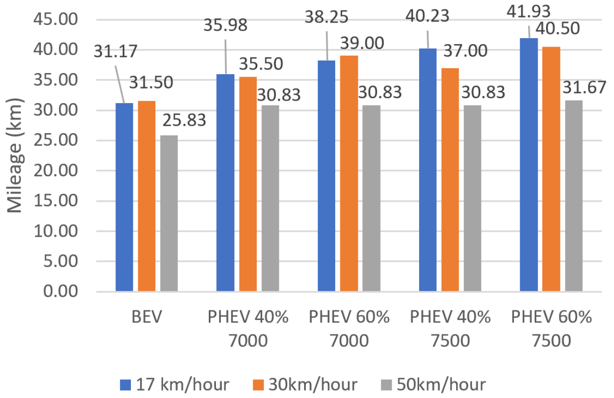

Figure 7. Mileage Comparison.

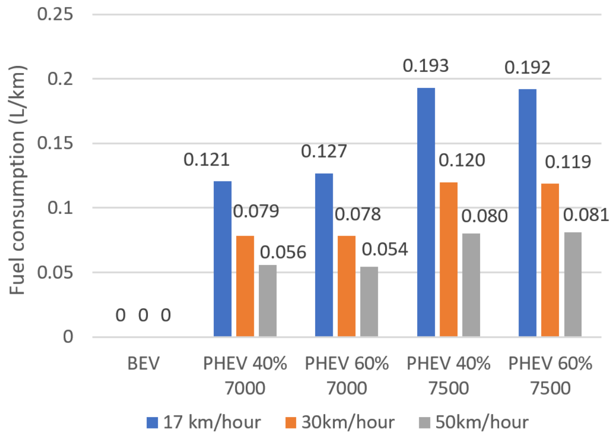

Figure 8. Fuel Consumption Comparison.

The predicted optimum value by BPNN-GA and BPNN-PSO is the fuel consumption of 6.007857 L and mileage of 83.1233 km. This optimum value can be obtained by vehicle speed of 36.32 km/hour, the SOC activation condition of 48.72%, and the ICE RPM of 7500. The optimum design value is then compared with the experimental data shown in Table 4.

Table 4 compares mileage and fuel consumption from the optimization results and experiment data. The effect of each input parameter on mileage and fuel consumption can be seen in Figure 7 and Figure 8. Since ITS's PHEV is a series hybrid car, its movement relies only on an electric motor. Thus the speed of the vehicle corresponds to the amount of electrical current drawn from the battery. The faster the vehicle goes, the more energy is drawn from the battery, and the battery drains faster. For example, from Figure 7, the vehicle with a speed of 17 km/hour has the furthest mileage since the current needed to run the vehicle is smaller than the current generated by the alternator. This condition affects the vehicle's fuel consumption since the engine works for an extended period.

Engine RPM is proportional to the amount of energy generated by the generator and the fuel consumption. As the engine RPM goes faster, fuel consumption and energy generated increase. It also affects mileage coverage since more energy is generated to charge the battery, so the mileage goes up proportional to engine RPM. Battery SOC activation takes effect when the ICE turns on to charge the battery. It heavily depended on the chemical of the battery. In the LiFePO4 battery used in ITS's series PHEV, the charging characteristic showed that it could charge faster at around 40% of SOC, similar to what Tseng [19] found in its journal. At around 30% to 50%, the LiFePO4 battery is around its maximum charging efficiency, and the amount of current drawn is in balance with the change of the voltage, thus higher energy drawn. Nearing 85% SOC, the current drop significantly while the voltage remains unchanged at its maximum voltage [20]. The battery SOC activation parameter affects how long the engine works, how much fuel consumption is, and how much energy can be stored in the battery, thus also affecting the mileage.

At the speed parameter of 17 km/hour, the activation condition of SOC 60%, and the RPM of 7500, with the longest distance traveled, the total fuel consumption decreased by 5,992 L or approximately 49.93% of the initial experiment consumption. However, the driving distance is also reduced by 54.107 km or about 39.4% of the experiment data. However, this is still acceptable because the percentage reduction in fuel consumption is higher than the reduction in driving distance. Compared with data with input speed parameters of 30 km/hour, 40% SOC activation conditions, and the RPM of 7000, with balanced mileage and fuel consumption values, the mileage increased by 36.123 km or about 76.85%. However, its fuel consumption increased by 2.251 L or about 59.8% from the experiment data.

The optimized EMS ruled-based parameter value obtained from this optimization was vehicle speed of 36.33

km/h, battery SOC engine activation of 48.73%, and ICE RPM of 7500. These parameters produce a vehicle achieving 83.12 km of mileage and a 0.072 L/km fuel consumption rate. It is achieved by balancing the mileage and the fuel consumption parameters. The vehicle speed and engine RPM parameters affect the current flows to the system. The vehicle's speed of 36.33 km/h and ICE RPM of 7500 was the most balanced configuration between the current drawn by the electromotor and the current generated from the generator. Battery SOC activation condition of 48.73% was the best SOC condition that balanced the time needed to operate the engine and the time required to charge the battery. Also, it was in the best condition to meet the charging characteristic of the $LiFePO_4$ battery.

3.3. Confirmation experiment

Completing the multi-response optimization using the BPNN-GA and BPNN-PSO method, the optimum mileage and fuel consumption value were obtained by setting the speed, SOC, and RPM at 36.33 km/h, 48.74%, and 7500 rpm, respectively. This set of parameters for the process was later chosen as the input to obtain confirmation experiment results. Furthermore, the results of the comparison of speed, SOC, and RPM between optimization-methods prediction and confirmation experiments are presented in Table 5.

This errors happens because there is a slight difference in BPNN modeling. This study has a mean square error (MSE) of 0.0017. In the prototype, there is a possibility of an efficiency decrease in vehicle transmission or power transmission on the cable. The optimization results still follow the study's objectives, where the error limit for this study is less than 10%.

3.4. Efficiency Calculation

The efficiency of the optimized parameter needs to be compared to the experiment parameter. This comparison further validates the result of the optimization. Equations 1, 2, and 3 are used to calculate the efficiency of the vehicle. The efficiency comparison can be seen in Figure 9.

The efficiency of the PHEV 40% at a speed of 17 km/h does not change compared to the experimental data because the value of optimization results is the same as in the experiment design parameters. At a speed of 30 km/hour, the increase in vehicle efficiency is 2.1%. At a speed of 50 km/hour, the increase in vehicle efficiency is 1.1%. This condition is influenced by the battery's performance at its optimum condition, in its rated voltage range which impacts maximum power expenditure [20], and the minimum load on the internal combustion engine. The BEV mode has the highest system efficiency since its only runs using an electric system.

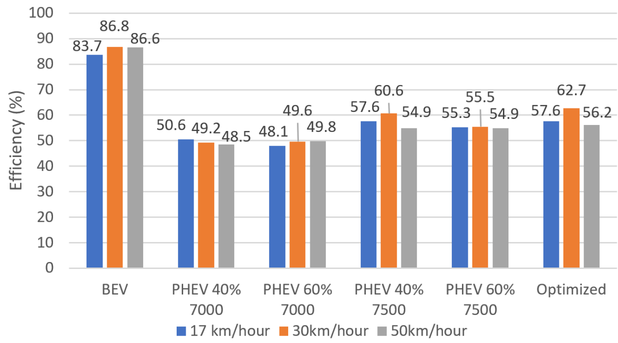

Figure 9. Comparison of average vehicle efficiency between experiment and optimized data.

4. Conclusion

In this study, the combination of BPNN-GA and BPNN-PSO has been applied to optimize the mileage and minimize the fuel consumption of the ITS's series hybrid car. The experimental works and optimization come up with the following concluding remarks:

- BPNN has been applied to predict the response, such as mileage and fuel consumption. The optimum BPNN topology with MSE of 0.0017 was achieved using two hidden layers, 12 neurons at each hidden layer, and tansig activation function.
- Both BPNN-GA and BPNN-PSO can optimize the rule-based EMS of ITS's series PHEV and produce the same result; hence both can be used to optimize ITS's series PHEV EMS for future study.
- The optimum rule-based EMS parameter for ITS's series PHEV was identified as vehicle speed of 36.33 km/hour, battery SOC activation condition of 48.74%, and ICE RPM of 7500 RPM.
- The combination of BPNN-GA and BPNN-PSO increases the ITS's series PHEV efficiency up to 2.1%.

References

[1] E. Karash, *Internal Combustion engine*. USA: Northern Technical University, 2019.

[2] E. A. Nanaki, "Chapter 2 - Electric vehicles," in *Electric Vehicles for Smart Cities* (E. A. Nanaki, ed.), pp. 13–49, Elsevier, 2021.

[3] W. Enang and C. Bannister, "Modelling and control of hybrid electric vehicles (A comprehensive review)," *Renewable and Sustainable Energy Reviews*, vol. 74, pp. 1210–1239, 2017.

[4] T. Katrasnik, F. Trenc, and S. R. Opresnik, "Analysis of energy conversion efficiency in parallel and series hybrid powertrains," *IEEE Transactions on Vehicular Technology*, vol. 56, no. 6, pp. 3649–3659, 2007.

[5] S. Onori, L. Serrao, and G. Rizzoni, "Adaptive Equivalent Consumption Minimization Strategy for Hybrid Electric Vehicles," in *ASME 2010 Dynamic Systems and Control Conference*, pp. 499–505, 2010.

[6] M. Biros, K. Kyslan, and F. Durovsky, "Optimization of hybrid vehicle drivetrain with genetic algorithm using Matlab and Advisor," *Journal of Engineering Science and Technology Review*, vol. 10, pp. 35–40, 2017.

[7] B. Huang, Z. Wang, and Y. Xu, "Multi-objective genetic algorithm for hybrid electric vehicle parameter optimization," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 5177–5182, 2006.

[8] C. Desai and S. S. Williamson, "Particle swarm optimization for efficient selection of hybrid electric vehicle design parameters," in *2010 IEEE Energy Conversion Congress and Exposition*, pp. 1623–1628, 2010.

[9] Z. Asher, A. Galang, W. Briggs, B. Johnston, T. Bradley, and S. Jathar, "Economic and Efficient Hybrid Vehicle Fuel Economy and Emissions Modeling Using an Artificial Neural Network," in *WCX World Congress Experience*, 2018.

[10] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *Journal of Pharmaceutical and Biomedical Analysis*, vol. 22, no. 5, pp. 717–727, 2000.

[11] S. Kuswadi, *Kendali Cerdas: Teori dan Aplikasinya*. Penerbit Andi, 2006.

[12] C. Gallo, *Artificial Neural Networks: Tutorial*. 01 2015.

[13] S. Kusumadewi, *Membangun Jaringan Syaraf Tiruan Menggunakan Matlab dan Excellink*. Graha Ilmu, Yogyakarta, 2004.

[14] D. Cook, C. Ragsdale, and R. Major, "Combining a neural network with a genetic algorithm for process parameter optimization," *Engineering Applications of Artificial Intelligence*, vol. 13, no. 4, pp. 391–396, 2000.

[15] B. Santosa, *Pengantar Metaheuristik Implementasi dengan Matlab*. ITS Tekno Sains, 2017.

[16] F. Yin, H. Mao, and L. Hua, "A hybrid of back propagation neural network and genetic algorithm for optimization of injection molding process parameters," *Materials & Design*, vol. 32, no. 6, pp. 3457–3464, 2011.

[17] Y.-a. Zhang, M. Sakamoto, and H. Furutani, "Effects of population size and mutation rate on results of genetic algorithm," in *2008 Fourth International Conference on Natural Computation*, vol. 1, pp. 70–75, 2008.

[18] R. S. Shahid Shabir, "A comparative study of genetic algorithm and the particle swarm optimization," *International Journal of Electrical Engineering*, vol. 9, no. 2, pp. 215–223, 2016.

[19] Y.-M. Tseng, H.-S. Huang, L.-S. Chen, and J.-T. Tsai, "Characteristic research on lithium iron phosphate battery of power type," in *MATEC Web of Conferences*, vol. 185, p. 00004, EDP Sciences, 2018.

[20] R. H. Bhuiyan, R. A. Dougal, and M. Ali, "A miniature energy harvesting device for wireless sensors in electric power system," *IEEE Sensors journal*, vol. 10, no. 7, pp. 1249–1258, 2010.