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Energy Management Strategy of HEV based on Simulated Annealing

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Abstract: Nowadays, the developments of hybrid electric cars are not something new. There are a lot of research are being done on how to increase the effectiveness of hybrid electric cars. One of the main aspects that are being aim is to reduce the fuel consumption while increasing the HEV performance. Artificial Intelligence such as Simulated Annealing for example is widely used to solve many engineering problem. This work focuses on the optimization of fuel and electrical power consumption in the hybrid electric vehicle (HEV) by utilizing a Simulated Annealing (SA) algorithm. The aim is to find the optimal control parameters of HEV such that the power loss is minimized. In this study, a simplified model of HEV is considered. The performance of the SA based algorithm is analyzed in terms of the statistical analysis of the power loss. The results show that the SA based algorithm is able to minimize the power loss and increase the efficiency of the HEV.
Keywords: Simulated Annealing, Energy Management Strategy, HEV

1. Introduction

Hybrid electrical vehicle (HEV) nowadays are not something new for us since there are a lots of research and studies that are being done about this technology. HEV is a vehicle that combines internal combustion engine system (ICE) with an electric propulsion system (hybrid vehicle drive train). This method is widely used in order to make the vehicle to have better fuel economy as it not only depend on petrol/diesel. With electrical propulsion system within the vehicle, the dependable for conventional type of fuel can be reduced. HEV also have several types but the most common that are being produced now are the hybrid electric cars.

So far there are various methods to improve the efficiency of the HEV. One of the most popular methods is to introduce Artificial Intelligence method to optimize the control parameters of the existing HEV. For such a case, many manufacturers have introduced many types of HEV simulators so that many experts and researchers can test the efficiency of the existing HEC, such as, PSAT [1], ADVISOR [2], and GT-SUITE [3]. Recently, there are various optimization algorithm have been introduced to tune the parameters of the HEV. These include Genetic Algorithm [4], [5], composite particle swarm, genetic algorithm and downhill-simplex [6], simultaneous perturbation stochastic approximation method [7], [8] and sequential approximate optimization (SAO) [9], which have been applied either to the simulator or the numerical model of HEV.

The main idea of this study is to find the optimal control parameter of HEV such that the total power loss is minimized. This improved control parameter is expected to cause the total power loss to be as low as possible. The Simulated Annealing is used as a tool to find the control parameter of HEV. The objective function is presented as the total power loss while the design parameter is treated as the control parameter of HEV. Thus, lower value of total power loss or the objective function indicates the effectiveness of the algorithm in optimizing the HEV. The control parameters or the gains are placed in the sub compartment of the HEV which in the engine, electric motor, electric generator, and battery. The Simulated Annealing is designed in the *mfile* while the HEV model is given in the Simulink of Matlab.

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2. HEV Model

A simple hybrid electric vehicle model is chosen due to its simplicity and practicality. The model is taken from MATLAB library archive to be applied in the simulation. This model consists of functioning circuit that will be able to produce output such as vehicle velocity, power loss, and etc. It is also made up from electrical and physical part. The block diagram of the simple HEV model as below:

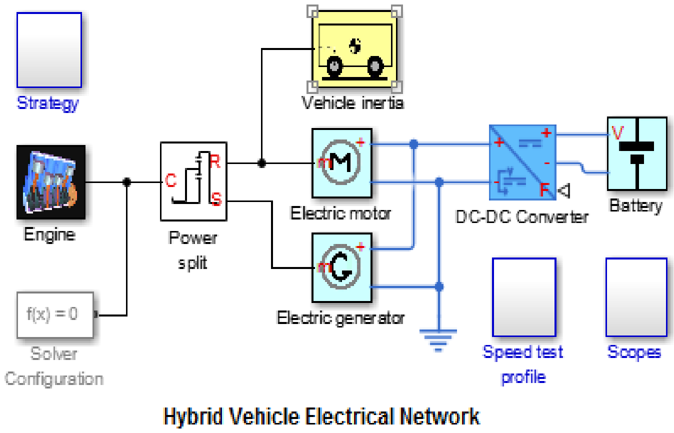
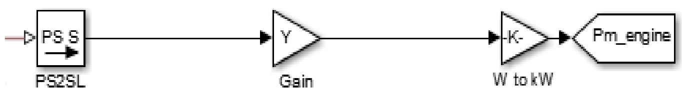
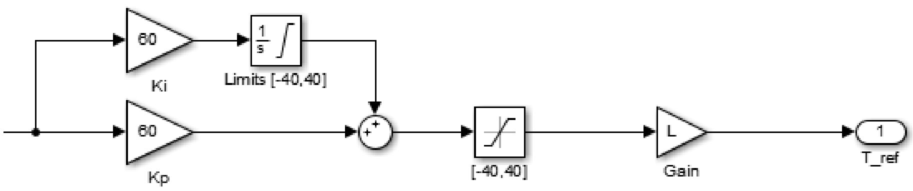


Fig. 1 - HEV models in MATLAB simulink

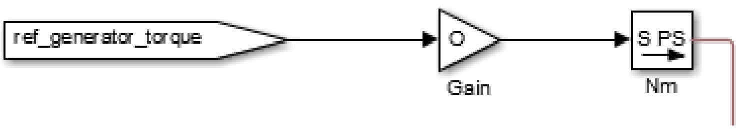
For tuning, there are four control parameters that are considered in this study, which are the engine, electric generator, electric motor, and battery as shown in Figure 2. For each of the parameter, we introduce a gain that are placed inside the sub componet, where gains Y, L, O and U are placed in the engine, motor, gegenrator and battery, respectively. Different value set at the gain will affect the output of the simulation which is the power lost. The reason to choose these control parameters are because during the driving simulation time, these parameters affect the electrical power and fuel usage by the model.



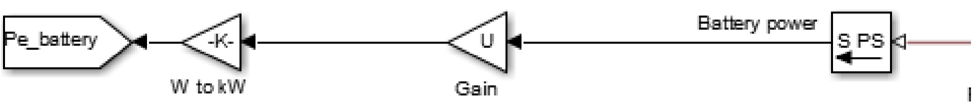
(a) Gain Y in the engine



(b) Gain L in the motor



(c) Gain O in the generator



(d) Gain U in the battery

Fig. 2 - The selected control parameters of HEV

The selection of the initial values of the gain is important due to several reasons. First is to obtain the default performance of the HEV model. It is important for the later analysis where the total power loss between default model and the optimized model will be compared. If the objective function is lowered after the simulation thus indicates that the optimization simulation aim is achieved. Secondly, this initial value is important to prevent error in the HEV model. When the gains are placed, the model is not the same anymore as the default model. So the datasheet of the model may be different. The default model can act as reference when running simulation. Any error or abnormality must be compared to it. Gain value 1 acted as default value since this value will not change the model performance.

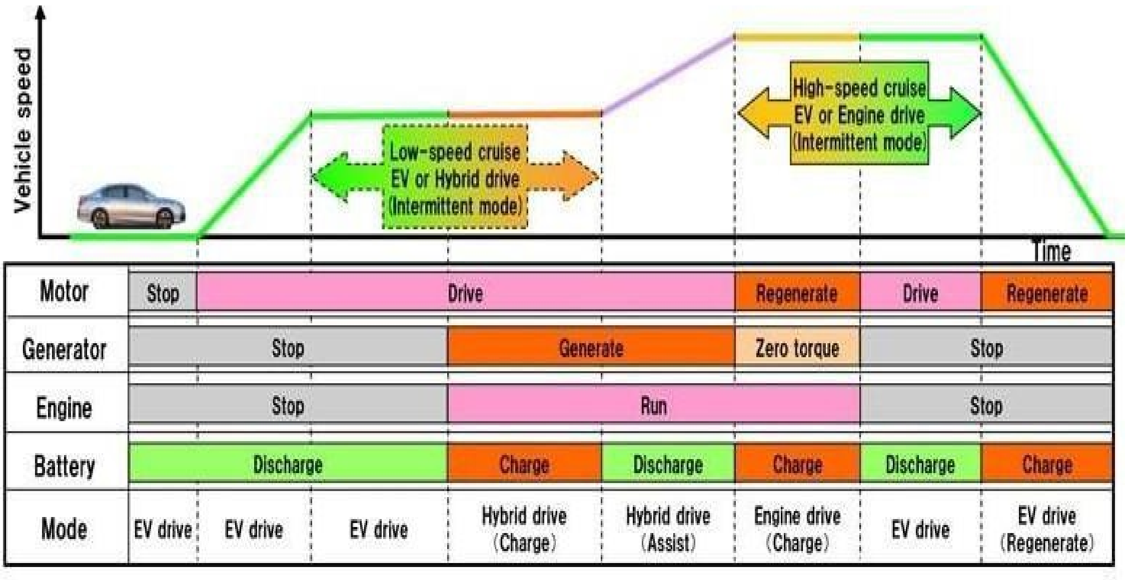


Fig. 3 - Sample of driving cycle

The simulation period is set to 40 seconds. This includes the acceleration and deceleration of the vehicle in order to mimic real movement of a vehicle. Figure 3 shows how the control parameters (generator, engine, battery, and motor) behaving during the simulation. Each of the parameter work together to produce the outputs, which are the fuel loss and electrical loss. The summation of both losses is the total power loss. In the MATLAB simulation, the total power loss represented as J1 variable, which is calculated by accumulating its values during the given period of simulation time, as shown in Figure 4.

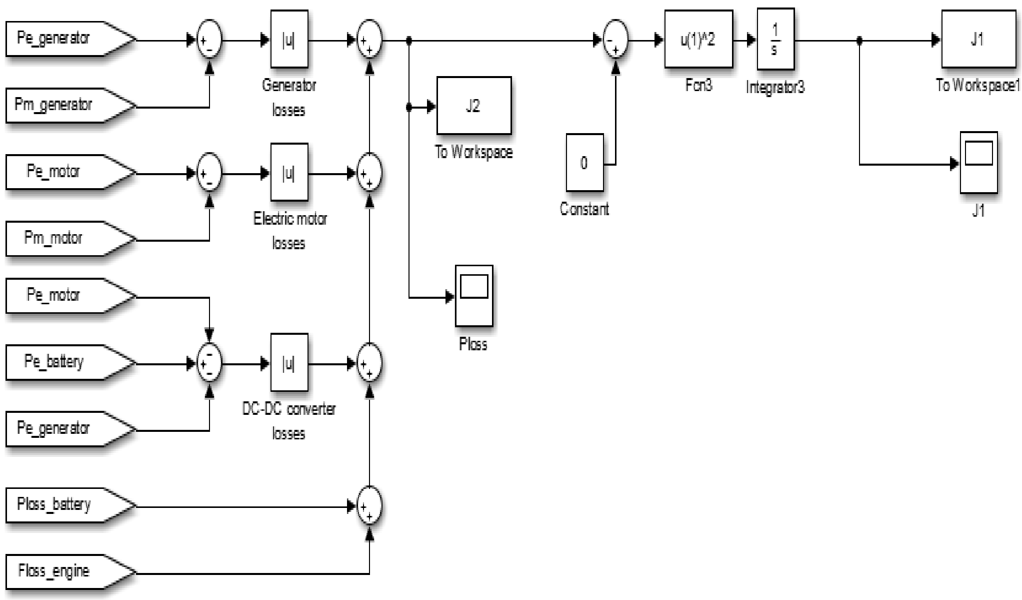


Fig. 4 - The calculation of total power loss in Simulink

Table 1 shows the default data of the hybrid electric vehicle before the simulation. These values must be received first by the command window of MATLAB. Without these values the simulation cannot be run. Initial power loss (J1) of the model is 320.927 with the gain in every parameter is 1. This value is very important in order to determine whether the simulation is effective or not. If the output produces when Simulated Annealing algorithm is injected to the model is lower than the initial value, it indicated that the optimization is successful.

Table 1 - The parameter of HEV

Type of value	*Default HEV datasheet*
Rpm	2000 rev\min
Wheel radius	0.3metre
Ratio	2
Initial speed	15km\h
Initial total power loss	320.9620

3. Simulated Annealing Algorithm

Simulated Annealing (SA) is an artificial intelligence method that are being use in order to find the best local optima for each function. This optimization solution involves evaluating the neighbors of a state of the problem, which are new states produced through conservatively altering a given state. In the travelling salesman problem, each state is typically defined as a permutation of the cities to be visited, and its neighbors are the set of permutations produced by reversing the order of any two successive cities. As heat is increase, it will travel into neighbor region to find the best local optima. When it began to cool slowly, it will try to stop at the best local optima. But this process may not confirm it to stop at better point. Thus, repeat heating and cooling will fasten the process of locating the local optima of the function. Figure 5 shows the flow chart of the SA algorithm, where $f(y)$ is the objective function, y is the design parameter, x is the best design parameter during the iteration process and t is the recorded temperature.

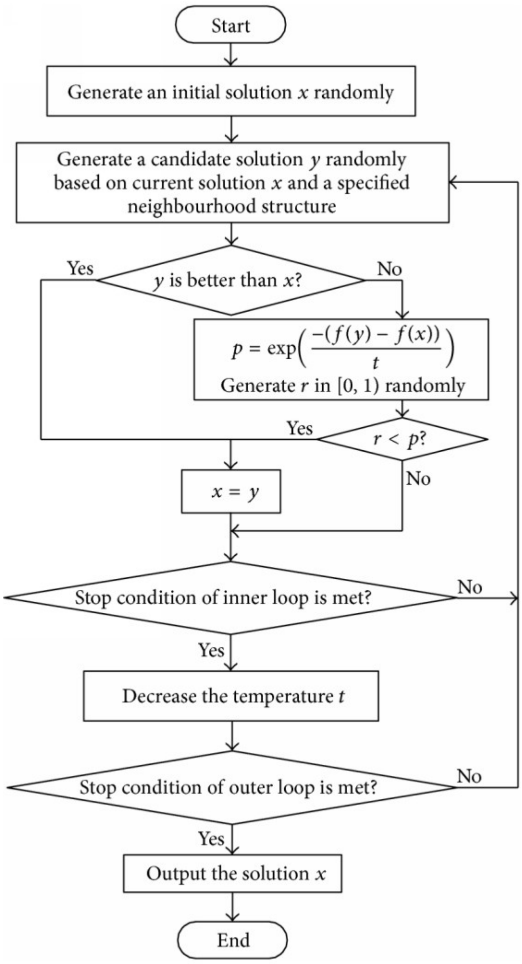


Fig. 5 - Simulated Annealing flow chart

In this study, SA algorithm is the method used to update the new value of gain (control parameter) in Section 2. Here, the objective function J1 in Figure 4 is defined as f and the gains Y, L, O and U are defined as design parameter vector y. Each of new value of gain will show different value of total power loss - which is the objective function. To attain the lowest total power loss, the simulation is executed until the convergence curve is saturated. These iterations produce various values of the total power lost and the lowest value is taken, which is at the end of the convergence curve. In terms of coding, SA is written in *mfile* coding feeds the updated control parameters to HEV model in Simulink. These two platforms (*mfile* coding and Simulink HEV Model) work together, as each of system will repeatedly sending data back and forth with each other.

4. Results and Discussions

Based on the result of the simulation, output which is the total power loss is obtained. As the gains are updated by the Simulate Annealing algorithm, the output values are also varied. The main objective is to produce the power loss which is lower from the initial or default value (320.92) when the gain is 1. The low total power loss indicated that the algorithm is effective on optimizing the hybrid electric vehicle model.

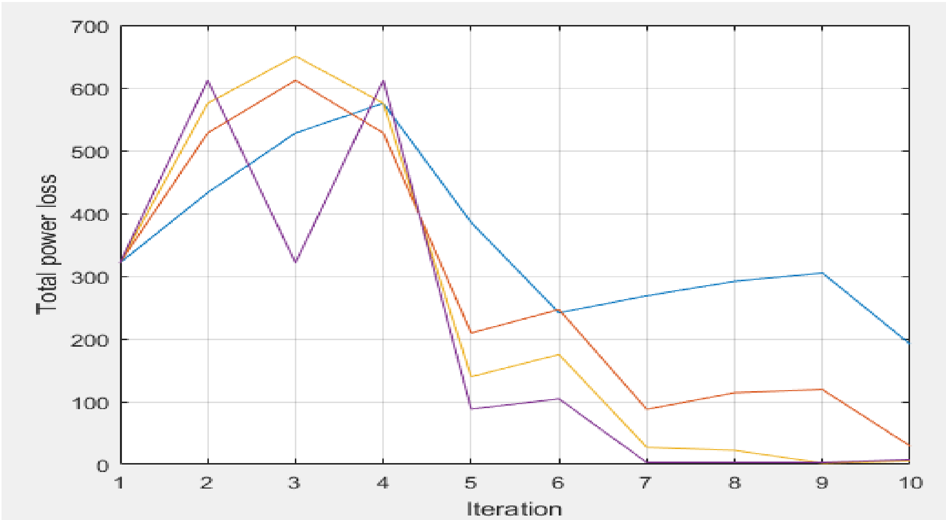


Fig. 6 - Total power loss for 10 iterations

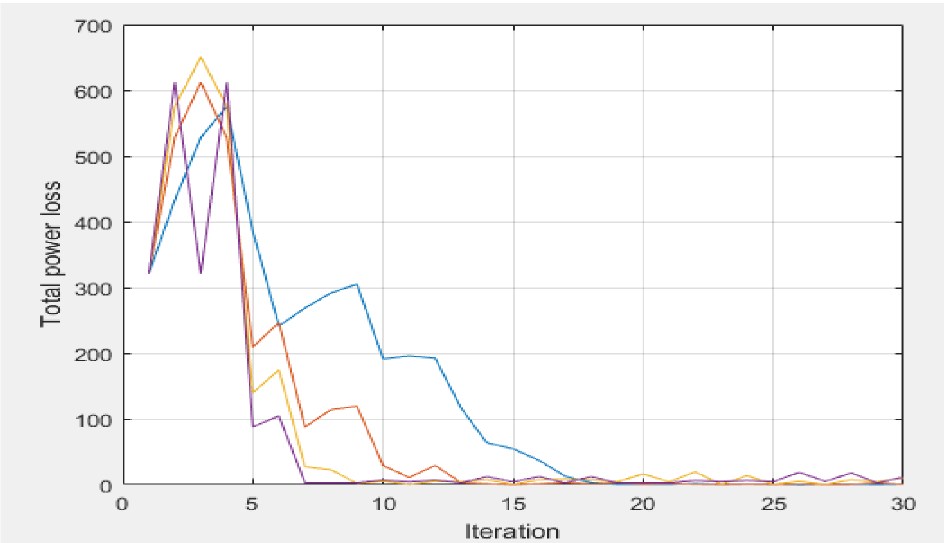


Fig. 7 - Total power loss for 30 iterations

The convergence of the objective function value or total power loss can be observed in Figures 6 and 7. In each figure, 4 trials are used to see the effectiveness of SA algorithm due to randomization effect in the algorithm. For example, in Figure 6, for first trial the simulation will do 10 times/iterations of the updated gains thus produce 10 values of total power loss. The first trial is shown by the blue line in Figure 6. Then, the second, third, and fourth trial are represented by red, purple, and orange lines. Even though the simulation uses 4 trials, each output results of the trial show identical pattern, which indicates the capability of the SA to minimize the total power loss.

In particular, from Figure 6, the initial total power loss is 320.92. This value is next increased for the first several iterations and suddenly began to drop until the 10^{th} iteration. But, not all trials have reached saturated value from the simulation. The values of the blue and red line still can drop if the simulation is continued. From Figure 7, the simulation is continued until 30 iterations. At 17^{th} iteration, all of the line has reached its saturation point which cause there is no significant change in values anymore. This indicated that the simulation have archive lowest total power lost that it has obtained.

Table 2 - Output performance result (total power lost)

Iteration	1^{st} trial	2^{nd} trial	3rd trial	4^{th} trial
1st	320.962	320.962	320.962	320.962
2nd	432.914	528.002	575.310	611.983
3rd	528.002	611.983	650.451	320.962
4th	575.310	528.002	575.310	611.983
5th	385.432	209.295	139.642	88.031
6th	241.414	246.736	174.952	104.320
7th	268.604	87.710	27.267	2.950
8th	291.694	114.090	22.458	3.181
9th	305.013	119.169	1.9752	3.006
10th	191.262	29.016	5.338	7.215
11th	195.829	10.784	0.5889	4.482
12th	192.432	29.016	5.338	7.215
13th	116.514	2.974	4.428	2.950
14th	63.429	1.396	7.695	12.121
15th	54.575	0.253	0.6391	4.482
16th	36.968	1.396	7.695	12.121
17th	12.768	2.950	8.326	**2.930**
18th	3.294	1.396	7.695	12.121
19th	0.4576	2.974	4.428	2.950
20th	0.4612	0.5433	16.191	3.181
21st	0.4576	1.940	4.428	2.950
22nd	1.785	0.769	19.113	6.616
23rd	0.584	**0.2401**	0.6091	4.813
24th	0.875	0.7692	13.655	6.616
25th	0.5843	0.2401	0.6091	4.813
26th	**0.0590**	0.9920	5.338	18.392
27th	0.5808	0.2539	**0.5881**	5.2014
28th	0.6938	0.3898	7.6014	17.462
29th	0.2467	2.974	4.407	2.946
30th	0.7815	0.5433	10.392	11.360

Table 3 - Output performance result (initial, worst, best and average)

Power loss type | Trial	1^{st} trial	2^{nd} trial	3^{rd} trial	4^{th} trial
Initial power loss	320.9620	320.9620	320.9620	320.9620
Worst power loss	575.3101	611.9832	650.4511	611.9836
Best power loss	0.05940	0.24013	0.5881	2.9306
Average power loss	140.7991	95.2584	87.4481	74.010

Table 4 - Optimal control parameters

Gains	1st trial	2nd trial	3rd trial	4th trial
Y	1.05	1	0.40	1.80
L	0.05	1.387e-16	0.09	0.20
U	1.15	1	1.30	1.800
O	1.05	1	1	1
Total Power loss	**0.05940**	**0.24013**	**0.5881**	**2.9306**

The values of the graph in Figure 7 are shown in term of number in Table 2. From this table, the real values can be observed and analyses. Each of trial start with initial value of 320.9620, which is the initial total power loss before the Simulated Annealing is applied. At 30th iteration, the total power loss values have converged into very small values. This is because; the new gain updated by the Simulated Annealing algorithm is very ideal thus producing very low value of power loss output. Table 3 summarizes the statistical analysis of the total power loss tuned by SA for 4 trials, while Table 4 shows the corresponding optimal control parameters. It shows that the SA algorithm is effective in minimize the total power loss of the given HEV plant.

5. Conclusion

From the data that have been obtained, this project proves that hybrid electric vehicle performance can be improved by using the artificial intelligence algorithm. The total power lost converges from 320.9620 to 2.9306 at 30th iteration for the 4th trial. The tuning within the system requires Simulated Annealing optimization to allow the substitution of the new gain values occurs automatically. This is because gain tuning requires a system that can do the new value searching. The new gain value successfully generates new power loss value which is more efficient. The main contribution that can be highlighted is gain control in the system to allow objective function to be optimized. To conclude, the project meets the main objective in term of obtaining the lower objective function. Beside that it also shows how Simulated Annealing algorithm helps in term of obtaining the design parameter so that the total power loss or objective function is minimized.

Acknowledgement

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