# Investigation of the Effects of a fuel blend on Engine performance by Response Surface Methodology

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## ABSTRACT

The aim of this paper is to model a response surface that is able to find a more defined brake specific fuel consumption (BSFC) as a function of speed. Engine driving patterns of power output against crankshaft speed was one of the methods employed. The load which is the normalized cylinder air mass in percentage is one of the variables used. The response surface which is directly related to fuel conversion is investigated through the analysis of BSFC. The BSFC is the energy flow divided by the mechanical power out. An engine performance simulation which predicts engine performance quantities such as power, torque, airflow volumetric efficiency and fuel consumption was used. This includes physical models for extending the predictions to include cylinder and tailpipe out emissions. The fuel for this research was an ethanol blend. The surface created was used to create a table, for fuel efficiency.The table is required to operate the engine as near to the bottom of the BSFC bowl as possible. The results qualified the ignition engine as a good representative of present day engines.

**Keywords:** Brake Specific Fuel Consumption (BSFC), Ethanol, Engine, Smoother surface

## 1.Introduction

Researchers around the worlds are trying to find ways to minimize environmental pollution and degradation. These pollutions contribute to the amount of carbon emissions into the atmosphere. The current study focuses on power generation through internal combustion engines (ICE).

A lot of similar studies using the RSM technique have been done. Elkelawy et al. (2020) investigated the significance of the four reaction parameters such as methanol to oil ratio, catalyst concentration, mixing speed, and reaction time and their combined effect on biodiesel yield is through twenty-nine of the pre-designed and performed experiments. Box-Behnken design (BBD)based on response surface methodology (RSM) was applied for process optimization. Elkelawy et al. (2020) used a quadratic regression model, instead of a linear regression model, this was established for biodiesel yield prediction with a coefficient of determination R2 of 0.9861. An

maximum biodiesel yield of 93.38% is accomplished at 203.5:1 mill methanol to oil ratio, 0.57 wt% catalyst concentration, 52 min reaction time and 530 rpm mixing. Tshivhase (2018) studied the airport industry which is a well-known contributor to carbon emissions. Tshivhase and Vilakazi 2018) focused on the mining industry which is also a strong contributor of carbon emissions

Elkelawy et al. (2020) obtained results that showed that there is a superior compatibility among the calculated yield of 93.38% and the experimental data of 93.2%. The estimated biodiesel fuel properties met with the American society for testing and materials (ASTM) D6751 standards. Engine operating parameters optimization have been executed using central composite design method (CCD) to achieve an optimum break thermal efficiency of a lone cylinder DI-engine fueled by biodiesel/diesel mixtures. Engine input parameters were considered as engine load and blends percentage for the optimization of engine response represented in break thermal efficiency (BTE), unburned hydrocarbon (UHC), and Nitrogen oxide (NOx) emissions. Examination of inconsistency (analysis of variance) ANOVA indicated that the quadratic representation was statistically important. RSM optimizer results indicated that the best possible values of BTE, UHC, and NOx were 13.656%, 120.7748 ppm, and 234.8926 ppm, respectively, at the maximum value of biodiesel mixture of 70% and break power of 2.05 kW. A validation test was performed and the error percentage is found to be within the range of 5%. The error percentage for BTE, UHC, and NOx was found to be 3.34%, 1.35%, and 2.31%, respectively. Tshivhase and Kainuma (2019) addressed the emissions of carbon into the atmosphere by proposing a single period, multi-supplier low carbon mixed integer model. This model was proven to reduce carbon emissions in the supply chain and also find the optimum distribution levels among different facilities including factories.

Park and Song (2017) evaluated the fundamental effects of the NG substitution ratio (NSR) on the combustion, performance and nitrogen oxides (NOx) emission of a dual-fuel engine in steps of 10% as the energy fraction of the fuel. Various advanced technologies, including dual-fuel combustion, have been developed to meet reinforced

emission regulations in the automobile industry. In this work, natural gas (NG) was added from 0 to 30%. Tshivhase and Kainuma (2018) identified the existing literature gaps and possible future research focus with respect to carbon emission reduction by looking at literature done between 1995 1nd 2018. In the 1990s due to improved computer models a consensus was formed that stated that greenhouses gases were deeply involved in most climate changes and emissions were bringing discernable global warming. During the same decade, scientific research in emissions has included multiple disciplines.

Park and Song (2017) found out that although the NOx emission significantly improved because of the higher specific heat capacity of air NG mixtures, the in-cylinder pressure decreased with increasing NG fraction because of a longer ignition delay, which also detrimentally affected the brake specific fuel consumption (BSFC) by decreasing the brake thermal efficiency (BTE) of the engine. The injection timing was optimized using a design of experiments (DoE) approach to minimize the BSFC under various load and NSR conditions. The

optimal injection timing was more advanced with lower load and higher NSC conditions. Additionally, the optimal Pareto fronts for improved performance and NOx emission of the dual-fuel engine were obtained from a multi-objective Pareto optimization. Tshivhase and Kainuma (2019) designed and solved a mathematical model with the help of a software package to optimize the costs. The problem was solved using a mixed integer linear program (MILP) which required a binary which was applied between the customer bases and the warehouses. Park and Song (2017) results suggested suitable intake and exhaust valve timing strategies to control the BSFC and NOx emission of a dual-fuel engine.

Lopez et al. (2016) evaluated BSFC and emissions (NOx, SO2 and CO) using three different load conditions (50%, 75% and 100%) using similar olive pomace methyl esters/diesel blends. In this work, with the aim of selecting the optimal operating conditions of a diesel engine (with regard to load and biodiesel blend) besides reducing both main exhaust emissions and BSFC (brake-specific fuel consumption) a methodology based on multiple response optimization has been proposed. Engine testing was followed by the design of the global desirability function in terms of both engine load and biodiesel blends. Tshivhase and Kainuma (2019) reviewed the literature of what has been studied with respect to carbon emissions and also identify the gaps in the literature using a systematic literature review approach. Content analysis was used to categorize existing literature on the various topics and methods over time in the area of carbon emissions in the supply chain.

Lopez et al. (2016) eventually found a direct correlation between emissions and load. Finally, to ensure minimum values of BSFC under three levels of emissions reduction (10%, 20% and 40%) optimum engine operating ranges, in terms of load rate and biodiesel blends, are studied.

Uslu and Celik (2020) investigated the effects of i-amyl alcohol/gasoline fuel blends on spark ignition (SI) engine performance and emissions experimentally, predicted by Artificial Neural Network (ANN) and optimized with Response Surface Methodology (RSM). Test engine was operated with pure gasoline and gasoline-isoamyl alcohol (isopentanol) fuel mixtures with different proportion at different engine speeds and various compression ratios (CR). With respect to obtained data from experiments, an ANN model, which is an Artificial Intelligence (AI) application, has been developed to estimate outputs such as brake mean effective pressure (BMEP), brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), nitrogen oxides (NOx), hydrocarbon emission(HC) and carbon monoxide (CO) according to CR, fuel blending ratio (by vol.%) and engine speed (rpm). Abdalla et al (2019) examined the engine performance and emissions of gasoline by applying a response surface methodology (RSM) optimisation approach. Fusel oil–gasoline blends were used to operate an engine at various speeds and loads. The optimal fusel oil–gasoline blend mix ratio was determined to minimise fuel consumption and nitrogen oxide and hydrocarbon emissions and to maximise the brake power (BP).

Uslu and Celik (2020) applied RSM to find suitable engine operating conditions. According to results, the ANN model can estimate performance and emission parameters of engine by correlation coefficient (R2) between 0.94 and 0.99. Uslu and Celik (2020) found out that the max. mean relative error (MRE) is less than 7% compared with outcomes obtained from tests. The RSM study demonstrated that, i-AA ratio of 15% at 8.31 CR and 2957.58 rpm engine speed are the optimal engine operating parameters. In this way, the ANN model with RSM support was found to be an effective tool for predicting and optimizing engine outputs with minimum test.

Abdalla et al (2019) stated that the results demonstrate that the engine load and speed have a significant effect on performance and emissions. In addition, the blended fuels (F10 and F20) were shown to reduce NOx emissions. Furthermore, insignificant effects on engine performance were observed for fusel oil compared with pure gasoline. The design of experiments (DoE) method, which is a statistical technique, indicated that F20 was the optimum blend ratio among the three studied fuels, based on the RSM. The optimal parameters were a load corresponding to 60% of the wide open throttle engine load and an engine speed of 4500 rpm for the F20 blend, resulting in a high desirability value of 0.852 for the test engine, with values of 67.6 kW, 235.17 g/kW.h, 0.118%vol, and 1931.4 ppm for the BP, brake-specific fuel consumption, CO emission, and NOx emission, respectively.

The aim is to find an area of minimum fuel consumption by modelling a response surface to some preprocessed data. The engine performance simulation predictive combustion engine model emulates a 4-cylinder engine. The load is the normalized cylinder air mass in percentage. Standard GTPOWER engine models are easily converted to real-time capable models these models may provide accurate and physically based engine boundary conditions to the rest of the vehicle. Wave dynamics are captured through a robust solution of the NAVIER-Stokes equations. The results are applicable to any size engine from the smallest utility engine to the largest marine application. The results tend to be highly accurate and fully predictable combustion models. These include various solutions for modelling combustion and emissions These solutions play an integral role for engine simulation to accurately predict engine performance, fuel consumption and engine-out emissions. These model also allow for successful analysis at full and part load as well as real-time real-time transient operation for advanced combustion concepts. Many related studies have been done on ICEs as a way of reducing the amount of emissions into the atmosphere and hence minimizing environmental pollution.

The BSFC is around 250 g/Kwh and 200 g/Kwh for spark ignition and compression ignition engines respectively. This is usually represented as a contour plot as a function of engine speed and torque of the mean effective pressure. The lowest BSFC is represented by an island usually at mid-engine speeds and high torque (load) close to peak full load torque. The most efficient engine operating point have the same brake specific fuel consumption even if the engine is operating at different speed and load. When we are given the number of crankshaft rotations for a complete engine cycle, number of cylinders, cylinder bore, piston stroke, mean effective pressure, engine speed and fuel mass flow rate, we can calculate the cylinder capacity, the engine brake effective torque, the engine brake effective power and the brake specific fuel consumption.

Fossil fuel like petrol and diesel are characterized by a very high density but due to the combustion process and the ICE working principle only a fraction of the total fuel energy ends up as mechanical energy at the crankshaft. After combustion around 30% of the energy is lost through heat in the engine compartments and another 30% is lost in the exhaust gases and this allows for about 40% as indicated energy from which we extract the friction and pumping losses and meaning that the overall engine efficiency ends up between 25%-40%. The fuel mass flow rate is measured function of the engine torque and engine speed since it measures the variation of the fuel mass in time and the the fuel mass flow rate is also called the hourly fuel consumption .The higher the engine speed and the load , the higher the fuel mass flow rate .And , from this perspective , the most fuel efficient operating points are at low speed and load which is not always the case since we need to know how much crankshaft power we can extract from the fuel. It is well-known that the engine operating points are between 1500 -4000 rpm and 90-150Nm, and in this area the conversion of the energy from fuel to crankshaft is the most efficient. The lower the intake air throttling and overall engine losses, the higher the efficiency. The highest fuel conversion efficiency is obtained at mid-engine speeds and high load.

Based on such previous studies it will be advisable to address the issue of normal fuel efficiency by finding the minimum fuel consumption.

## 2. Materials

### 2.1. Properties of Fuel

The physiochemical properties of the fuel are shown in table 1.

Table 1: The fuel’s characteristics and quantity

| Fuel property | Unit | Bioethanol [$C_2H_5OH$] |
|---|---|---|
| Density at 15 °C | kg $m^{-3}$ | 790 |
| Kinematic viscosity at 40 °C | $mm^2\ s^{-1}$ | 1.13 |
| Oxygen | Mass% | 34.7 |
| Cetane number | — | 5, 8 |
| Octane number | — | 110 |
| Latent heat of vaporization | MJ $kg^{-1}$ | 0.91 |
| Lower calorific value | MJ $kg^{-1}$ | 25.22, 26.70 |
| Flash point | °C | 13 |
| Auto-ignition temperature | °C | 332.8, 366.0 |
| Water content | mg $kg^{-1}$ | 2024 |
| Stoichiometric fuel/air ratio | — | 1/9.01 |
| References | 1 and 34–39 | |

**(ResearchGate)**

Ethanol fuel is most often used as a motor fuel, as a biofuel additive. It is commonly made from biomass. The production of ethanol has increased in the last few years. Most cars on the road can run on blends of up to 10 % ethanol.

### 2.2. Response Surface Methodology


Figure 1: The transportation of products between facilities

Fig.1 illustrates the flow of products between facilities. The transportation costs of the products also depend on the distance between the two facilities that is the plant, warehouses and customer centres.

Response surface methodology gathers statistical based mathematical methods and is among the most relevant multivariate techniques for optimization and engine modelling. This method also measures the assembly among the engine input factors and the engine output responses.

$$\boldsymbol{b = f(\,a_1\,,\,a_2, a_3\,,\,a_4 \dots a_n)} \qquad (1)$$

Where , $\boldsymbol{a_1\,,\,a_2, a_3\,,\,a_4 \dots a_n}$ are the engine input factors and $\boldsymbol{b}$ is the engine output

$$\boldsymbol{b = j_0 + \sum_{i=1}^{k} j_i\, B_i} + \cdots \qquad (2)$$

Linear regression modelling by response surface methodology

Where, ***j***represents regression coefficients

It is also presumed that the engine input parameters are uninterrupted.

Response surface methodology (RSM) is a technique to determine design factor settings to optimize the performance of a product. It combines design of experiments, regression analysis and optimization methods in a general purpose strategy to optimize the expected value of a stochastic response. In their landmark paper, Box and Wilson (1951) describe the development and application of this sequential method to chemical process design, in which yields of particular compounds were maximized. Since that time the method has been applied successfully in many areas. Experimental design plays an important role in several areas of industry. Experimentation is an application of treatments applied to experimental units and is then part of a method based on the measurement of one or more responses. It is necessary to observe the process and the operation of the system well. One of the most commonly used experimental designs for optimization is the response surface methodology (RSM). Because it allows for the evaluation of the effects of multiple factors and their interactions on response variables. The RSM is a widely used mathematical and statistical method for modeling and analyzing a process in which the response is affected by various variables and the objective of this method is to optimize the response. The parameters that affect the process are called dependent variables, while the responses are called dependent variables.

Therefore, the main goals of a RSM study are to understand the topography of the response surface including the local maximum, local, minimum and ridge lines and find the region where the most appropriate response occurs. The RSM investigates an appropriate approximation relationship between input and output variables and identify the optimal operating conditions for a system under study or a region of the factor field that satisfies the operating requirements.

**2.3 Experimental Design**

From the engine performance simulation engine data, the columns of interest are extracted including the load and speed. The data is also processed before fitting so as to pick up the minimum BSFC values from each sweep. The aim is to find minimum fuel consumption by modelling a response surface to some preprocessed data. The engine performance simulation predictive combustion engine model emulates a 4-cylinder engine. The load is the normalized cylinder air mass in percentage.

Table 2: Engine's Speed, load and BSFC

| SPEED = SPEED 1.0e+03 * | LOAD = LOAD | BSFC = BSFC 1.0e+04 * |
|---|---|---|
| 2.8414 | 0.2975 | 0.0406 |
| 2.8414 | 0.2970 | 0.0396 |
| 2.8414 | 0.2962 | 0.0397 |
| 2.8414 | 0.2948 | 0.0397 |
| 2.8414 | 0.2939 | 0.0397 |
| 2.8414 | 0.2923 | 0.0406 |
| 2.8414 | 0.2913 | 0.0421 |
| 2.8414 | 0.2909 | 0.0449 |
| 2.8414 | 0.2919 | 0.0503 |
| 3.7780 | 0.4185 | 0.0321 |
| 3.7780 | 0.4184 | 0.0315 |
| 3.7780 | 0.4184 | 0.0311 |
| 3.7780 | 0.4185 | 0.0309 |
| 3.7780 | 0.4183 | 0.0310 |
| 3.7780 | 0.4184 | 0.0307 |

BSFC is the brake specific fuel consumption in g/KWh which is the energy flow divided by the mechanical power out. This response surface can later be used as part of a hybrid vehicle optimization algorithm.

## 3. Results and Analysis

The preprocessed data is fitted with a fuel efficiency surface using the locally weighted smoothing linear regression (lowess) computed from p which is the coefficient structure and x and y are normalized by mean and standard.

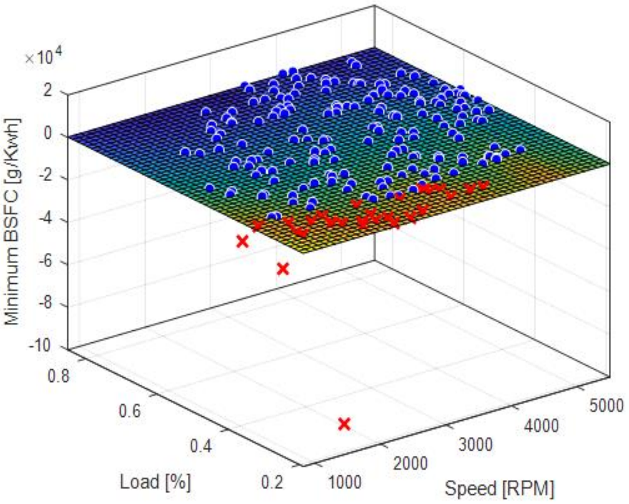


Figure2(a)

```
out = excludedata( Speed, minBSFC, 'Range', [0, 400] );
>> f2 = fit( [Speed, Load], minBSFC, 'Lowess', ...
'Normalize', 'off', 'Exclude', out )
```

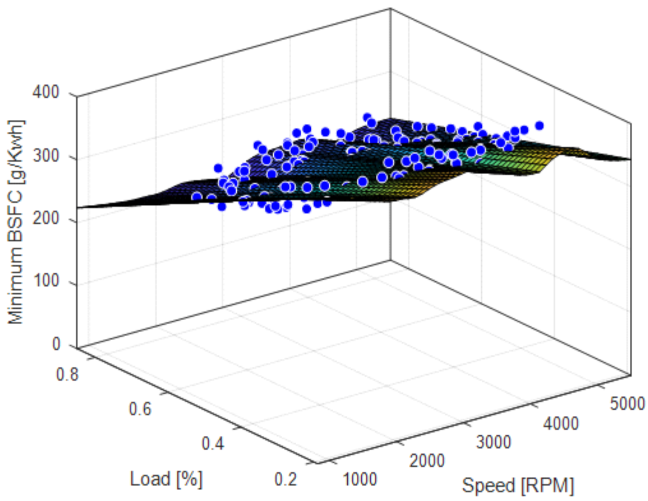


Figure2(b)

```
zlim([0,400])
```

The plot of speed, load and BSFC is then plotted and problematic points are then removed as the BSFC cannot be negative. The BSFC can only start from 0. x and y are still normalized between the mean and the standard. In order to have a clear picture of the BSFC it is necessary to zoom into the axis. A contour plot is created to see the region where the BSFC is really low, this is necessary since we want to operate the engine efficiently. Based on the developed model based optimization, the performance of an engine is computed different speeds and loads.Fig.2 (a) presents the speed, load and BSFC plots for BSFC is between the zero and the 400.The reason for this is to get a much closer look at the surface. The effect of limiting the z axis tends to us more problem points.BSFC can never be negative and hence the negative points are eliminated by keeping the limits of the z axis to between zero and infinity.

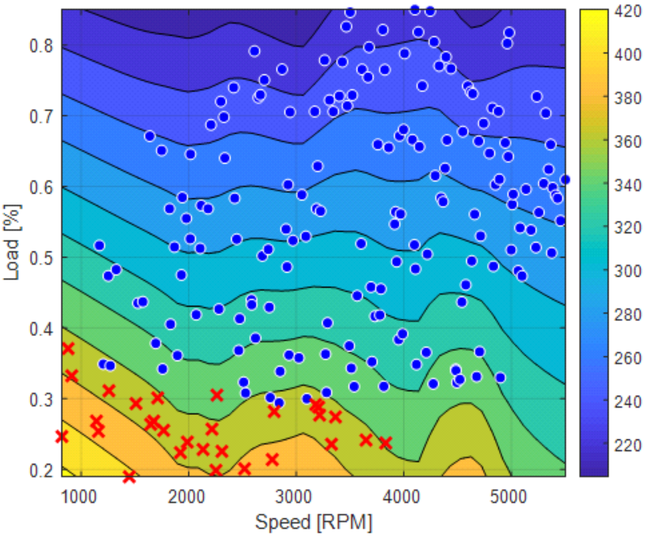


Figure2(c)

```
zlim([0,400])
>> plot( f2, [Speed, Load], minBSFC, 'Exclude', out,
'Style', 'Contour' );
xlabel( 'Speed [RPM]' );
ylabel( 'Load [%]' );
colorbar
```

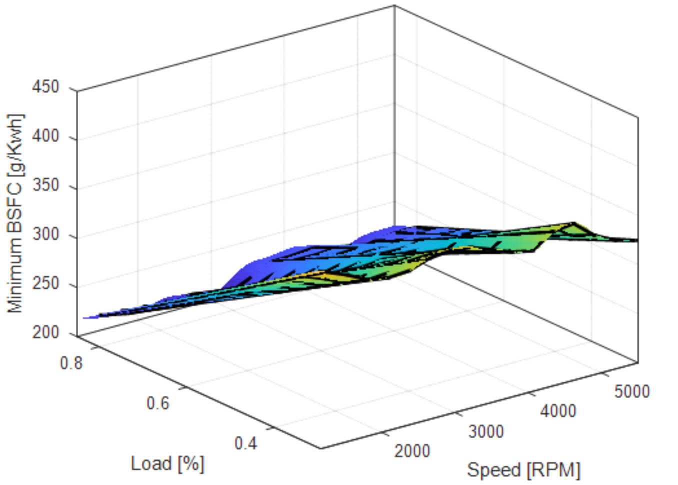


Figure2(d)

```
> h = plot( f2 );
h.EdgeColor = 'none';
hold on
mesh( tSpeed, tLoad, tBSFC, ...
'LineStyle', '-', 'LineWidth', 2, 'EdgeColor', 'k', ...
'FaceColor', 'none', 'FaceAlpha', 1 );
hold off
xlabel( 'Speed [RPM]' );
ylabel( 'Load [%]' );
zlabel( 'Minimum BSFC [g/Kwh]' );
```

Fig.2(b) allows for us to zoom in on the part of z-axis of interest. Fig.2(b) shows the same speed and load axis as before. In this case of z-axis being between zero and 400 there is a much clearer view of the surface which looks much more wrinkled than in previous research.

The contour plot Fig.2(c) with these z limits shows much fewer points and shows the contours much clearly especially the area of low BSFC which is what is favored. These are clearly shown on contour plots which are basically 2D plots.

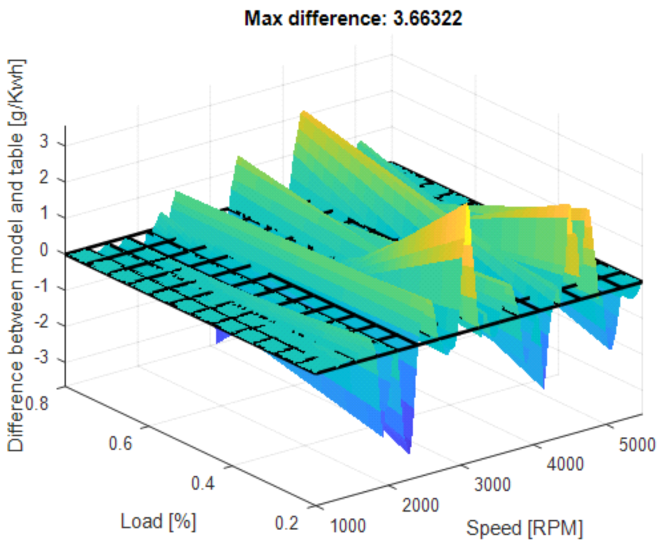


Figure2(e)

```
[tfSpeed, tfLoad] = meshgrid( ...
linspace( 1000, 5500, 8*17+1 ), ...
linspace( 0.2, 0.8, 8*13+1 ) );
tfBSFC_model = f2( tfSpeed, tfLoad );
tfBSFC_table = interp2( tSpeed, tLoad, tBSFC, tfSpeed,
tfLoad, 'linear' );
tfDiff = tfBSFC_model - tfBSFC_table;
```

A table is created from the contour plot surface by evaluating the model over a grid of points, speed and load breakpoints have variables created for them. The main point here is to try and get rid of the very high values of BSFC. Fig.2(d). The table that is created is then plotted against the original model with the grid showing the table breakpoints. The table accuracy is checked by first viewing the difference between the model and the table by plotting their difference on a smoother grid. This difference is then used in the prediction accuracy between these two products to determine the accurate table size. Fig.2(e) has the maximum difference as 3.66 which is reasonable.

## 4. Discussions and Conclusions

The influence of engine parameters which include engine load and engine speed in modelling a response surface is investigated. At very high engine loads the fuel consumption tends to be very low that is above 0.8. And, at very low loads like o.2 and o.3 the fuel consumption is critical. At mid-loads such as between 0.4 and o.8, the fuel consumption tends to be neither critical nor little. The influence of engine parameters that is engine load and engine speed in modelling a response surface are investigated. At very high engine loads the fuel consumption tends to be very low. The BSFC is also favorable at very high speeds. At lower speeds, the fuel consumption is really high especially and super low speeds. Other way of minimizing the brake specific fuel consumption is by shifting the engine load into a more efficient area while maintaining the same engine speed. This control strategy is only possible in hybrid electric vehicles (HEV), where engine excess torque can be used to generate electrical energy and charge the battery. In vehicle with automatic transmissions, the BSFC map is used as a reference to calculate the shift lines for best fuel efficiency. In hybrid electric vehicles, the BSFC map is used in Energy Management strategies to calculate the torque split between engine and electric machine for best fuel efficiency. Lower air intake air temperature allows for a larger engine speed area with maximum torque, a higher power output or to increase the compression ratio for the reference engine.

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