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Modelling, simulation, six sigma and their application in optimization of electrical vehicle design

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1. Introduction

Six Sigma is a structured, disciplined, data-driven methodology and process where the focus is placed on improving business performances using tools with an emphasis on statistical analysis (Breyfogle, 2003; Harry & Schroeder, 2000; Pande & Holpp, 2002; Pyzdek, 2003). It has evolved and grown over the years, and today is being used by companies such as GE, Honeywell, Motorola, DOW, DuPont, American Express, Ford, GM, TRW Automotive, and many others to improve the business performance. Several companies in manufacturing and pharmaceutical industries even mandate the practicing of these tools in their everyday business operations. According to (Wortman, 2001), Motorola credited the Six Sigma initiative for saving $940 million over three years and AlliedSignal reported a $1.5 billion savings in 1997.

In recent years, there has been increasing interest in both research and application of the Six Sigma methodology (Nonthaleerak & Hendry, 2006; Snee, 2004). Details on the history of Six Sigma and success stories of its implementation can be found in literature such as (Jones, 2007; Nonthaleerak & Hendry, 2006; Snee, 2004). Nonthaleerak and Hendry (Nonthaleerak and Hendry 2006) have provided an extensive review of the literature in this area.

Before a Six Sigma project can be started in any organization, a decision maker usually asks the following two questions: "How much is the project cost?" and "How long will it take?". The answers to these questions can determine the fate of the project. Unfortunately, due to its data-driven nature and wide use of statistics, a typical Six Sigma project requires large amounts of data to be collected. The data collection can be both costly and time consuming. Many projects that could potentially improve the quality of products never got started because of the high cost and long time associated with data collection. The use of modeling and simulation can help solving this dilemma. Zhan (Zhan, 2008) used a first principle model for brushed DC permanent magnetic motors and Six Sigma tools to improve a motor speed control design based on MATLAB (Pratap, 2006; The MathWorks, 2008) simulation results. Under the assumption that all the motor parameters such as inertia, inductance,

resistance, friction, and torque gain are random variables with known probability distributions, one thousand sets of motor parameters were randomly generated. These "randomly generated" motors were then simulated to collect data for statistical analysis including Design of Experiments (DOE) (Mathews, & Mathews, 2004; Montgomery, 2008; Taguchi, 1987; Taguchi, 1993) and Response Surface Method (Myers, & Montgomery, 1995). It was proven to be an effective way of improving the motor speed control algorithm based on the results of Monte Carlo analysis (Casella, 2004; Liu, 2001) A similar modeling and simulation based approach was used in (Zhan, 2009) to solve the Monte Carlo analysis for the inverse problem of motor PWM control. In this paper, the same approach is used to solve a design optimization problem for electrical vehicles.

The rest of the paper is organized as follows: In Section 2, an optimization problem for electrical vehicles is introduced; The application of Design of Experiments (DOE) to identify the main factors is discussed in Section 3; The Response Surface Method (RSM) is used to find a solution to the optimization problem in Section 4; Section 5 includes the conclusion and brief discussion for future research work in this area. The MATLAB code that was used to derive the results in this paper is included in the appendix so that interested readers can easily reproduce these results.

2. Design Optimization for Electrical Vehicles

The design of electrical vehicles involves many challenges due to the complexity of the system (Ehsani *et al.*, 2005; Gillespie, 1992; Husain, 2003). A vehicle dynamics based model was derived in (Zhan *et al.*, 2009) to develop component level requirements based on basic performance requirements such as the maximum driving range, maximum cruise speed, maximum acceleration, etc. In theory, any variation in a particular parameter can cause the performance of the electrical vehicle to be different. However, the influences of the parameters are different. Small change in some parameters can cause large change in the vehicle performance, while relatively large change in other parameters may not have much impact on the vehicle performance.

In order to calculate the maximum driving range, the aerodynamic drag D_A (Gillespie, 1992) needs to be calculated first

$$D_A = \frac{1}{2}\rho V^2 C_D A \tag{1}$$

where V is the vehicle speed (ft/sec), A is the frontal area of the vehicle (ft²), C_D is the aerodynamic drag coefficient, and ρ is the air density (lb-sec²/ft⁴).

$$\rho = 0.00236 \left(\frac{P_r}{29.92}\right)\left(\frac{519}{460+T_r}\right) \tag{2}$$

where P_r is the atmospheric pressure in inches of mercury and T_r is the air temperature in degrees Fahrenheit.

The maximum driving range is determined by

$$d_{max} = 63.29 \frac{\eta W_b}{D_A+R_x+W sin(\theta)} D_{se} \tag{3}$$

where W is the gravity force, θ is the angle of the inclined surface, W_b is the weight of the battery, η is the efficiency of the battery/motor subsystem, D_{se} is the specific energy density of the battery (MJ/kg), and R_x is the rolling resistance. Details of the derivation and definitions can be found in (Zhan *et al.*, 2009).

The rolling resistance can be modeled as the vehicle static weight W multiplied by the coefficient of rolling resistance f_r:

$$R_x = f_r W \tag{4}$$

Under the assumption that the vehicle is traveling at a constant speed, the maximum driving range can be plotted as a function of the vehicle speed for a given set of parameters, as shown in Fig. 1. It can be seen that the driving range is reduced if the vehicle speed is increased. When design parameters are chosen to take different values, this curve will move up or down accordingly. Clearly, one would like to select the parameters such that at any given speed, the driving range is longer. The following metric is proposed to measure the driving range performance

$$P = \int_0^{Vmax} d_{max}(V) dV \tag{5}$$

In other words, the area underneath the curve in Fig. 1 is an indication of the vehicle driving range performance. *Vmax* in equation (5) is the maximum cruise speed. In Fig. 1, it is assumed that *Vmax* is equal to 85 mph.

Naturally, one can ask: How should we choose the design parameters to maximize the performance index *P*? For each given set of parameters, *P* can be calculated. But there are eleven parameters and each parameter can take thousands of different values. The combinations can be astronomical. To make the numerical search realistic, one needs to narrow down the combinations to a level that can be handled by a typical desktop computer. Initial simulation revealed that the performance index *P* is more sensitive to certain design parameters than others. The Design of Experiments is a Six Sigma tool that can be used to identify the parameters that have major impact on the results. The design engineer can then focus on these important parameters by assuming all other parameters are constant. This will not provide an optimal design, but should yield a suboptimal solution. The main advantage is the significantly reduced computation time and memory required for the parameter selection.
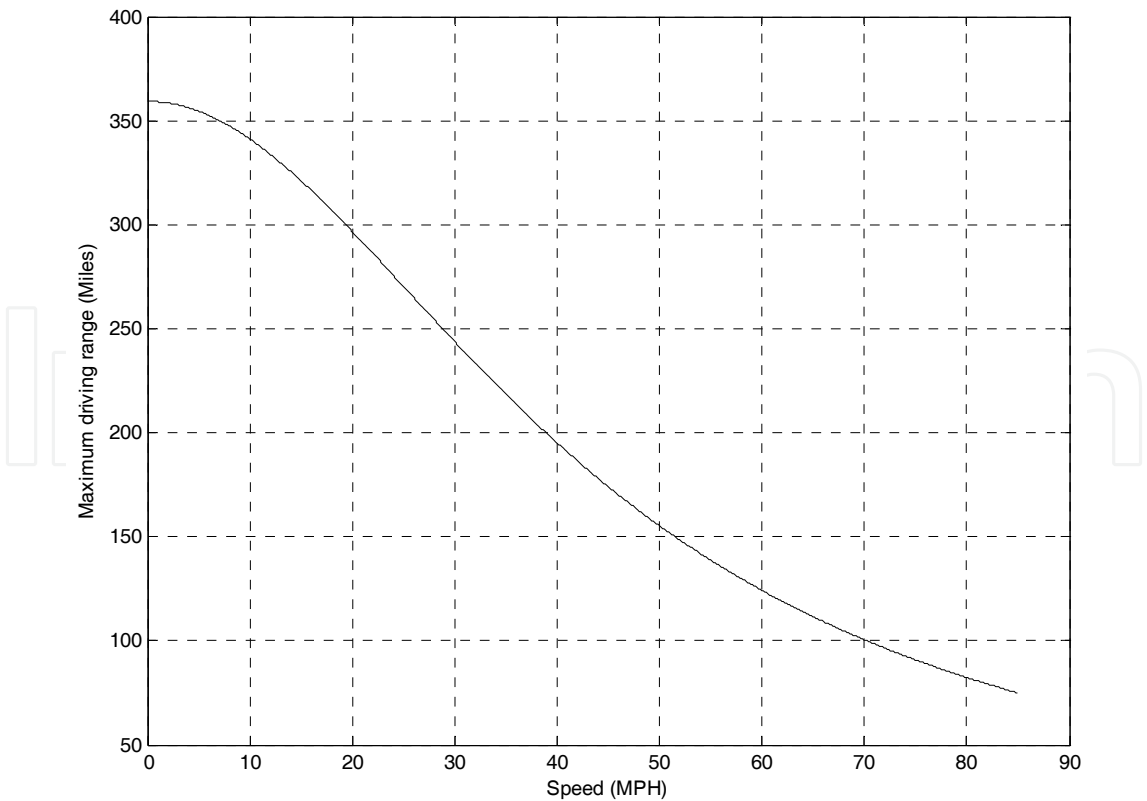

Fig. 1. Driving range as a function of vehicle speed

3. Design of Experiments

A two-level, N-factor full factorial DOE matrix requires 2^N runs. To calculate the performance index P using equation (5), the following eleven parameters are needed

- $Vmax$: the maximum cruise speed
- W: the total vehicle weight
- W_b: the weight of the battery
- D_{se}: the specific energy density of the battery
- η: the efficiency of the battery/motor
- f_r : the coefficient of rolling resistance
- A: the frontal area of the vehicle
- C_D: the aerodynamic drag coefficient
- θ: the angle of the inclined surface
- P_r : the atmospheric pressure in inches of mercury
- T_r : the air temperature in degrees Fahrenheit.

Among the eleven parameters, some are environmental factors, e.g., the atmospheric pressure, the air temperature, and the angle of the inclined surface. Typically, an optimal or suboptimal design is selected under one set of nominal environmental conditions. In this paper, we use the nominal values of 29.92 inches of Hg for atmospheric pressure, 59 ºF for air temperature, and a flat surface ($\theta = 0$).

There are other parameters that take specific values due to other requirements. For example, one can assume that the body of the vehicle has been designed, thus the frontal area of the vehicle has a fixed value (e.g. A = 34 ft²); the maximum cruise speed has been determined to be 85 mph. Since the total vehicle weight W includes the battery weight W_b, there is a coupling between W and W_b. To avoid the coupling between these two factors, a new factor W_0, defined as the weight of the vehicle without the battery, is used

$$W_0 = W - W_b \tag{6}$$

As a result, there are six remaining parameters that need to be analyzed. The DOE matrix was created using Minitab (Meyer, & Krueger, 2005), as illustrated in Table 1. The -1 and 1 represent the two extreme levels for each factor. These values are defined in Table 2.

Notice that for six factors, there are $2^6 = 64$ runs in the DOE matrix. The simulation runs were carried out in MATLAB using mathscript files attached in the appendix (SpdDisOptimization.m and EVSimdoeSixFactors.m). The DOE test matrix was set up in EVSimdoeSixFactors.m, which calls SpdDisOptimization.m to calculate the performance index P in equation (5). The resulting value P from simulation was recorded in the last column of the Table 1 with a common multiplier of 10⁴, labeled as "Area*10^4".

Based on the results in Table 1, the Pareto Chart of the standardized effects was plotted, as illustrated in Fig. 2. It can be seen that the top three factors are: D_{se}, W_b, and the interaction between them. Therefore, the conclusion is that the design optimization effort should be focused on D_{se}, W_b, and their interaction.

Run	W0	Wb	Cd	fr	eta	Dse	Area*10^4	Run	W0	Wb	Cd	fr	eta	Dse	Area*10^4
1	-1	-1	-1	-1	-1	-1	0.3766396	33	-1	-1	-1	-1	-1	1	1.5065585
2	1	-1	-1	-1	-1	-1	0.3544879	34	1	-1	-1	-1	-1	1	1.4179517
3	-1	1	-1	-1	-1	-1	0.9257004	35	-1	1	-1	-1	-1	1	3.7028017
4	1	1	-1	-1	-1	-1	0.8790451	36	1	1	-1	-1	-1	1	3.5161803
5	-1	-1	1	-1	-1	-1	0.3384682	37	-1	-1	1	-1	-1	1	1.3538727
6	1	-1	1	-1	-1	-1	0.319306	38	1	-1	1	-1	-1	1	1.277224
7	-1	1	1	-1	-1	-1	0.8361176	39	-1	1	1	-1	-1	1	3.3444704
8	1	1	1	-1	-1	-1	0.7956222	40	1	1	1	-1	-1	1	3.1824888
9	-1	-1	-1	1	-1	-1	0.3437897	41	-1	-1	-1	1	-1	1	1.3751589
10	1	-1	-1	1	-1	-1	0.3232284	42	1	-1	-1	1	-1	1	1.2929137
11	-1	1	-1	1	-1	-1	0.8430283	43	-1	1	-1	1	-1	1	3.3721131
12	1	1	-1	1	-1	-1	0.7997976	44	1	1	-1	1	-1	1	3.1991903
13	-1	-1	1	1	-1	-1	0.3100408	45	-1	-1	1	1	-1	1	1.2401632
14	1	-1	1	1	-1	-1	0.2922114	46	1	-1	1	1	-1	1	1.1688458
15	-1	1	1	1	-1	-1	0.7643174	47	-1	1	1	1	-1	1	3.0572697
16	1	1	1	1	-1	-1	0.7266873	48	1	1	1	1	-1	1	2.9067492
17	-1	-1	-1	-1	1	-1	0.4059882	49	-1	-1	-1	-1	1	1	1.6239527
18	1	-1	-1	-1	1	-1	0.3821104	50	1	-1	-1	-1	1	1	1.5284414
19	-1	1	-1	-1	1	-1	0.9978329	51	-1	1	-1	-1	1	1	3.9913317
20	1	1	-1	-1	1	-1	0.9475421	52	1	1	-1	-1	1	1	3.7901683
21	-1	-1	1	-1	1	-1	0.3648423	53	-1	-1	1	-1	1	1	1.4593693
22	1	-1	1	-1	1	-1	0.344187	54	1	-1	1	-1	1	1	1.376748
23	-1	1	1	-1	1	-1	0.9012696	55	-1	1	1	-1	1	1	3.6050785
24	1	1	1	-1	1	-1	0.8576187	56	1	1	1	-1	1	1	3.430475
25	-1	-1	-1	1	1	-1	0.3705785	57	-1	-1	-1	1	1	1	1.4823142
26	1	-1	-1	1	1	-1	0.348415	58	1	-1	-1	1	1	1	1.3936602
27	-1	1	-1	1	1	-1	0.9087188	59	-1	1	-1	1	1	1	3.6348752
28	1	1	-1	1	1	-1	0.8621195	60	1	1	-1	1	1	1	3.4484778
29	-1	-1	1	1	1	-1	0.3341998	61	-1	-1	1	1	1	1	1.3367993
30	1	-1	1	1	1	-1	0.3149812	62	1	-1	1	1	1	1	1.2599247
31	-1	1	1	1	1	-1	0.8238746	63	-1	1	1	1	1	1	3.2954985
32	1	1	1	1	1	-1	0.7833123	64	1	1	1	1	1	1	3.1332492

Table 1. DOE test matrix

	W_0 (lbs)	W_b (lbs)	C_D	f_r	η	D_{se} (MJ/kg)
-1	3800	500	0.4	0.014	77%	0.2
1	4000	1400	0.55	0.016	83%	0.8

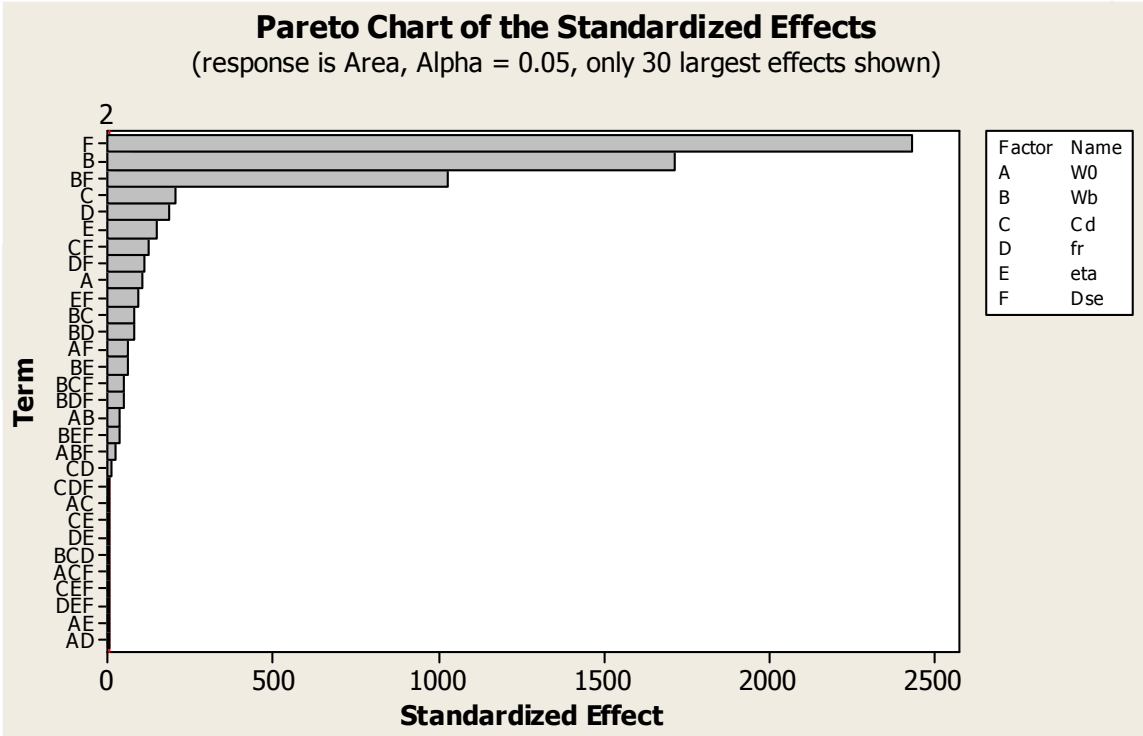Table 2. Definitions of extreme values for each factor

Fig. 2. Identification of main factors

The conclusion from the Pareto Chart can be verified with the Main Effect Plot and the Interaction Plot in Figs. 3 and 4.

In Fig. 3, the effects of these factors with steeper slopes are more significant on the results than others. Fig. 3 also indicates the direction of impact, for example, lower W_0, higher W_b, lower C_D, lower fr, higher η (eta), and higher Dse will lead to larger value for index P. In Fig. 4, larger differences between slopes of the two lines inside each box imply more significant interactions between the horizontal and vertical factors related to the box. It can be seen that the most significant interaction is the one between W_b and D_{se}.

The simulation result can also be used to create the Contour Plot of the performance index P as a function of the two main factors D_{se} and W_b, as illustrated in Fig. 5. The -1 and 1 levels for the two factors are defined in Table 2. The points in between the two extreme values are obtained using linear interpolation. For simplicity, the factor of 10^4 is not included in the index P, labeled as "Area".
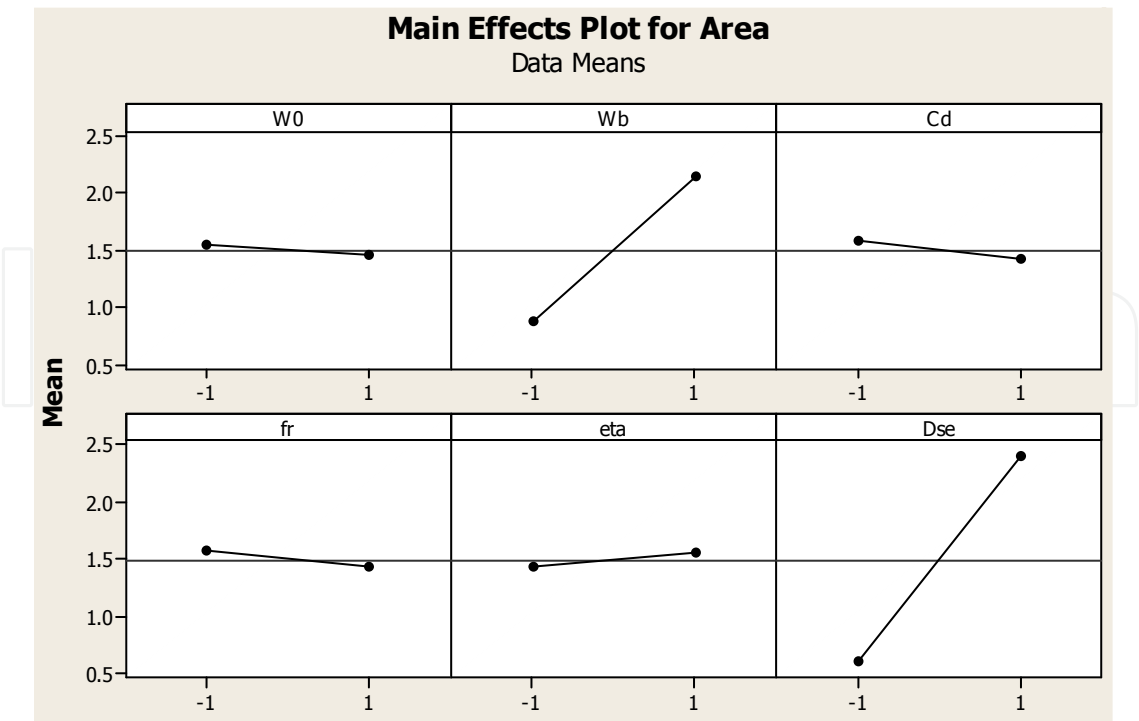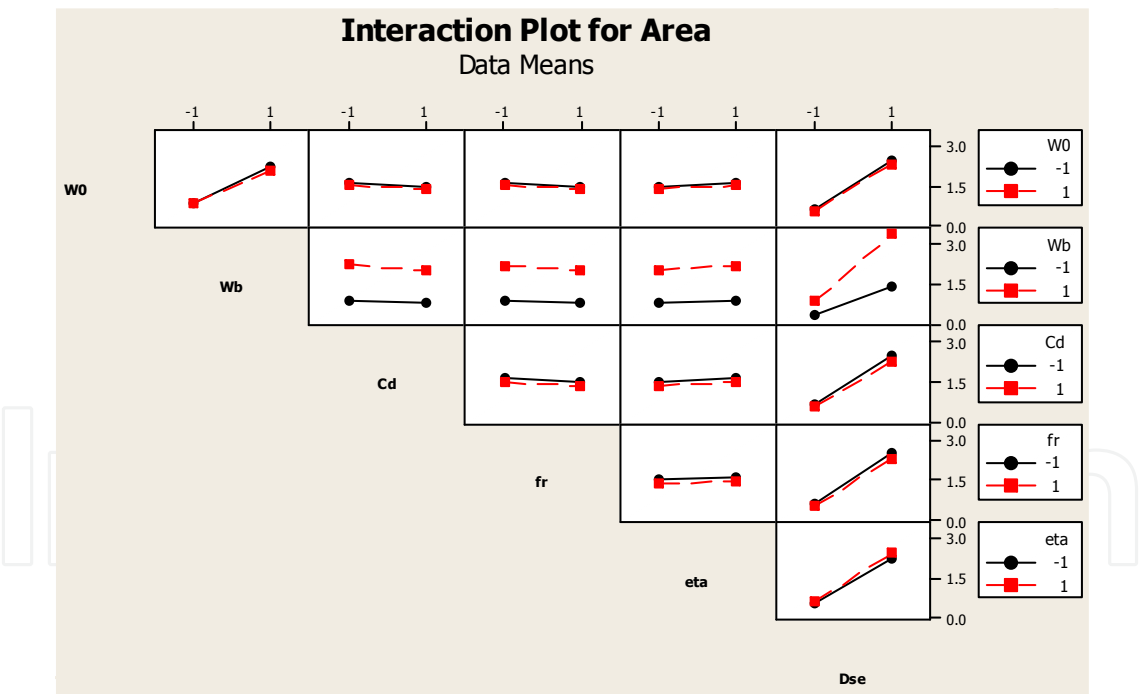
Fig. 3. Impact of the six factors

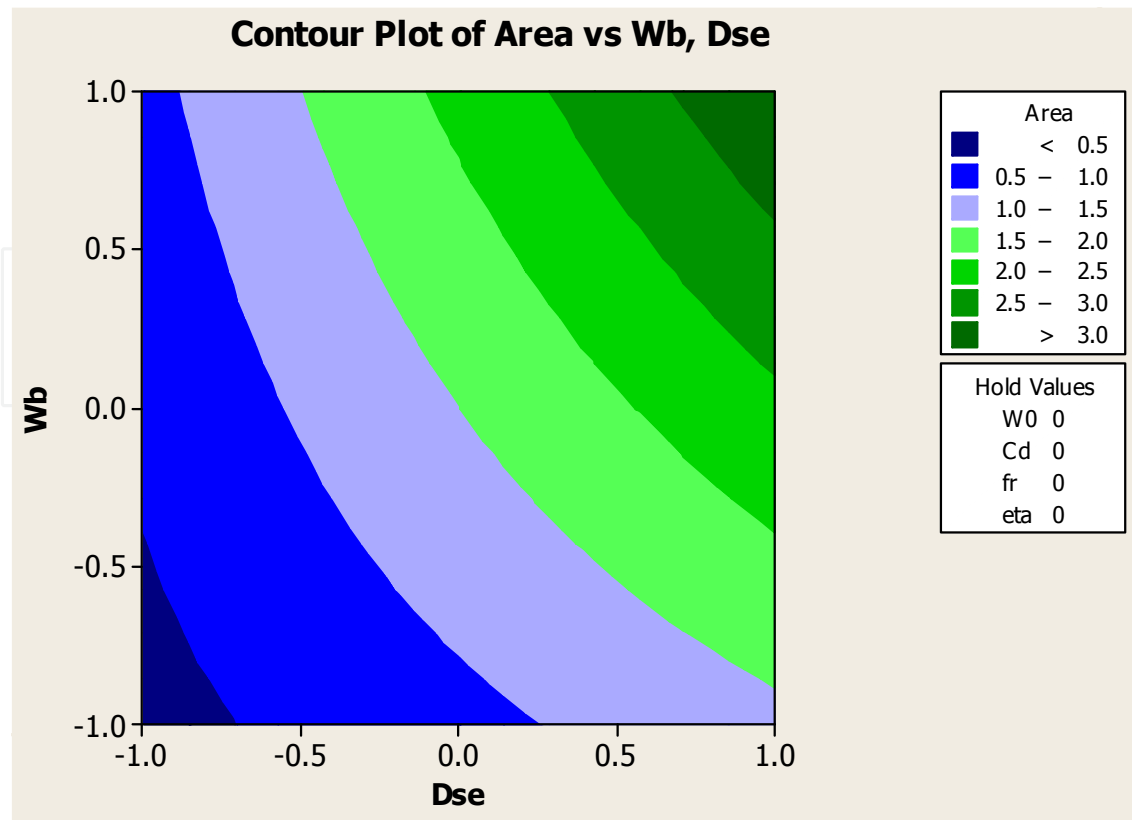Fig. 4. Impact of the interactions between factors

Fig. 5. The index P as a function of D_{se} and Wb.

To illustrate the different impacts of the factors, a mathscript file ThreeCasePlotting.m was written (see Appendix) to plot three different cases:

Case 1: Worst case D_{se} and W_b and best case for other factors.

Case 2: Best case D_{se} and W_b and worst case for other factors.

Case 3: Best case D_{se} and W_b and nominal values for other factors.

The graphs for these three cases are illustrated in Fig. 6. It can be seen that there is a big difference between Case 1 and the other two cases. The difference between Cases 2 and 3 is relatively small. In other words, if D_{se} and W_b are not selected properly, then the result will not be good, even if all other parameters are selected properly. On the other hand, if D_{se} and W_b are selected properly, then the selection of other parameters will not make much difference. Noticing that D_{se} and W_b are the specific energy density and the weight of the battery, the DOE analysis tells us that the battery technology is the key to the success of electrical vehicles.
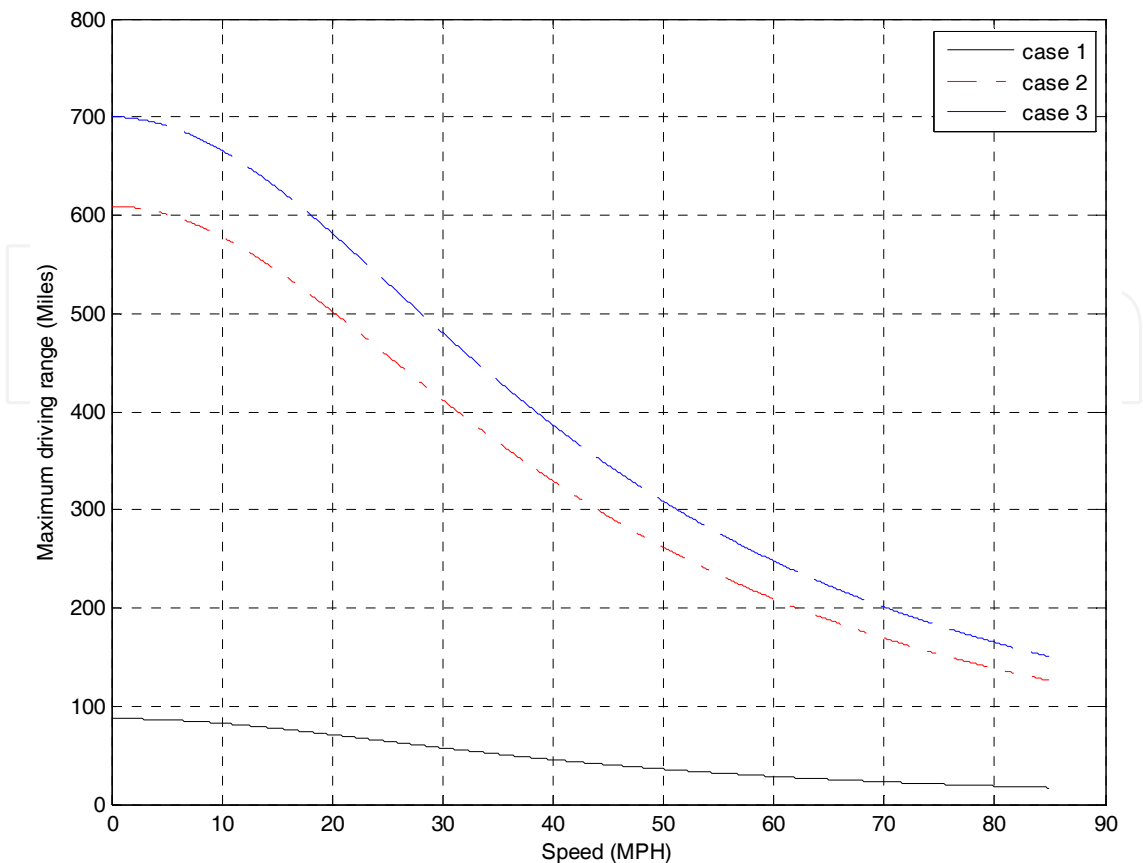
Fig. 6. Three cases for performance index.

4. Response Surface Method and Optimization

In Section 3, the specific energy density and weight of battery are identified as the two main design parameters that have major impact on the performance index P. In this section, these two parameters will be studied to optimize the performance and the associated cost.

It has been analyzed in Section 3 that larger values for battery weight and the specific energy density can improve the driving range performance. However, the batteries with higher specific energy density are more expensive. The cost associated with the specific energy density value is usually nonlinear. If the specific energy density is doubled, the price of the battery is more likely to be quadrupled. For the same type of battery, the cost associated with weight is usually linear. Doubling the weight of battery means twice as many battery units, thus twice the cost. Based on the above analysis, the following cost function is defined for performance/cost optimization

$$J = K_1 \left(\frac{D_{se}}{D_{se0}}\right)^2 + K_2 \frac{W_b}{W_{b0}} + K_3 \frac{P_0}{P} \tag{7}$$

where K_1, K_2, and K_3 are weights for each term, D_{se0}, W_{b0}, and P_0 are the nominal values for each term that are used to normalize each term. The normalization for each term is necessary, since without normalizing, one of the terms will dominate the cost function and make other two terms irrelevant. The average values in Table 1 can be used as the nominal values.

With the 15%, 35%, and 50% weights on the three terms, the cost index becomes

$$J = 0.15 \left(\frac{D_{se}}{0.5}\right)^2 + 0.35 \frac{W_b}{950} + 0.5 \frac{15000}{P} \tag{8}$$

The objective of optimization is to minimize the cost function J. Clearly, larger performance value P, lower specific energy density, and lower battery weight will result in smaller J. Minimizing J requires a trade-off between cost and performance: higher performance P will drive up the cost.

Since the performance index P can be calculated as a function of specific energy density and weight of battery, one can calculate the cost function J as a function of the specific energy density and the weight of the battery.

Since the focus is on the specific energy density and weight of battery, in addition to the nominal values for the atmospheric pressure, the air temperature, the angle of the inclined surface, and the frontal area of the vehicle, we further assume that

- $W_0 = 4000$;
- $C_D = 0.45$;
- $f_r = 0.015$;
- $\eta = 0.8$.

The Response Surface is plotted in Fig. 7 by letting the battery weight vary from 500 lbs to 1400 lbs at an increment of 10 lbs and the specific energy vary from 0.2 MJ/kg to 0.8 MJ/kg at an increment of 0.01 MJ/kg. The mathscript code for creating the Response Surface is attached in the Appendix (TotalOptimization.m). The contour of the cost function, i.e., the values for D_{se} and W_b with constant levels of cost function values, is plotted on the (D_{se}, W_b) plane. From Fig. 7, it can be seen that the optimal value for cost function is achieved inside the oval shaped curve. The optimal parameter values can be calculated in MATLAB as: W_b= 970 lb, D_{se} = 0.58 MJ/kg.
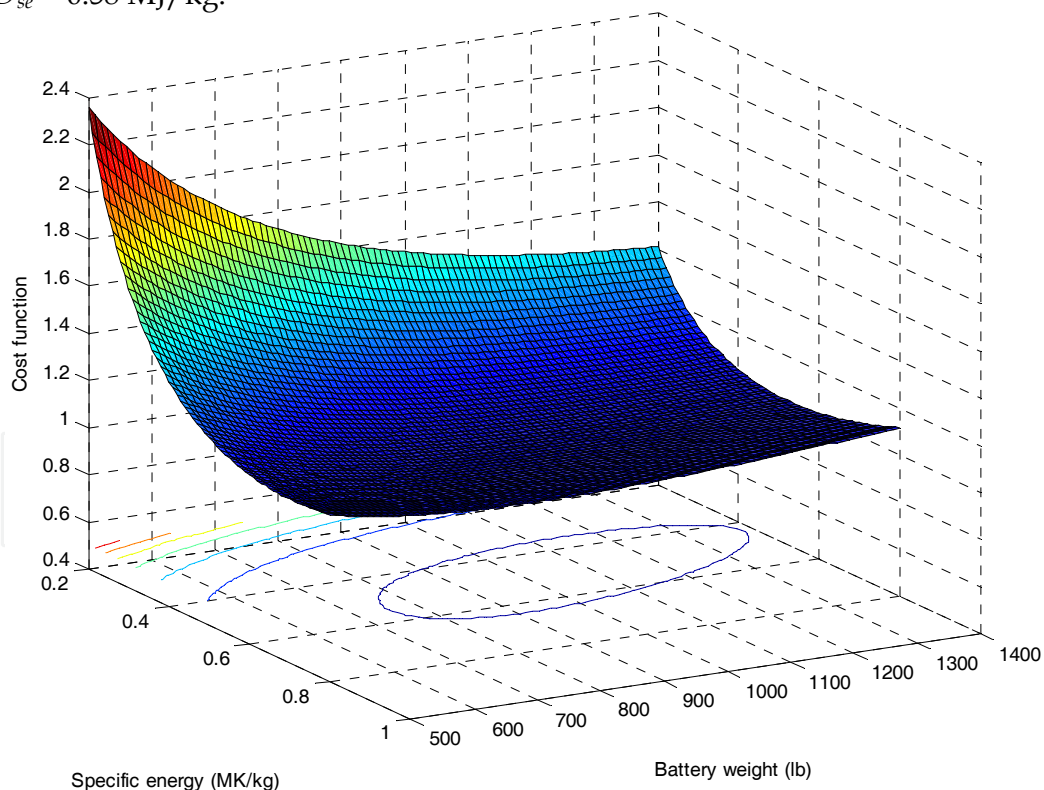

Fig. 7. Cost function as a function of battery weight and specific energy density

The optimization of cost function using RSM was made possible after the DOE analysis that narrowed down the design parameters to two.

5. Conclusion and Discussion

This paper discusses a design optimization problem for electrical vehicles using Six Sigma tools such as DOE and RSM. The analysis was carried out in the MATLAB simulation environment. The DOE technique was used to narrow down the number of design parameters to be analyzed. Some parameters were assumed to be constant during the DOE analysis. The selection of these constant parameters and their values may influence the conclusions one can draw from the DOE analysis, but the approach used in this paper would work in a similar way with different choices. For example, the friction coefficient can be assumed to be constant and the frontal area can be selected as a factor in DOE matrix, which makes more sense if the vehicle body is still being designed. The Response Surface Method was applied to find the optimal design parameter values for the battery weight and the battery specific energy density. Both cost and performance are taken into consideration in the optimization process. The weights in the cost function are determined by the actual cost for the batteries and the importance of the performance.

Only the maximum driving range was considered as the performance of the vehicle, but the method works in a similar way if other performance metrics are used. Future research work includes considering other vehicle level performance requirements such as maximum cruise speed, 0-60 mph acceleration time, and maximum gradeability (Ehsani *et al.*, 2005; Gillespie, 1992; Husain, 2003; Zhan *et al.*, 2009). In analyzing some of these dynamic requirements, detailed models for the motor, battery, and transmission need to be included in the model. The approach used in this paper can be applied to many other engineering design and optimization problems. It is a quick and cost effective way of using Six Sigma method in engineering applications.

6. Appendix: MATLAB Code

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                    SpdDisOptimization.m                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%total weight
W=W0+Wb;
%gravity force due to surface incline
Wx=W*sin(theta);
%rolling resistance
Rx=fr*W*cos(theta);
% Max speed
Vmax=85;  %mph
clear V_i
area=0;
dv=0.01;
k=0;
dmax_prev = 63.29*eta*Wb*Dse/(Rx+Wx);
for V=dv:dv:Vmax,
  %Aerodynamic drag
  Da=1/2*rho*(V*5280/3600)^2*Cd*A;
  dmax=63.29*eta*Wb*Dse/(Da+Rx+Wx); %max distance
```

```matlab
    area =area+ dv* dmax_prev-1/2*dv*(dmax_prev-dmax);
    dmax_prev=dmax;
    k=k+1;
    V_i(k)=V;
    dmax_i(k)=dmax;
end
% figure
% plot(V_i, dmax_i)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                 %
EVSimdoeSixFactors.m                              %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
clear all
% The parameters that are fixed:
theta =0;% degree surface incline.
Pr=29.92;%in-Hg, air pressure
Tr=59;  % degree F, air temperature.
A=34;    % ft^2    frontal area.
%air density
rho=0.00236*(Pr/29.92)*(519/(460+Tr));  %lb-sec^2/ft^4
% Define the two levels for the factors.
W0min=3800;              %lb   weight without the battery, but with motor and gear box.
W0max=4200;              %lb   weight without the battery, but with motor and gear box.
Wbmin=500;               %lb    weight of battery.
Wbmax=1400;              %lb    weight of battery.
Cdmin=0.4;               %drag coefficient.
Cdmax=0.55;              %drag coefficient.
frmin=0.014;             %Coefficient of rolling resistance.
frmax=0.016;             %Coefficient of rolling resistance.
etamin=0.77;             %  motor/battery efficiency.  0.75 means 75%.
etamax=0.83;             %  motor/battery efficiency.  0.75 means 75%.
Dsemin=0.2;              % (MJ/kg)  specific energy
Dsemax=0.8;              % (MJ/kg)  specific energy
doematrix=[ % RunOrder  W0  Wb  Cd  fr  eta Dse
1  -1 -1 -1 -1 -1 -1
2  1  -1 -1 -1 -1 -1
3  -1 1  -1 -1 -1 -1
4  1  1  -1 -1 -1 -1
5  -1 -1 1  -1 -1 -1
6  1  -1 1  -1 -1 -1
7  -1 1  1  -1 -1 -1
8  1  1  1  -1 -1 -1
9  -1 -1 -1 1  -1 -1
10 1  -1 -1 1  -1 -1
```

```
11 -1  1  -1  1  -1 -1
12  1  1  -1  1  -1 -1
13 -1 -1  1  1  -1 -1
14  1 -1  1  1  -1 -1
15 -1  1  1  1  -1 -1
16  1  1  1  1  -1 -1
17 -1 -1 -1 -1  1  -1
18  1 -1 -1 -1  1  -1
19 -1  1 -1 -1  1  -1
20  1  1 -1 -1  1  -1
21 -1 -1  1 -1  1  -1
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23 -1  1  1 -1  1  -1
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25 -1 -1 -1  1  1  -1
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27 -1  1 -1  1  1  -1
28  1  1 -1  1  1  -1
29 -1 -1  1  1  1  -1
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31 -1  1  1  1  1  -1
32  1  1  1  1  1  -1
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38  1 -1  1 -1 -1  1
39 -1  1  1 -1 -1  1
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42  1 -1 -1  1 -1  1
43 -1  1 -1  1 -1  1
44  1  1 -1  1 -1  1
45 -1 -1  1  1 -1  1
46  1 -1  1  1 -1  1
47 -1  1  1  1 -1  1
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49 -1 -1 -1 -1  1  1
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52  1  1 -1 -1  1  1
53 -1 -1  1 -1  1  1
54  1 -1  1 -1  1  1
55 -1  1  1 -1  1  1
56  1  1  1 -1  1  1
```

```
57  -1  -1  -1  1   1   1
58  1   -1  -1  1   1   1
59  -1  1   -1  1   1   1
60  1   1   -1  1   1   1
61  -1  -1  1   1   1   1
62  1   -1  1   1   1   1
63  -1  1   1   1   1   1
64  1   1   1   1   1   1];
for i=1:64,
    RunOrder(i)=doematrix(i,1);
    if doematrix(i,2)==1
        W0_i(i)=W0max;
    else
        W0_i(i)=W0min;
    end
    if doematrix(i,3)==1
        Wb_i(i)=Wbmax;
    else
        Wb_i(i)=Wbmin;
    end
    if doematrix(i,4)==1
        Cd_i(i)=Cdmax;
    else
        Cd_i(i)=Cdmin;
    end
    if doematrix(i,5)==1
        fr_i(i)=frmax;
    else
        fr_i(i)=frmin;
    end
    if doematrix(i,6)==1
        eta_i(i)=etamax;
    else
        eta_i(i)=etamin;
    end
    if doematrix(i,7)==1
        Dse_i(i)=Dsemax;
    else
        Dse_i(i)=Dsemin;
    end
    W0=W0_i(i);
    Wb=Wb_i(i);
    Cd=Cd_i(i);
    fr=fr_i(i);
    eta=eta_i(i);
    Dse=Dse_i(i);
```

```
    SpdDisOptimization
    area_i(i,1)=area;
end
area_i
save sim_area area_i -ascii


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                  %
ThreeCasePlotting.m                                %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%

clear all
% The parameters that are fixed:
theta =0;% degree surface incline.
Pr=29.92;%in-Hg, air pressure
Tr=59;  % degree F, air temperature.
A=34;   % ft^2    frontal area.
%air density
rho=0.00236*(Pr/29.92)*(519/(460+Tr));  %lb-sec^2/ft^4
% Define the two levels for the factors.
W0min=3800;
W0max=4200;
Wbmin=500;
Wbmax=1400;
Cdmin=0.4;
Cdmax=0.55;
frmin=0.014;
frmax=0.016;
etamin=0.77;
etamax=0.83;
Dsemin=0.2;
Dsemax=0.8;
% Define three set of values for the factors.
% set 1: worst main factor and best other factors.
% set 2: best main factor and worst other factors.
% set 3: best main factor and nominal other factors.
for i=1:3,
  if i==1,
    W0_i(i)=W0min;
  elseif i==2,
    W0_i(i)=W0max;
  else
    W0_i(i)=(W0min+ W0max)/2;
  end
  if i==1,
```

```matlab
    Wb_i(i)=Wbmin;
  else
    Wb_i(i)=Wbmax;
  end
  if i==1,
    Cd_i(i)=Cdmin;
  elseif i==2,
    Cd_i(i)=Cdmax;
  else
    Cd_i(i)=(Cdmax+ Cdmin)/2;
  end
  if i==1,
    fr_i(i)=frmin;
  elseif i==2,
    fr_i(i)=frmax;
  else
    fr_i(i)=(frmin+ frmax)/2;
  end
  if i==1,
    eta_i(i)=etamax;
  elseif i==2,
    eta_i(i)=etamin;
  else
    eta_i(i)=(etamin+ etamax)/2;
  end
  if i==1,
    Dse_i(i)=Dsemin;
  else
    Dse_i(i)=Dsemax;
  end
  W0=W0_i(i);
  Wb=Wb_i(i);
  Cd=Cd_i(i);
  fr=fr_i(i);
  eta=eta_i(i);
  Dse=Dse_i(i);
  SpdDisOptimization
  area_i(i,1)=area;
  if i==1,
     color_i='-k';
  elseif i==2,
     color_i='-.r';
  else
     color_i='--b';
  end
  area
```

```matlab
    plot(V_i, dmax_i, color_i), hold on,
end
grid on, xlabel('Speed (MPH)'), ylabel('Maximum range (Miles)'),
legend('case 1', 'case 2', 'case 3')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                       %
TotalOptimization.m                              %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%

clear all
% The parameters that are fixed:
theta =0;
Pr=29.92;
Tr=59;
A=34;
rho=0.00236*(Pr/29.92)*(519/(460+Tr));
W0=4000;
Cd=0.45;
fr=0.015;
eta=0.8;
i=0;
for Wb00=500:10:1400,
   i=i+1;
   Wb_i(i)=Wb00;
   Wb=Wb00;
   j=0;
   for Dse00=0.2:0.01:0.8,
     j=j+1;
     Dse_j(j)=Dse00;
     Dse=Dse00;
     SpdDisOptimization
     J(i,j)=0.15*(Dse/0.5)^2+0.35*Wb/950+0.5/(area/15000);
   end
end

[Jmax_j, index_i]=min(J);
[Jmax, index_j]=min(Jmax_j);
Optimal_Dse=Dse_j(index_j)
Optimal_Wb=Wb_i(index_i(index_j))
surfc(Dse_j,Wb_i,  J), xlabel('Specific energy (MK/kg)'),
ylabel('Battery weight (lb)'), zlabel('Cost function')
```

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If you do not measure, you do not know, and if you do not know, you cannot manage. Modern Quality Management and Six Sigma shows us how to measure and, consequently, how to manage the companies in business and industries. Six Sigma provides principles and tools that can be applied to any process as a means used to measure defects and/or error rates. In the new millennium thousands of people work in various companies that use Modern Quality Management and Six Sigma to reduce the cost of products and eliminate the defects. This book provides the necessary guidance for selecting, performing and evaluating various procedures of Quality Management and particularly Six Sigma. In the book you will see how to use data, i.e. plot, interpret and validate it for Six Sigma projects in business, industry and even in medical laboratories.

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