An Application of Genetic programming for Lithium-ion Battery Pack Enclosure Design: Modelling of Mass, Minimum Natural Frequency and Maximum Deformation Case

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Abstract
For ensuring the safety of battery pack and its enclosure, the mechanical design is crucial for generating lower deformation, lower stresses and vibrations during its actual operation. In addition, the minimum mass of battery pack is needed for lower energy consumption of pack. Therefore, the problem to be solved can be formulated as multi-objective optimization and much desire one for electric vehicle industry application. In this paper, the application of evolutionary approach of Genetic programming (GP) is illustrated for battery pack casing design considering the design requirements having higher mechanical performance. Data generated from finite element simulation was used as input in GP. The analysis concluded that the GP perform satisfactorily. GP models for three design outputs predicted the values in compare to actual values with errors RMSE and MAPE of .00154 and .00715, .000033 and 1.16, .52 and .48, respectively. These results can be used to design the battery pack enclosures. The similar models can be applied to different independent parameters to find out the possible relation in between them to correlate the results, find out the criticality of the individual parameter and then optimize the design accordingly.

Keywords: electric vehicles; battery pack enclosure; design optimization; genetic programming

1. Introduction

Much of research has also been focused on increasing the range and safety design of EVs [1-3]. The range of the EV depends on the performance of battery module. The performance (capacity, life cycle) of the battery module depends on the individual performance of the cells and their arrangement (configuration) in series or parallel. The ideal performance of module/pack should follow the uniformity and equalization
criteria. However, this is not always the case. During the mass manufacturing of cells and assembly of cells into a module/pack, there are slight variations due to the uncertainties in the operating manufacturing conditions [4-7]. Over the period of time, this problem accumulates and leading to the uneven temperature distribution and incomplete charge/discharge of several cells in the pack. These problems result in lesser available capacity.

Besides, other area of interest related to the safety of battery pack and its components is its mechanical design [8-11]. This is because with the enormous growth in production of EVs and subsidized policies of government of developing economies, the battery operated vehicles shall be commercialized in near future. Therefore, the safety during the impact caused due to unforeseen accidents shall be of major concern. In the practical operation of EV, the battery pack and its enclosure might be affected by the severe environmental elements, such as the external vibration or those induced by the different road grades [11-14]. Those elements will generate stress and deformation. The battery pack safety relies on its mechanical performance, such as the capabilities of anti-deformation and bearing the vibratory impulse. If those capabilities of battery pack enclosure can’t meet the practical requirements, the battery pack might malfunction or the short circuit occurs. More seriously, the battery might explode, leading to serious accidents [15]. Therefore, the battery pack and its components casing is quite important in terms of battery, EV and road safety. Besides, the light-weighted EV is always more favored, since it may save space for other components of the vehicle and even increase the nominal capacity of the battery pack so as to reinforce the cruising capacity of vehicles. Besides safety design of battery pack, the new trends of research being focus is on the development of design and disassembly methods for sustainable and cost effective recycling [16-17].

The present work illustrates the application of evolutionary approach of genetic programming (GP) for producing efficient design of battery pack enclosure. The advantage of using GP is that it has the ability to build the models based on only the data. The GP models represents explicit relationships between the outputs (deformation, frequency, weight) and the design variables of battery pack enclosure (thicknesses of the enclosure). The explicit relations can easily be optimized using conventional optimization methods. Thus, the extensive computation can be avoided. The enclosure shall be designed in ANSYS for specific electric vehicle study and the design parameters with conditions will be used in MATLAB for the implementation of genetic programming. If needed, the variations in genetic programming shall be introduced to formulate accurate and explicit models, when optimized result in appropriate design conditions.

2. Research problem

The research problem to be solved in this paper is a multi-objective optimization. The problem is to find the appropriate values of thicknesses of battery pack casing while considering the design requirements for higher mechanical performance. For multi-objective optimization, the formulation of the models for each of the output (deformation, frequency, weight) is vital. Therefore, the objectives of the present work is as follows:

1. To design the battery pack enclosure in ANSYS
2. To conduct the finite element analysis of battery pack enclosure
3. To develop mathematical models by use of genetic programming.
4. Optimization of models for mass, natural frequency and maximum deformation using genetic programming.

In this paper, ANSYS (Fig.1) is used to model the battery pack enclosure and loading conditions are defined. The inputs are the thicknesses of battery pack enclosure (total of 6 variables, thickness varies from 1-5 mm, temperature vary from 30-40 degree celsius). The finite element based mechanical analysis is performed. Experimental design method is used for the sampling of finite element designs. Genetic programming is then applied to formulate the models.
3. Genetic Programming (GP)

Genetic Programming (GP) is a gradual refining process which resembles with the procedure of biological evolution [18]. The general frame of the algorithm included can be clarified as underneath:

1. In the initial step, the algorithm makes an irregular/random introductory population. This is likewise called the original/first generation. A practical, terminal set and populace estimate are characterized in this progression. The terminal set includes the input parameters and constants of the model and the functional set includes the arithmetic functions.

2. The successions of new populaces have been produced and the present era is utilized at each progression to make the next population. Guardians (more often than not models having higher fitness) have been chosen from the present populace who transfer their genes (vectors) to their children. The new population is created as:

   a) Fitness estimation of every individual from the present populace is registered for scoring. The target work [18] utilized as a part of the present investigation is structural risk minimization standard as represented in equation 1.

   \[
   SRM = \frac{SSE}{N} \left( 1 - \left( \frac{g}{N} \log \left( \frac{g}{N} \right) + \log \left( \frac{g}{N} \right) \right) + \left( \frac{g}{2N} \right)^{-1} \right) \tag{1}
   \]

   where \(g\) represents the number of basis functions of a model with best fit amid development phase of GP, \(N\) represents the number of training samples, and \(SSE\) represents formulated model’s sum of square of error for the training data.

   b) The developed fitness scores have been then transferred to more precise and more utilization range of values.

   c) Members (parents) have been chosen as per heir fitness.

   d) Three types of children are created for the next generation. Children are reproduced from the parents by mutation or by crossover.

   e) The current population is replaced with the children of best fitness value for reproducing the next generation with best fitness.
4. Results and Discussion

GP is applied on the set of data generated from ANSYS. The set of data can be referred from [16]. The simulations of GP have been done in MATLAB (R2010b) with the population size of 300 and the maximum generations is set at 200. Other parameters are kept same as mentioned in [18]. There were 27 runs conducted using GP approach. The parameter settings such as iterations, population and generations were varied. The iterations were varied at value of 5, 10 and 15. The population size was kept at 800 for each iteration, while the generations were varied at 150, 180 and 200. The reason for such variations in the parameter settings is because the performance of model depends on these parameters which influences the convergence criterion of GP. All the models are compiled and compared. The final model is chosen as based on the minimum value of the MAPE (figure 2).

![GP model for Mass](image1)
![GP model for Maximum deformation](image2)
![GP model for Minimum natural frequency](image3)

**Figure 2** Performance of Genetic programming models for three outputs

The developed models have shown the high precision prediction of the experimental data which suggest that the model can be used for prediction of the possible experimental values thus reducing the human efforts in this direction. Temperature ($x_6$) was found to be significant. These results can be used to design the battery pack enclosures. The similar models can be applied to different independent parameters to find out the possible relation in between them to correlate the results, find out the criticality of the individual parameter and then optimize the design accordingly.

5. Conclusions

Based on the conducted analysis in the paper, the lower value of RMSE (.00154 and .00715, .000033) and MAPE (1.16, .52 and .48) of the models reveals the satisfactory ability of GP algorithm. Therefore, the GP models can be easily optimized using any conventional optimization methods based on search/iterative type to reveals the optimum value of thicknesses of battery pack enclosure resulting in higher mechanical performance.
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