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RESEARCH ARTICLE

Optimization of cost to customer of power train in commercial vehicle using knapsack dynamic programming influenced by vehicle IoT data

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Abstract

The automotive original equipment manufacturers (OEM) current challenge of deriving the optimized cost to customer for the product when the product is configured dynamically. For every OEM the product they sell is bounded by warranty terms, thus the product configuration they offer should be reliable to withstand the warranty period. This paper discusses the optimization of cost of the power train configuration, which is offered to the customer and incorporated with the product cost and the provisional warranty cost. For a target cost, the product planner must configure a power train configuration that should adhere to the target cost. However, selecting the power train configuration only based on cost will defeat the vehicle's performance. Thus, power train configuration is governed based on the reliability factor of the power train components which is derived using vehicle IoT data derived from live running vehicles. The cost to customer is calculated as the sum of product cost and provisional-warranty cost calculated based on the dynamic reliability predicted using the vehicle's Internet of Things (IoT) data. In this paper, for the target cost to the customer set by the product planner to select the best fit power train configuration for the product line, is formulated as a 0-1 knapsack problem, and dynamic programming is used to find the optimized cost to customer which is the sum of two variables the product cost and provisional warranty cost. The findings using this method is encouraging as the use of combinatorial optimization techniques and the vehicle IoT data model for deriving the dynamic reliability data are working in tandem to provide an optimum cost output.

Keywords: Combinatorial optimization, Knapsack problem, Cost to Customer Optimization, Vehicle IoT data, Dynamic Programming.

Introduction

In the competitive commercial vehicles market, customers are started giving more preference to total cost of ownership (TCO) towards that preference, the customers are expecting the vehicles to perform more, with less down time. Thus, in recent times, the standard warranty period of commercial vehicles which are earlier 3 or 4 years, are increased to 5 or 6 years, as the customer prefer to own a vehicle that comes with more coverage in terms of breakdown. There are two challenges to the OEM's: the provisional cost of warranty calculation method needs to be changed, as the regular method of calculating the failure and then calculating the warranty cost per vehicle is not profitable. Similar optimization of powertrain selection based on lightweight components and fuel efficiency was taken as a main reference to formulate this problem (Wilhelm, Hofer, & Cheah, 2017). The Figure 1 shows the warranty cost % w.r.t. revenue in the last 9 years, shows the warranty cost to the company is increasing and not decreasing, moreover, this will impact the brand name of the company. Thus, it is seen as a serious issue. Every company will be allocating provisional warranty cost for each vehicle, due to the increase in warranty period, the provisional warranty cost needs to be calculated in a precise manner. The reliability factor is considered as the element to calculate the provisional warranty cost based on the actual usage of the vehicle data. In this paper, the cost to customer by optimizing the warranty cost with respect to the target cost is given for the powertrain components, the results are encouraging.

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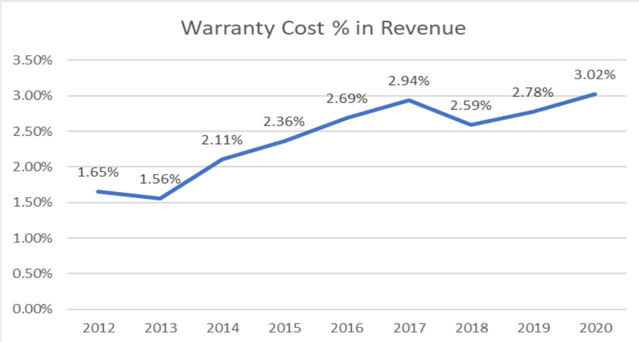

Figure 1: Warranty cost % in revenue [2]

Cost to Customer

In the commercial vehicle industry, the powertrains are configured using usage, application, and affordability of the customer. During the product configuration, for the given application and usage, the system will recommend a powertrain configuration based on the product's reliability, which may not be affordable by the customer, as the configuration cost will be more than the expectation. Thus, the customer will start reconfiguring and select a configuration that matches the budget. Product cost optimization has been using executed using multiple variables like price sensitivity analysis (Mayer & Steinhardt, 2016), price optimization based on capacity constraints (Gallego & Wang, 2014) and price optimization for budget constraint customers (Mayer, Klein & Seiermann, 2013) encourages to formulate cost to customer as the target variable for the problem. Moreover, this forms the current practical problem of the industry. As the selected configuration is not recommended may lead to the multiple failure of parts and increase the warranty cost to the OEM. The cost to customer of the vehicle is calculated based on the product cost and provisional warranty cost for the product. The provisional warranty cost per vehicle model is calculated based on the below formula (1), which may not provide the precise warranty cost.

$$\text{Provisional Warranty cost per vehicle} = \frac{\text{Total warranty expenditure of the vehicle model for a period}}{\text{Total number of vehicle model sold}} \quad (1)$$

The actual warranty cost per vehicle is often higher than the provisional warranty cost of the vehicle model. This affects the profitability of the organization and thus, demand for a precise provisional warranty cost calculation based on the dynamic configuration of the model.

Dynamic Reliability Calculation Using Vehicle Iot Data

The important cost component to the customer in the product pricing is the provisional warranty cost, the best method to warranty cost is to calculate the reliability of the component. For a component based on the type of failure, two types of reliability can be used: parallel and series reliability calculation (Qazizada & Pivarčiová, 2018). After the introduction of BS6 vehicles the electronics in the vehicles have increased and the operating data captured from the vehicles are increased. There are multiple Electronic Data Controller (EDC) in the vehicle, namely, Engine Control Unit (ECU), Body Control Unit (BCU), Aftertreatment Control Unit (ACU), Anti-Lock Braking System (ABS) control unit and the telematics data in the vehicle which capture the operating data from the vehicles and transfer the bigdata to cloud data storage for the organizations to consume the data for further analysis and prediction. There are three types of data as shown in Figure 2 which is used for the reliability prediction. They are failure data of the components from job card, vehicle IoT data and telematics data which are the operating data of the components and lastly, the master data of the contracts, parts, etc.,

Reliability Calculation Framework

The reliability factor for each component in the powertrain is calculated using the framework shown in Figure 3. The framework is built using multiple data sources and mathematical algorithms, which are explained below.

Step 0: Data source

Using the three data lakes with multiple data sources, as a first step, the data lake is formed as a single data lake. Multiple data sources are available across various systems that need to be collated and make a common data source for easy data accessibility.

Step 1: *Data preparation*

After all the data sources are structured into a common data source, data labeling for the three types of data needs to be completed for the three major data models. The data sources for three data models are prepared and mapped for the data models: part failure data, vehicle contract data and operating condition data are summarized. The data frequency for each data table needs to be ensured for the calculation.

Step 2: *Data model*

The data model for each data source is prepared using the relevant mathematical formula designed to get the failure data, vehicle AMC and contract data model and the Operating condition with telematics data. The mathematical

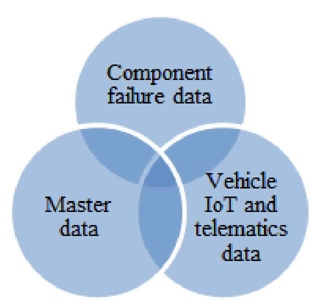

Figure 2: Three components used for reliability prediction

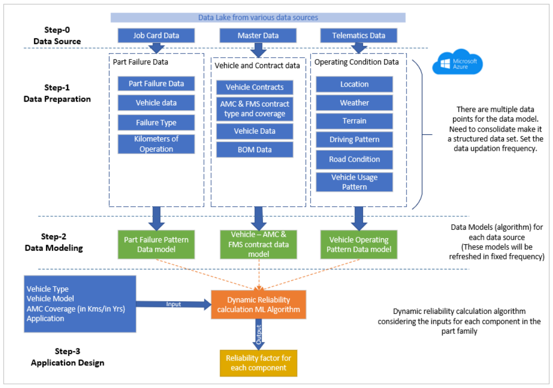

Figure 3: Reliability calculation framework using vehicle IoT and telematics data

algorithms used in each data model are sensitive data that cannot be declared. The algorithms selected for each data model are selected based on the machine learning algorithms.

Step 3: *Final application design*

The final machine learning algorithm will predict the reliability for each component of the powertrain using the consolidated deep learning algorithm with the various master data inputs like vehicle type, vehicle model, application, etc., the reliability factor will be calculated based on various operating conditions and store the results against each component and operating conditions.

Mathematical Formulation

The problem is formulated as a 0-1 knapsack problem, since the optimization of cost to customer matches the knapsack problems fundamentals like, there is a capacity of the bag which is equal to the target cost of the customer for the powertrain, the objects to be filled in the bag equals the powertrain configuration with the product cost and warranty cost. The challenge is optimizing the cost to customer by balancing the product cost and warranty cost using the weight called reliability data governed by the vehicle IoT data. Thus, this problem qualifies for the 0-1 knapsack since we cannot do any partial filling of powertrain configuration against the target cost as Table 1 provides the equivalent variables for the knapsack problem elements.

This problem is solved using a dynamic programming method as the number of possible configurations will increase as the number of powertrain components increases. The variable in this problem is not just the simple combinatorial elements and leave the choice of the picking to the program, it should be a full combination. In this paper we have assumed a powertrain consists of engine, clutch, gearbox, and rear axle components only and each part family has multiple options like 3 engine options, 5 gear box options, 6 clutch options and 7 rear axle options. There are 21 variables with values, and all are governed by various reliability values based on the dynamic vehicle IoT

Table 1: knapsack problem elements mapping of current problem elements

Knapsack problem elements	*Cost to customer optimization*
Capacity	Target cost of the powertrain
Elements to be filled with value	Powertrain configuration options with product and warranty cost
Weights for optimization	Reliability variable for each configuration

data. Table 2 shows the illustrative details of the powertrain components with various operating conditions and reliability factor for each component predicted using the reliability calculation framework.

Assumptions

- This calculation is done for a powertrain combination that will be offered to multiple vehicles.
- All the powertrain options (engine, gear box, clutch, and rear axle) are technically feasible, thus making 3 x 5 x 6 x 7 = 630 configurations possible.
- The reliability factor derived is through a detailed logic of vehicle IoT data which is assumed to be a dynamic variable updated every month after the substantial bigdata for analysis.

Since the number of variables is more and the target cost is dynamic, as it will change from customer to customer, this problem was planned to be executed in a dynamic programming method. The summation of product cost and provisional warranty cost calculates the total cost to the customer. The formula for those variables is given below (2) (3) and (4) which will be used for calculating the cost of a customer during optimization of the problem.

$$\text{Product Cost} = \sum_{i=0}^{n} C_i \tag{2}$$

$$\text{Provisional Warranty Cost} = \sum_{i=0}^{n} (1 - R_i).C_i \tag{3}$$

$$\text{Cost to Customer} = \sum_{i=0}^{n} C_i + \sum_{i=0}^{n} (1 - R_i).C_i \tag{4}$$

Dynamic Programming

This problem will be solved using dynamic programming; it requires an optimal substructure and overlapping sub-problems to solve a problem. In this technique, the problem is broken into sub-problems and saves the result for future purposes, thus, we will not compute the results again. The subproblems are optimized to optimize the optimal solution, known as the optimal substructure property. In this 0-1 knapsack problem both elements are available. Thus, we are using dynamic programming techniques to solve the problem. In this problem, we use top-down dynamic programming with memoization to overcome the overlapping sub-problems, since memoization will store the results of all the previously solved sub-problems and return the results from memory if we encounter a problem already solved.

Table 2: Details of Powertrain Components With Value And Reliability Parameters (Illustrative)

Part Family	Part	Product Cost	Terrain	Weather	Driving Score	Reliability factor	Provisional Warranty Cost
Engine	E1	250,000	Hilly	Summer	7.0 - 7.9	0.91	22,500
Engine	E1	250,000	Flat	Summer	8.0 - 8.9	0.93	17,500
Engine	E1	250,000	Flat	Rainy	7.0 - 7.9	0.89	27,500
Engine	E1	250,000	Hilly	Rainy	8.0 - 8.9	0.92	20,000
Engine	E1	250,000	Hilly	Winter	8.0 - 8.9	0.91	22,500
Engine	E1	250,000	Flat	Winter	9.0 - 9.9	0.94	15,000
Gear Box	G1	89,000	Hilly	Summer	7.0 - 7.9	0.89	9,790
Gear Box	G2	95,000	Flat	Summer	8.0 - 8.9	0.93	6,650
Gear Box	G3	145,000	Flat	Rainy	7.0 - 7.9	0.99	1,450
Clutch	C1	32,000	Hilly	Rainy	8.0 - 8.9	0.86	4,480
Clutch	C2	45,000	Hilly	Winter	8.0 - 8.9	0.88	5,400
Clutch	C3	38,000	Flat	Winter	9.0 - 9.9	0.85	5,700
Rear Axle	R1	189,000	Hilly	Rainy	8.0 - 8.9	0.95	9,450
Rear Axle	R2	175,000	Hilly	Winter	8.0 - 8.9	0.93	12,250
Rear Axle	R3	154,000	Flat	Winter	9.0 - 9.9	0.94	9,240

Execution Process

Step 1: Constraints for the powertrain configuration

In this problem, first break the problem into sub-problems and try to solve the sub-problems. Based on the selection of the constraints from the customer like target cost, terrain, weather and driving pattern, the possible powertrain options from each part family will be filtered. From the filtered options, E x G x C x R powertrain configurations can be possible, which must be executed and ensure each valid configuration consists of one element of each part family.

Step 2: Product cost and Provisional warranty cost calculation

In the possible powertrain configuration, the product cost and provisional warranty cost calculation will be executed and the computation of cost to customer will be executed. In the output where the cost to customer is higher than the target cost, those indexes will be discarded and only the valid inputs that are lesser than the target cost will be selected for further optimization.

Step 3: Reliability factor calculation

For every valid configuration, the reliability factor is calculated. Since power train is a combination of 4 components, each component in the assembly has an individual reliability factor. Since the powertrain reliability depends on the failure of any of these 4 components, the powertrain reliability is calculated as a series reliability (Rusiński et al., 2019), in which the reliability factor of all individual components is multiplied and derive the reliability factor, this factor is called powertrain reliability factor and this factor will be used during the optimization.

$$\text{Reliability Factor} = E_i \text{ x } G_i \text{ x } C_i \text{ x } R_i \qquad (5)$$

Step 4: Optimization

In the filtered configuration, the highest and nearest cost to the target will be selected and optimized against the reliability factor. Thus, this optimization is done against the cost vs. reliability of the product, it is always better to provide the powertrain configuration with highest reliability factor, but it may not satisfy the customer cost target. In many cases, the provisional warranty cost is higher and due to low reliability factor, thus, making the cost to customer higher than the target. The dynamic programming technique will provide the best value to the customer and the company by optimizing the provisional warranty cost. Thus, the customer will be getting the more reliable product and the company will not be spending less on the provisional warranty cost thus it affects the profitability.

Figure 4 illustrates the working of the algorithm for a similar exercise, for the target capacity the algorithm expands the possible combination and selects the optimized capacity which satisfies the constraints. In the illustrative figure, the problem has a choice of selecting any item from the list which satisfies the highest capacity and profit. The same logic is used, with a modification of instead of any item from the list, one item should be mandatorily available from each part family and ensure the cost to the customer and powertrain reliability factor.

Results and Discussion

As discussed for this problem, there can be 630 possible powertrain configurations, in this illustrative example, the customer has provided the target cost as value of 600,000 and selected the values for each variable as flat terrain, summer weather and 8.0-8.9 driving score as their major operating condition for the powertrain. Applying the filter in the 630 configurations will filter the product variants from each product family, as in Table 3. From these 8 possible variants, 12 power train configurations can be possible. The dynamic programming with memoization technique is used as a recursive function to fill the two-dimensional array and store the results of the sub-problems which will be possible powertrain configuration.

For the 12-powertrain configuration, the product cost, provisional warranty cost, cost to customer and powertrain reliability factor will be calculated using the formulas (2), (3), (4) and (5), respectively. The calculated output will be stored in a table as illustrated in Table 4 after computation, the unique index name will be generated for identifying each powertrain configuration. After the data table is filled using the memoization method in dynamic programming technique, the optimization process will be initiated.

In the process of optimization, the system will start comparing the cost to customer against the target cost and eliminate the indexes which are not match the target cost, in this case, 4 records will be excluded from the optimization process. The remaining 8 records will start the optimization

Table 3: Selected product variants for the customer filter

Part family	*Product variants*
engine	E1, E2, E3
Gear Box	G1, G2
Clutch	C2
Rear Axle	R2, R3

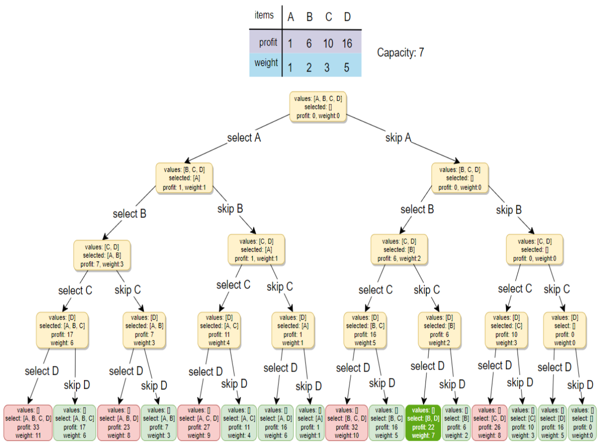

Figure 4: Illustrative figure of dynamic programming algorithm working logic

by comparing the cost to the customer and powertrain reliability factor. The higher the cost to the customer is better for the organization at the same time, the higher the powertrain reliability factor. In the below case, index E1G2C2R2 has the highest powertrain reliability factor, but the cost to customer is lower. For the index E3G1C2R2 the cost to the customer is high and the powertrain reliability factor is optimum, thus,

this will be selected as the optimized powertrain configuration for the selected customer configuration as illustrated in Figure 5.

Analysis of the Results

The provisional warranty cost calculated using this method was compared against the actual warranty cost and found the accuracy as 80 to 85%. In this method, the provisional warranty cost is calculated based on each component's reliability factor, which is predicted using the vehicle IoT data processed using machine learning (ML) algorithm. The data accuracy depends on many external parameters like data capture of the vehicle and the failure data capture, service update capturing, etc. The accuracy of the data is improving as time goes on. When the initial model was made, the accuracy was approximately 50% with multiple fixes in the data capturing pipeline, the accuracy has improved to 80 to 85%, which seems to be encouraging.

Table 4: Filtered data of the selected configuration

Engine	Gear Box	Clutch	Rear Axle	Index	Power train Reliability Factor	Product Cost	Prov. Warranty Cost	Cost to Customer
E1	G1	C2	R2	E1G1C2R2	0.76	559,000	46,800	605,800
E1	G2	C2	R2	E1G2C2R2	0.81	567,000	32,410	597,410
E1	G1	C2	R3	E1G1C2R3	0.71	545,000	39,805	584,805
E1	G2	C2	R3	E1G2C2R3	0.7	549,000	41,980	590,980
E2	G1	C2	R2	E2G1C2R2	0.69	576,000	46,910	622,910
E2	G2	C2	R2	E2G2C2R2	0.73	581,000	21,890	602,890
E2	G1	C2	R3	E2G1C2R3	0.7	566,000	28,783	594,783
E2	G2	C2	R3	E2G2C2R3	0.74	549,000	31,235	580,235
E3	G1	C2	R2	E3G1C2R2	0.77	572,000	27,890	599,890
E3	G2	C2	R2	E3G2C2R2	0.78	569,000	28,740	597,740
E3	G1	C2	R3	E3G1C2R3	0.81	577,000	24,823	60,1823
E3	G2	C2	R3	E3G2C2R3	0.79	562,000	29,752	591,752

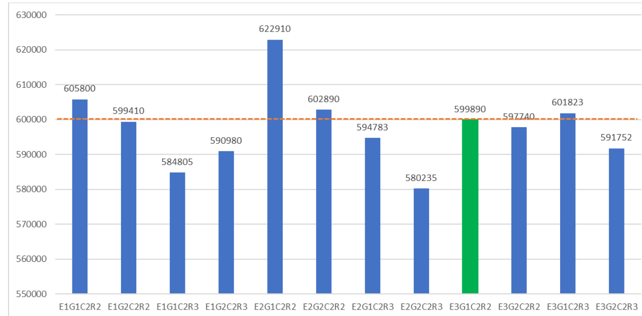

Figure 5: Graph showing the optimized cost to customer for the target cost

Challenges

There are multiple challenges in this methodology, getting the failure data, vehicle IoT data and telematics data for the component level in the vehicle is challenging. The failure data and usage data can be retrieved for certain components or systems only, proliferating the captured data to other nearby components may affect the accuracy. As the electronification of vehicles are improving, the data from each vehicle system will be available in digital form, which will be used for the reliability calculation. It may take some more time, whereas this methodology can be used more in electric vehicles as there are fewer moving parts and most of the parts are electrified thus, capturing the data from each system will be much simpler and can be used for predicting the reliability of the system.

Conclusion

This method explores multiple opportunities to expedite the algorithm for various other use cases. The innovative part of this work is using the vehicle IoT data predicted using the current technique of machine learning method and the combinatorial optimization of the problem is solved using classical 0-1 knapsack dynamic programming technique is a unique attempt solving an automotive industry's current problem. The method used in this paper is an experimental attempt to improve the provisional warranty cost calculation method and thus, improve the cost to customers using a powertrain system with four components. The results are encouraging after fixing multiple layers of data issues and now in a commendable state, it's a continuous improvement journey that will take some more time to improve the accuracy of the data. For this problem, instead of considering as a 0-1 knapsack problem, the entire problem can be constructed as a deep learning model and can be optimized using multiple selection variables. In this method, we have used the classical mathematical model to solve the problem, which may take more time when the number of components increases. Thus, deep learning optimization methods will be best option to execute the problem in a shorter time span and better accuracy considering the volume of data.

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