Big Data and The Future of Vehicle Diagnostics

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Introduction

Dealers pride themselves on the quality and accuracy of service they provide. They know that they are the genuine service option, and that their technicians are highly trained and supported by the manufacturer’s diagnostic information. Yet, industry-wide benchmarking indicates that some manufacturers see fixed-right-first-time (FRFT) metrics as low at 90% – one of every ten vehicles leaves the service lane without being fully repaired. Needless to say, this can hurt customer retention and brand loyalty. In fact, “My vehicle is fixed right the first time” was the fifth most important selection criteria for consumers in Carlisle & Company’s 2014 Consumer Sentiment Survey (Figure 1).

In Carlisle’s industry-wide Technician Survey, technicians estimated that they spent roughly one-third of their time on diagnostic work (Figure 2); in many cases this is billed directly to the customer. While this time is necessary to properly repair a car, it significantly reduces a technician’s efficiency. Vehicles are also becoming more complex; their interdependent systems require more advanced diagnostic tools.

In short, FRFT rates and technician efficiency won’t improve until diagnostics improve. Improving these metrics requires making higher quality and intuitive diagnostic tools/systems available to technicians. New big data analytics models, such as Artificial Neural Networks, could improve the speed and accuracy of repair identification immensely.

Adding Intelligence to the Diagnostics Backend

When technicians supplement formal diagnostic procedures by using their own experience and that of their coworkers, they often can complete a repair more quickly. This heuristic knowledge is invaluable during the repair process. The technicians’ knowledge supplements the OEM’s diagnostics instructions, and each shop depends on the collective experience of its staff. Consider the following situation:

A technician in California runs through the diagnostic process on a vehicle, which results in a handful of trouble codes. This is the first time the shop has seen this specific situation, so it takes the technician 2.5 hours to get to the root cause. From that point forward, it takes only ½ hour to diagnose that particular problem in similar vehicles, because that shop now knows what to look for.

This situation occurs at hundreds of dealerships across the country. Much of this diagnostic time could have been avoided if some way existed to share the experience of techs across the OEM’s dealer network. Of course, OEMs have some processes now that assimilate this
knowledge – usually via monitoring tech support volumes or a dealer reporting process. However, this process is manual and changes occur slowly. An intelligent diagnostics system should be able to utilize machine learning that can adapt. A system based on the collective experience of the dealer network could effectively compile and share all of the technicians’ heuristic knowledge. How?

**Artificial Neural Networks**

**Case Study - Artificial Neural Networks and Cancer Detection**

Artificial neural networks (ANNs) are computational models that imitate the brain in order to solve problems based on numerous inputs. Unlike algorithm-based computing that follows specific instructions, ANNs learn by example and experience. As a result they are highly effective at identifying patterns and ‘learning’ over time – they get more accurate as the volume of data increases and they assimilate more examples. Most recently, they have been featured in various news outlets for their accuracy in diagnosing cancer.

One specific case is a breast cancer detector, built by Brittany Wenger for a Google competition, using cloud computing power (Wenger). Fine Needle Aspiration (FNA) is considered the least invasive procedure for breast cancer diagnosis; however, it is also the least accurate. Ms. Wenger’s neural network crunches nine inputs that can be collected by FNA (such as bare nuclei, and clump thickness) and compares them against a vast reservoir of patient data. The result? She has designed a neural network that can identify malignant tumors with 99% accuracy based on a very basic set of inputs.

Artificial Neural Networks and other big data algorithms are attractive approaches to automotive diagnostics because they can recognize trends in highly complex data. Today’s diagnostic processes rely on basic fault-tree analysis, checking each step until the solution is found. At the simplest level an ANN diagnostic approach would look like this:

*The technician would identify and enter into the diagnostic database all of the symptoms of the vehicle, including DTCs, specific readings, observations, and any other symptoms. The database would then compare the vehicle state to a large sample of similar symptoms. Based on the vehicle state and historical data of similar vehicle states, it would push back to the technician a ranked list of most likely solutions/repairs.*

This approach learns over time, as long as an appropriate feedback loop is in place. This loop would consist of the vehicle info, vehicle state, diagnostic steps that identified the root cause, final repair and parts used. Much of this data already exists and can be correlated based on repair order extracts, op codes, and FRFT metrics. Given enough repairs, the system would become more accurate at identifying the source of the trouble over time.

One potential downside of the ANN approach might be unusual or infrequent repairs that fall through the cracks. That is, the system might not suggest repairs with a low sample size. However, this is mitigated by the learning nature of an ANN. For example, a new model may not see a specific repair until late in the lifecycle. The first handful of cases for this repair may take a
long time to diagnose. But, the system will correct itself as the sample size for that repair grows and the system incorporates factors such as mileage.

**Figure 3 – Simplified Feedback Loop Diagram for Intelligent Diagnostics**

![Simplified Feedback Loop Diagram for Intelligent Diagnostics](image)

Figure 3 highlights a simplified model for developing an ANN-style diagnostic database. The diagnostic system identifies the top repairs/diagnostic steps to take, based on the current state of the vehicle and its database of repair events. The technician tries each of the most likely repairs. When one fixes the problem, the vehicle state and information flow back to the database and are married to the repair (along with the parts used that affected the repair).

Since an ANN learns over time, it would integrate the collective experience of technicians. It would identify trends that led to specific repairs, and what fixed the issue, network-wide. This approach sounds complex, but it has been successfully executed in other industries and evaluated for the automotive space, as far back as 2009 by VW AG² (Müller). Implementing this system would require collecting the necessary data from dealer service bays. Fortunately, OEMs already extract a large mass of data from dealers.

What additional data is required? The system needs to know the vehicle state at the time of the repair, the diagnostics steps that identified root cause, and the repair and parts that fixed the problem. These items can be collected via a combination of onboard diagnostics, offboard diagnostics, and technician observations.

**Diagnostic Front End – Onboard, Offboard, and Observation**

Onboard diagnostics occur on the vehicle’s engine control unit (ECU) and/or on the cloud through the telematics connection. They are not invasive; they don’t disrupt regular driving, but simply monitor the vehicle and any deviations from that vehicle’s usual behavior. Offboard
diagnostics are the processes that occur at the dealer, with a technician plugging into the vehicle’s systems, cycling subsystems, and taking measurements such as voltage or pressure readings. These procedures are invasive and can only occur in the shop, because they disrupt regular driving (i.e. you can’t pull a spark plug on cylinder #3 and measure voltage with telematics while driving).

**Onboard Diagnostics—Leveraging Telematics Data**

Today’s vehicles are impressive engineering achievements; they are reliable and robust, but unexpected failures occur when the product enters the real world. While some failures are unavoidable, many could be prevented if OEMs collected real-time updates from their vehicles. A telematics data connection could turn every unit in operation into a live, real-world test rig to log and record data. In fact, the vehicle’s ECU already monitors a number of onboard sensors. Onboard diagnostic strategies are already common among Heavy Equipment and Truck industries.

**Case Study – Onboard Diagnostics by Heavy Equipment and Truck OEMs**

Whereas early automotive telematics efforts were focused on safety and infotainment, heavy equipment and truck OEMs, as well as 3rd parties, approached telematics as a tool for increasing fleet manager profitability. Such features as remote diagnostics, fleet monitoring, and productivity reports are standard. Effective end-users employ these features to minimize vehicle downtime and fuel waste while maximizing profitability.

Remote systems also allow faster and more accurate repairs by eliminating diagnostic time and allowing parts to be pre-picked. Volvo Truck is able to significantly reduce downtime as a result (Volvo).

Currently, onboard diagnostic sensors focus largely on emissions systems. In order to be effective, OEMs must expand these onboard diagnostics to include all of the vehicle subsystems. In the short term, existing telematics data such as vehicle mileage and VIN would be combined with vehicle state (driving behaviors, fault codes, etc.) and pushed back into the diagnostics database.

Accessing onboard information allows the OEM to compare the vehicle to nationwide trends that resulted in repairs or failures. This data can be combined with repair information and used to recognize conditions that precede, say, an O2 sensor or brake job. However, it is essential that OEMs respect customer privacy concerns, so the appropriate barriers must be put in place to protect the data. As the robustness of the onboard diagnostic data improves, effective prognostics can be executed to complete repairs before the failures even occur.
Offboard Diagnostics – Improving the Dealer Data Pipeline

Offboard diagnostic tools and processes provide the information the technician gathers while the vehicle is on the lift. What these tools don’t show are the steps the technician took during the repair or what the final repair was. Currently, technicians rely on plug-in diagnostics hardware coupled with software to identify fault codes, test subsystems, and take measurements that can identify an unknown issue’s root cause. Unfortunately, a single diagnostic trouble code (DTC) only tells the tech the subsystem that is at fault, and not why the failure occurred. It can still take a number of troubleshooting steps to find the actual cause. More importantly, technicians’ top-box satisfaction with the tools’ ability to accurately diagnose a vehicle’s problem is only 59% (Figure 4).

To power an ANN, these tools must automatically cycle vehicle subsystems and push each measurement into the database. Using the VIN, these measurements can be joined with telematics data stored on the cloud.

Two data flows are key to offboard diagnostics – quantitative and qualitative. Quantitative data includes troubleshooting measurements such as voltage, DTCs, vehicle mileage, etc. These data elements are essential and can be recorded and uploaded automatically by an effective diagnostic tool, with few manual steps for the technician. This can be supplemented by the technician’s qualitative observations of symptoms. Phrases such as “white smoke”, “burning odor”, or “squeal, AC belt” describe qualities that devices don’t capture. Customer descriptions can also be fed into the qualitative database. This is another layer of intelligence, but adds some additional manual work for the technician during the process.

Finally, the repair that solved the issue must be recorded. OEMs already collect repair information, as well as fixed-right-first-time metrics through regular dealer extracts. Steps must be taken to accurately clean and review these extracts. At the most basic level, the diagnostic database will marry repair orders to the symptoms and measurements that preceded them.

Conclusion

The goal of improving existing diagnostic processes is to increase FRFT rates, enhance service capacity, increase customer pay sales, reduce warranty costs, and, ultimately, drive customer retention. This paper presents a big data approach that can successfully utilize the heuristic, “experiential” knowledge within the dealer network as an effective strategy to reach that objective.

At the enterprise level, the data would be particularly useful in identifying potential recalls based on systems and parts with high failure or error rates. The data would also stimulate engineering and service process improvements. For the supply chain, the data from onboard diagnostic feeds could be used to help forecast parts sales, predict demand, and anticipate forward parts deployment. These predictive analytics would help the OEM identify potential, impending failures, and notify the customer to get their car repaired before it even breaks.
information could also be used for targeted, timely marketing of maintenance intervals and regular service.

There are many barriers to overcome to achieve full implementation: integration of the data, its security, and its ownership. For this reason, Carlisle believes that this topic represents an area that could benefit from industry collaboration. A well implemented connected diagnostic process would improve not only our vehicles but the customer experience, technician efficiency, and shop profitability.

If you are interested in participating in this collaborative effort or have more questions please contact Chad Walker at cwalker@carlisle-co.com
Sources


Who We Are
Carlisle & Company is the preferred provider of aftersales strategic guidance and tactical solutions for the world’s leading motor vehicle brands. Our expertise is in consulting, benchmarking, research, service operations and non-profit consulting.

Global OEMs in the automotive, agriculture, commercial truck, construction, diesel engine, industrial products, mining and power equipment sectors have been coming to Carlisle for over 20 years. Our capabilities are global, with a particular focus on North America and Europe.

We have built our reputation on our history of performance, our strong values and culture, and the integrity and creativity of our people.

Research
Working collaboratively with most of the global automakers, Carlisle produces various research products that allow OEMs to better understand the people side of the service business:

- Annual Customer Sentiment Survey: Probes into the values, likes, dislikes, satisfaction, and loyalty of dealer and non-dealer service customers.
- Annual Service Manager Survey: Covers such topics as technical support, tools and equipment, service information, and technical training. The 2013 edition of the survey covered 28 brands and received responses from nearly 9,000 service managers.
- Annual Parts Manager Survey: Covers such topics as parts availability, delivery, order processing support, parts marketing, etc. The 2013 edition of the survey covered 35 brands and received responses from over 11,000 parts managers.
- Annual Service Advisor Survey: Covers such topics as demographics, job history, career development, compensation, customer processes. This survey was piloted in 2013 with six brands and received over 4,000 responses.
- Annual Service Technician Survey: Covers such topics as recruitment, retention, satisfaction, and training needs. The 2013 edition of the survey covered 15 brands and received responses from approximately 9,000 technicians.