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Product life cycle platform for vehicle effective fault prediction and proactive maintenance

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Abstract: The fault prediction engine have been developed for predicting the faults in automobiles and it ensured the proactive live maintenance. Tests were performed to determine the fault prediction engine's characteristics and test cases under different conditions. There are lot of requirements to save time, money and space in the automobile service sector. And discusses the fault prediction engine that defines and Creates Rules for Event Detection and also capability to add model based for Fault Prediction. This will enable Proactive approach of Uptime by informing Customer, Dealer Workshop about the possible fault for enabling proactive services

Keywords: on-board data, off-board data, machine learning, fault prediction, automotive diagnostics, logged vehicle data

1. INTRODUCTION

Fault detection and diagnosis has been an active area of research for the last few decades, which is an essential part ofmodern industries to ensure safety, product quality and efficient. A system is developed, considering relation amonginput and output parameters of subsystems and components of the automobile system in normal and failed conditions. The approach is not only helpful to maintenance personnel in effective diagnosis but also in guiding designers in development of reliable automobile systems, accident investigations of automobiles, etc.,

The main problems raised by the processes taking place within automobile service sectors is the time and space consumption during the fault is being dragonized, in holdingthe stocks of the spares, and their uncertainty. Computationalintelligence will give the answer of the fault diagnosis research community to these problems and how it is expected to move under disturbances.

This introduces the reader to the area of computational intelligence techniques and to their significant and abundant applications to fault prediction. Fault prediction represents an important contemporary research field, due to the ever- increasing need for safety, maintainability and reliability of automobile service sector.

The Unified Rule Base Fault Prediction Platform for HardData and Light and Medium Data, BS-IV & BS-VI variants with Machine Learning Rule Based capabilities should be able to detect & generate CASE for Uptime Center Team with real time view of Vehicle Health Parameters, Location. This will enable Proactive approach of Uptime by informing Customer, Dealer Workshop about the possible fault for enabling proactive services.

It is desired that truck makers has to offer better reliability to their clients, which clearly requires a move in the worldview. Better approaches for contemplating segment upkeep, booking and substitution need to be presented. Factual lifetime expectations are no more adequate,and workshop tasks should be arranged and their outcomes dissected at the degree of individual vehicles.

Support technique being utilized in vehicle industry is typically responsive that outcomes in decrease of lifetime of vehicle and furthermore loss of cash. Prescient upkeep is required on this phase to beat these issues. It is accounted forby European Commission that there will be half addition in transport vehicles inside 20 years [1]. It will require compelling methodologies to keep up the vehicle execution.

Vehicles having exceptionally complex structure need a powerful upkeep technique. Three sorts of upkeep methodologies are being utilized in vehicle industry, prescient support, restorative upkeep, and preventive support. Preventive upkeep is performed after a deficiency has happened. It is utilized for rare disappointments when the fix is very exorbitant. Preventive support is the regular practice inthe vehicle business, where vehicle parts are updated every so often. As opposed to preventive and restorative upkeep, in prescient support [2], current state of framework/vehicle is examined to anticipate what is most likely going to fall flat.

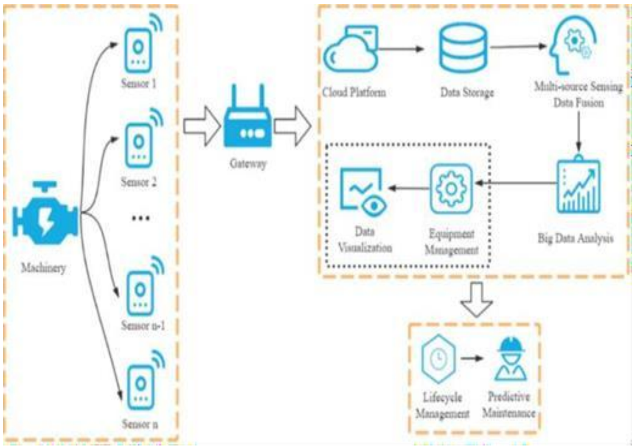


Fig. 1. Fault prediction and maintenance [13]

A. *Fault Prediction Engine Platform*

The initial moves towards an unaided strategy for finding valuable relations between estimated flags in a Volvo truck, both during ordinary tasks also, when a shortcoming has happened. The intriguing connections are found in a two- advance method. In the initial step every single substantial model, characterized by a MSE limit, are found. In the secondstep the model parameters are concentrates after some time tofigure out which are critical. Besides, a technique for doing encompassing separating is introduced. It lessens the impactsof the encompassing conditions which give progressively steady (after some time) signal relations. The technique is assessed on a dataset from a controlled shortcoming infusiontest with four unique shortcomings. One out of the four issueswere obviously found while the others were stirred up [3].

B. Fault Classification

The off-board information sources LVD and VSR and presents early aftereffects of anticipating air blower disappointments. Three unique classifiers are assessed what'smore, both F-score and a cost work is utilized as assessment standards [7]. In addition, the paper examines the issue of thedataset not being aid and classifiers learning person truck conduct rather than indications of wear. The paper reasons that utilizing these offboard information sources is suitable as infoinformation for foreseeing vehicle upkeep, but it will requiremuch more work.

FAULT PREDICTION AND ISOLATION

The Unified Rule Base Fault Prediction Platform for HDand LMD, BS-IV & BS-VI variants with Machine Learning Rule Based capabilities should be able to detect & generate CASE for Uptime Center Team with real time view of VehicleHealth Parameters, Location [8]. This will enable Proactive approach of Uptime by informing Customer, Dealer Workshop about the possible fault for enabling PROACTIVEservices. The application should have the following capabilities:

A. Source Data ETL Module

Source Data extraction, processing and loading module tobe developed. Telematics Fault Code Data, Vehicle Parameters Data. This data comes via MQ Channel at near real time frequency.

B. Rule Engine

Define and Create Rules for Event Detection and also capability to add Machine Learning based Models for Fault Prediction. Fault diagnosis of automobile systems is critical,as it adds-up to repair and maintenance time. It is, therefore,desired to make it efficient and effective. One of the conventional approaches is to use the fault tree diagram. Theapplication this engine is to leverage machine learning to create rules on Vehicle Fault codes, Parameters & Combination of both. It should be able to improve these rulesas Insights from Vehicle DATA is captured in the previous history also from the future data obtained.

C. Case Based Reasoning

Case-based reasoning means using old experiences / previously recorded data to understand and solve new problems. In case-based reasoning, a rule engine remembers aprevious situation similar to the current one then it uses that tosolve the new problem. Case- based reasoning can mean adapting old solutions to meet new demands using: old casesto explain new situations, using old cases to critique new solutions, reasoning from precedents to interpret a new situation, create an equitable solution to a new problem

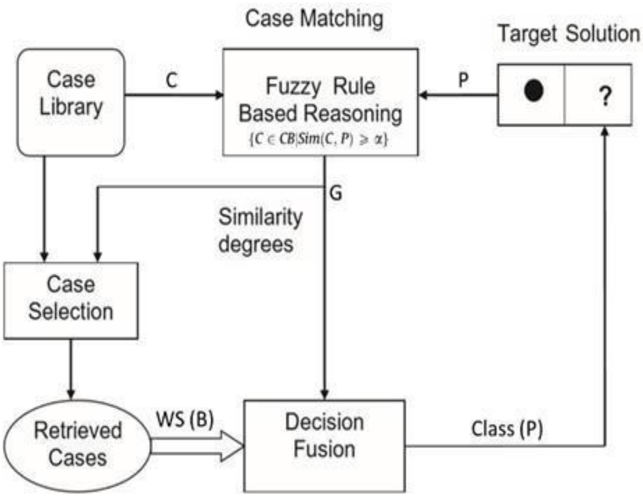
D. Fuzzy Logic

Target problem P requires similar cases in the case library.The matching between P and C is guided by a set of fuzzy rules, which evaluates similarity between cases in varying situations. Every case in the case library is evaluated via fuzzyreasoning for its similarity with target P based on the weightassigned, and those cases that receive similarity degrees abovea specified threshold are selected.

$$Out(P) = \frac{\sum_{C_i \in G} Sim(C_i, P) \cdot Out(C_i)}{\sum_{C_i \in G} Sim(C_i, P)} \quad (1)$$

Out(P) are Out (Ci) are the output values for target P andcase Ci, respectively. Should the problem be a classification one, we need to launch a voting procedure to choose the most possible class from a set of cases available in the library.

Fig. 2. Fuzzy rule for case based reasoning



The purpose of the decision fusion step is to find a new solution to the target problem by modifying and aggregatingknown solutions of the retrieved cases.

$$VS(B) = \sum_{C_i \in G} \begin{cases} Sim(C_i, P), & \text{if } Class(C_i) = B \\ 0, & otherwise \end{cases} \quad (2)$$

Prediction problems, the outcome of the target problem Pis predicted as a weighted average of the outcomes of the retrieved cases as given by

$$G = \{C \in CB | Sim(C, P) \geqslant \alpha\} \quad (3)$$

The values of similarity of the retrieved cases that have the same outcome can be accumulated into a voting score (VS) for the associated class. In general, the voting score for a candidate class B is calculated by WS (B)

$$Class(P) = \arg\max_{\forall B} [WS(B)] \quad (4)$$

Finally, we select the class with the largest voting score asthe predicted class for target P.

E. Integrations

Integration of Telematics Data into the Fault Prediction Engine: Telematics Fault Code Data, Vehicle ParametersData. This data comes via MQ Channel at near real time frequency.

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TABLE I. EUROPEAN STATIONARY CYCLE (ESC) OF BS III & BS IV

Work Load	Tag	Year 1	Year 2
Telematics	Yearly Projections	20000	85000
	Number of Active Telematics Devices	20000	105000
	Frequency (Mins)	5	5
	Vehicle Utilization	50%	50%
	DTU Size(Kb)	10	10
	Concurrency	30%	30%
	Number of Inserts	2880000	15120000
	Day Wise Data (GB)	27.46582	144.1956
	Year Wise Data (TB)	9.790063	51.39783
Industrial IoT	Yearly Projections	500	750
	Number of Active Telematics Devices	500	1250
	Frequency (Mins)	5	5
	Machine Utilization	70%	70%
	DTU Size(Kb)	10	10
	Concurrency	100%	100%
	Day Wise Data (GB)	0.480652	0.720978
	Year Wise Data (TB)	0.171326	0.256989
Enterprise Data	Yearly Projections (TB)	0.3	0.8

ALT_DI D	String	Alter Type
Device ID	String	IMEI number of the telematics device.
Sequence Number	Integer	Numbering packets in a sequence to track them
Driver ID	String (will be '0000000000' when USB is removed)	10-digit integer which is as identity for driver. Thesame is being created as text file from web portalafter entering all license info of driver. And this text file is kept in USB 2.0 pen drive. Driver will plug this in telematics wiring harness USB slot.
Latitude	Float	Specifies the preciselocation of the device(vehicle)
Longitude	Float	Specifies the preciselocation of the device(vehicle)
UTC	Integer	Coordinated Universal Time to define time stamps of packets senatorreceived
#		

F. Onboard Data

Huge scope information obtaining on vehicles (on-board)is troublesome as the vehicles are continually progressing. Information must be put away ready for recovery at a workshop or on the other hand transmitted through a telematics entryway. As vehicles move across landmasses andoutskirts, remote downloads get costly and thus by and by constrained to little pieces of information [9]. In-vehiclestockpiling of information streams isn't yet attainable as theyrequire enormous measure of capacity which despite everything is exorbitant in installed frameworks.

TABLE II. EUROPEAN TRANSIENT CYCLE (ETC) OF BS III & BS IV

Driver ID Alert	**Type**	**Remark**
^		

The advancement cost part of huge scope on-board logging arrangements is moreover a significant motivation towhy it has not been done previously. The logging gear must be grown, thoroughly tried and mass-created. This doesn't fitwell with the extreme rivalry in the vehicle segment where vehicle makers need to see a reasonable monetary advantagefor each capacity remembered for the vehicle.

The on-board information comprises of thousands of signs from the sensors and ECUs, that are imparted through a CANarrange. They are sent over and again with a predetermined recurrence and structure floods of nonstop information whichare utilized for vehicle control and status motioning betweenthe diverse vehicle parts.

Up until this point, constant vehicle on-board logging hasbeen constrained to armadas of test vehicles and with retrofitted logging hardware. These frameworks are costly andplanned for item improvement purposes. It is likely protectedto accept that any industrialized on-board checking or prescient support calculation must be restricted to existing equipment regarding sensors, signals and computational assets.

G. *Off- Board Data*

Most enormous organizations, similar to the Volvo Group, have collected a lot of information throughout the years in off- board databases. The information ranges from drawings and test results to upkeep records and vehicle use insights. Organized right, the information can be changed into information and demonstrate helpful in different application zones [10]. The upkeep records and use insights is quite compelling in this theory on the grounds that of their immediate and circuitous relationship with future vehicle

H. *Vehicle Measurements*

The use insights database, named the Logged Vehicle Data database (LVD), is restricted to amassed information. The information is totaled on-board each Volvo vehicle and is either transmitted remotely through a telematics entryway ordownloaded at a workshop. The update recurrence is, best case scenario once every month except typically every three and ahalf year. The recurrence is obscure from the earlier despite the fact that vehicles normally visit workshops for support. The LVD database incorporates amassed insights, for example, mean vehicle speed and normal fuel utilization, which have been gathered during ordinary activity. It gives important bits of knowledge in how use, market and client fragment influence key vehicle execution parameters. This isvaluable contribution to the improvement of future vehicle

TABLE III. EUROPEAN TRANSIENT CYCLE (ETC) OF BS III & BS IV

Fault Code	Type	**Remark**
^		
DTCA	String	DTC Packet
Device ID	String	IMEI number of the telematics device.
Sequence Number	Integer	Numbering packets in a sequence to track them
Latitude	Float	Specifies the precise location of the device (vehicle)
Longitude	Float	Specifies the precise location of the device (vehicle)
UTC	Integer	Number of seconds from Jan 1st 2000
Number of Fault Codes	Integer	Number of fault codes that were occurred
SPN1	Integer	Suspect Parameter Number which is a fault code that can occurs 1 to n times in a certain amount of time. Is equal to DTC number.
FMI1	Integer	Failure Mode Identification which is a fault code that can occurs 1 to n times in a certain amount of time. What type of fault is it
CM1	Integer	Status of fault code, what type is it. Occurs from 1 to n.
Occurrence nt1	Integer	How many p-codes occurred from 1 to n
SPN2	Integer	Suspect Parameter Number

		which is a fault code that can occurs 1 to n times in a certain amount of time. Isequal to DTC number.
FMI2	Integer	Failure Identification which is a fault code that can occur 1 to n times in a certain amount of time. What type of fault is it
CM2	Integer	Status of fault code, what type is it. Occurs from 1ton.
Occurrence Count2	Integer	How many p-codes occurred from 1 to n
SPNn	Integer	This packet is variable size, based on total faults available in vehicle.so n will SPN denotes that last SPN as nth SPN for which fault available in vehicle
FMIn	Integer	SPN/FMI /CM/OC is a group will be keep on repeating as per total no of faults available
CM n	Integer	Status of fault code, what type is it. Occurs from 1 ton.
Occurance Count N	Integer	How many p-codes occurred from 1 to n
#		

I. *Maintenance Records*

The Vehicle Maintenance Database (VSD) contains records of all support directed at a Volvo approved workshops. The information is utilized for quality insights during the guarantee time frame just as client invoicing. Thesections are organized with normalized fix codes and part numbers. The main driver is now and again indicated in the fix record at the same time, by and

large, must be deducted dependent on the announced fix activities.
A great part of the information in the VSR database are physically entered and regularly endure from human mix-ups,for example, mistakes, void records, or missing underlying driver. The VSR additionally contains precise mistakes presented by the way toward entering new information to thedatabase. The date of fix isn't the genuine date of the fix but instead the date of the passage to the database. Further, broadfixes are accounted for as back to back fixes a couple of dayssseparated. This doesn't make any issues in the day activity asthe reason for the framework is to connect solicitations to fixesand give the technician a diagram of the historical backdrop of a vehicle. The database is amazingly heterogeneous, as model year and vehicle particular influence the parameter setlogged to the database. Just a little subset of parameters is normal among all vehicles. As a rule, terms, more up to dateand further developed vehicles give more measurements. Thismakes it elusive huge datasets with a homogeneous set of parameters.

1. TABLE IV. EUROPEAN TRANSIENT CYCLE (ETC) OF BS III & BS IV

Claim	Wty Clm Type	Reference Date	External Number
010000047243	ZAMC	03-01-2017	1500R02415
010000049198	ZAMC	13-01-2017	4000069225-000002
010000034771	ZAMC	07-11-2016	4000028038-000001
010000049617	ZAMC	14-01-2017	1502R01446
010000061004	ZNRM	28-02-2017	4000110100-000001
010000056463	ZAMC	04-02-2017	4000087560-000001
010000031666	ZNRM	08-10-2016	4000018043-000001
010000299749	ZAMC	02-01-2018	4000571062-000001
010000049113	ZAMC	13-01-2017	4000069242-000002
010000513537	ZNRM	06-10-2019	4001820346-000001
010000155252	ZGHD	13-10-2017	4000438160-000001
010000043179	ZAMC	13-12-2016	4000047119-000001
010000183684	ZNRM	31-01-2018	4000618769-000001
010000195180	ZNRM	05-03-2018	4000674896-000001
010000212594	ZAMC	14-04-2018	4000747578-000001
010000179625	ZNRM	15-01-2018	4000592547-000001
010000268385	ZAMC	13-08-2018	4000965174-000001
010000422720	ZSPR	13-05-2019	4001505464-000001
010000422721	ZAMC	13-05-2019	4001505464-000002

2. CONCLUSION

The paper presents that the method is data driven and useextensive amounts of data, either streamed, on- board data orhistoric and aggregated data from off-board databases both during normal operations and when a fault has occurred. Themethods rely on a telematics gateway that enables vehicles to communicate with a back-office system. Data representations, either aggregations or models, are sent wirelessly to an off- board system which analyses the data for deviations. The method is evaluated on a dataset from a controlled fault injection experiment with different faults. These are later associated to the repair history and form a knowledge base that can be used to predict upcoming failures on other vehicles that show the same deviations of the on board and off board data, such as telematics Fault Code Data, Vehicle Parameters Data corresponding, are necessary data for the fault prediction engine.

J. *Problem Formulation*

The vehicle business is broadly utilizing physically built information-based techniques for diagnostics and prognostics. These are improvement asset serious and limits the appropriation to frameworks which are costly, security basicor under lawful commitment of checking. The interest for more uptime requires less impromptu upkeep which consequently drives support expectations. This requires progressively widespread arrangement of diagnostics or support forecasts as the frameworks that today are under analytic observing just record for a little portion all things considered. This benefits exploratory strategies dependent on genuine disappointments to deduct likely disappointment modes. This theory presents two techniques for information mining the vehicle support records and vehicle use information to learn utilization or wear designs characteristic of disappointments. This requires support records where the disappointment main driver can be deducted with precise dateor mileages of the fix. Further, progressively wide-spread selection of prescient support calls for programmed what's more, less human-asset requesting strategies, for example solo calculations with deep rooted learning. Such strategies are simpler to scale up and they would thus be able to be universally applied since a significant part of the demonstrating is robotized and requires practically no human communication. Managed and solo AI techniques have demonstrated effective to anticipate the need of upkeep.

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