Signal Abstraction for Root Cause Identification of Control Systems Malfunctions in Connected Vehicles

Rasoul Salehi[1] and Shiming Duan[2]

[1,2] *General Motors Research and Development, Warren, MI, 48092, US*
rasoul.salehi@gm.com
shiming.duan@gm.com

ABSTRACT

Today's automotive control systems have gained huge advantage from using integrated software and hardware to reliably manage the performance of vehicles. The integration of large-scale software with many hardware components, however, have increased the complexity of diagnosis and root cause analysis for a detected malfunction. High level of expertise and detailed knowledge of the underlying software and hardware are typically required to analyze a large list of variables and precisely identify the root cause of the malfunction. In this paper, an abstraction method is presented to identify the most important signals for a root cause analysis by leveraging data collected from a connected fleet of field vehicles. A novel label propagation methodology is proposed to select the most relevant signals for the root cause analysis by detecting linear and nonlinear correlations between an observed malfunction and candidate test signals of the control system. The proposed label propagation method eliminates the requirement for a priori known correlation kernel that is needed for a regression analysis. The signal abstraction method is applied and successfully tested for abstracting signals in the fuel control system, with high degree of interconnection between software and hardware, using data from more than 5000 connected vehicles.

1. INTRODUCTION

Advanced control systems such as vehicles include many hardware and software components that are managed for precise and reliable operation and monitoring of the system (Isermann, 2022). The high number of components and their interactions, however, have increased the difficulty of monitoring the vehicular system performance and detection of root causes for an observed malfunction (Xiong, Sun, Yu, & Sun, 2020; Komsiyska, Buchberger, Diehl, & Ehrensberger, 2021). One major challenge in diagnosis of such systems is the large number of signals (that includes both physical and calculated variables in a software) that are needed to be analyzed to find the unknown root cause(s) of the malfunction. Therefore, abstraction of the number of signals and reducing it to include only the most relevant for a particular failure mode analysis could help to decrease the complexity of diagnosing and reduce the trouble shooting time.

In addition to the large number of signals, the existence of causal relations between different elements in a control system adds complexity to the root case detection process because a malfunction in one component could impact multiple downstream or upstream components (Chioua et al., 2016). For example, in Figure 1, a failure in actuator 3 could create a disturbance for the performance of actuator 2. However, the system interconnection and feedback loops create a potential for the failure to propagate inversely from actuator 2 to actuator 3 through a path such as Actuator2 $\rightarrow$ System $\rightarrow$ Sensors $\rightarrow$ InFunc3 $\rightarrow$ OutFun3 $\rightarrow$ Actuator3. Therefore, root causing subsystems with feedback loops requires analyzing downstream and upstream components as well that increases the number of signals required for the analysis.

System abstraction is widely used to reduce order of models by decreasing the number of states in a dynamical model and their associated parameters; thus, simplifying the design and calibration processes. Different techniques are developed for model order reduction such as truncated balanced realization in which the model order reduces based on the Hankel singular values of the system. The reduced system states are then calculated from linear transformation of original states; therefore, the new states are in a different space and units. In (Choroszucha, Sun, & Butts, 2015), a balanced realization is presented to reduce the order of a close-loop engine air path model and its controller. Time-scale analysis is another method used to reduce the order of dynamical systems where dynamics with different time response are present. For a system with different set of slow and fast dynamics, the states could be decoupled based on eigenvalues of the linearized system (Naidu, 1988; Naidu & Calise, 2001). The reduced

https://doi.org/10.36001/IJPHM.2023.v14i3.3423

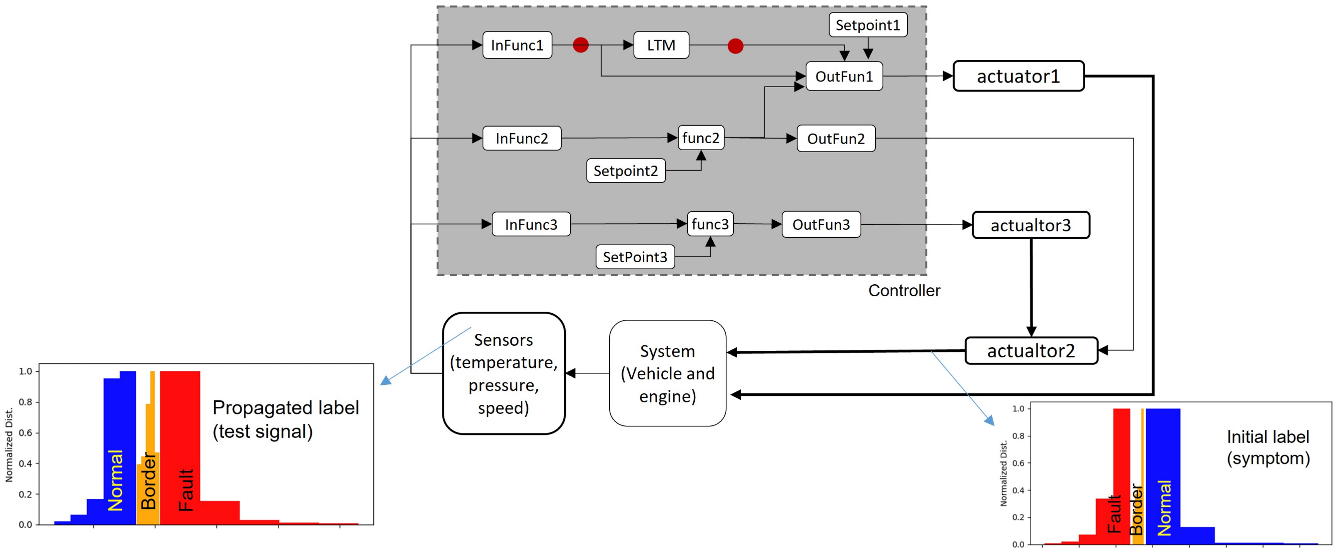


Figure 1. Illustrative example of symptom tracing by label propagation. The label that is created at the initial test point (symptom) is propagated to find matching patterns at other test points.

order models could be used, for example, to simplify a controller design. Singular perturbation is one of the reduction techniques for dividing a set of model differential equations into slow and fast dynamics. In (Moulin & Chauvin, 2011), the singular perturbation method is applied to ignore exhaust manifold and intake manifold pressure dynamics since their dynamics are much faster compared to the turbocharger rotational dynamics in an internal combustion engine model. Conversely, in (Sharma, Nesic, & Manzie, 2011), the singular perturbation methods are used to detect the slow dynamics of temperature in a thermodynamic system with fast pressure dynamics. As can be observed, the model reduction methods either ignore some of the system dynamics or introduce new coordinates by transforming the original state space in which the original physics-based states may not be interpreted anymore. Another method to reduce the system development complexity is to reduce the number of parameters that require calibration by detecting the most influential terms in the parameter space (Salehi & Stefanopoulou, 2020).

Even with abstracted model and parameters, advanced vehicle control systems still have many signals that increase complexity and time to analyze them for root cause detection during a diagnostics process. With hardware and software feedback loops, the diagnosis becomes even more complicated and requires a detailed understanding of the system and overwhelming experiments. Here, a signal abstraction method is proposed to detect signals that provide insights into a root cause by estimating the signals correlation with an observed anomaly. The novelties of the paper are two-fold. First, it is proposed to detect the correlation using a data driven label propagation method therefore, a priori knowledge of the correlation kernel is not required. Utilizing the label propagation technique makes it possible to apply this method for detection of both linear and nonlinear correlations. Second, the proposed signal abstraction method is validated experimentally by detecting the most valuable signals in root cause analysis of the fuel system in gasoline direct injection engines for a fleet of 5000 connected vehicles. Leveraging the connected fleet data reduces requirements of extra off-the-field lab experiments to simulate the failure operating conditions and shortens the analysis time.

2. SYMPTOM TRACING USING LABEL PROPAGATION

Hardware and software interconnection between variables (signals) in a control system creates signal observability (or correlation) which means changes in a signal is detectable by observing the behavior of (at least) one different signal. The observability can be affected, either increased or decreased, when a change happens to the system due to, for example, a degradation in a component. Figure 2 shows two illustrative examples for the change of observability due to system degradations. As illustrated, the observability, defined as estimation of changes in the output signal z by measuring variation of input signal x, reduces (Figure 2-a) or increases (Figure 2-b) after the fault occurs. For a complex system failure root cause analysis, domain experts look for changes in correlations as clues to the root cause and take this information into next stages to create a hypothesis for possible reasons that generated the failure. Here, we propose a data driven method to detect existing correlations between symptoms of a fault and other (test) signals measured by a metric of observability. Highly correlated signals are detected and suggested to be used, along with prior knowledge of the system operation, to identify unexpected relations that have been created after the

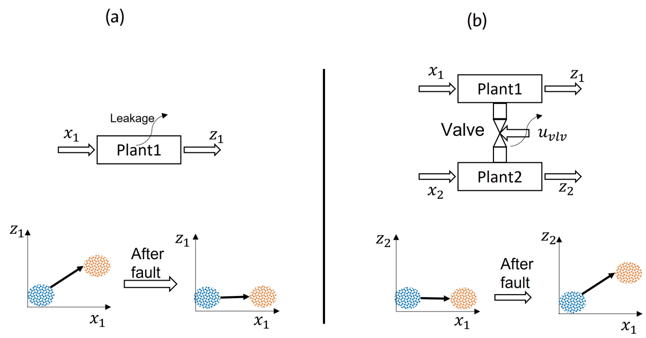


Figure 2. illustrations for (a) reduction of observability of signal z_1 from x_1 measurements when a fault is applied to the plant (b) creation of observability of z_2 from x_1 measurements when the valve is broken and stays open after a close command..

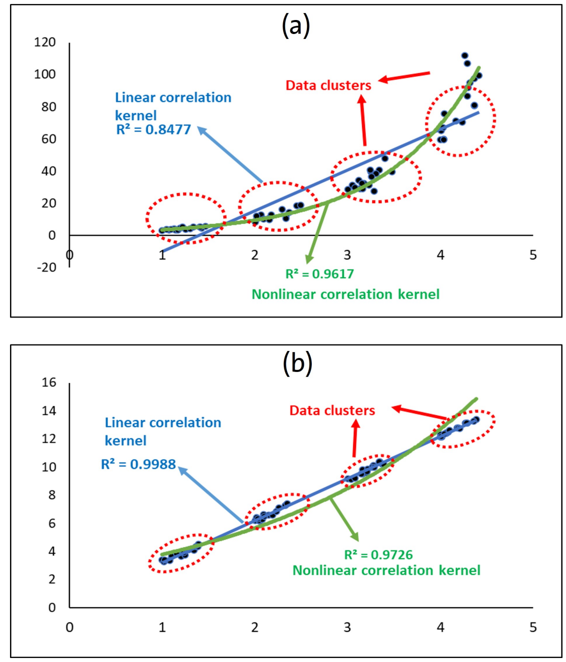


Figure 3. A kernel is needed to estimate a functional correlation between two variables. Using a wrong kernel could results to misdetection of an existing relation. In (a), the (exponential) nonlinear kernel detects a better correlation compared to the linear kernel while in (b) the linear kernel outperforms the exponential kernel.

fault occurrence as evidences to build a particular root cause hypothesis.

The observability of a symptom by a test signal is determined based on the correlation between the test signal (or variable) at a desired test point and the symptom signal at the initial labeling point (Figure 1). Typically, such correlation could be detected if a priori known linear or nonlinear kernel is available. The importance of the kernel selection is illustrated in Figure 3 using two sets of synthetic data. First, Figure 3-(a) shows how a nonlinear (exponential) kernel well detects the correlation. However, with a different dataset shown in Figure 3-(b), a simple linear regression reveals the existing correlation better than the nonlinear kernel. Thus, in root cause analysis applications where the correlation kernel is not known a priori, conventional regression could miss detecting an existing relation between a symptom and test signals.

To eliminate the requirement for the kernel, a data driven label propagation method is proposed that uses a support vector machine (SVM) to cluster test signals data. It is assumed here that if a variable is correlated with the selected symptom, one should be able to regenerate the labels assigned to the symptom data using the test signal data as they are collected at the same time stamp. Figure 4 shows how label propagation works for two illustrative examples one with a strong correlation (top) and the other without any correlation (bottom). First, in Figure 4-(a) and (c) "healthy" and "faulty" operation of the vehicle is detected based on the symptom "X". If there is an unknown correlation, one should be able to get a similar classification by looking at the test signal "Z" (Figure 4-(b)). Similarity of data classification using symptom "X" and test variable "Z" is used as an indication of existing correlation. On the other hand, as Figure 4-(d) shows, when there is no correlation, the classification results are very different if the test signal is used to classify healthy and faulty operation instead of the symptom variable.

The following explains how the label propagation problem is formulated in this paper. Let's assume X is a vector of samples $[x_1, x_2, \ldots, x_n]$ collected at n time steps for a variable measured as the symptom, Then, one can assign a corresponding label vector $Y = [y_1, y_2, \ldots, y_n]^T$ to the symptom signal samples as:

$$y_i = f(x_i) \tag{1}$$

where f is a mapping function defined, for example,

$$f(x_i) = \begin{cases} low & if \quad x_i < L \\ high & if \quad x_i \geq L \end{cases} \tag{2}$$

with L being a threshold. Let Z be a variable measured at another test point with the same sampling timestamp as X. If there exist a causal relation between Z and X such as $Z = g(X)$, then one should be able to calculate the initial label Y by composing f and g^{-1} and using Z instead of X:

$$Y = f(g^{-1}(Z)). \tag{3}$$

The existence of a causality between the pair $[X, Z]$ and its corresponding mapping function $f(g^{-1}(.))$ are detected using a support vector machine (SVM) algorithm that classifies Z as described in the following steps.

1. Label samples of symptom X based on the mapping func-

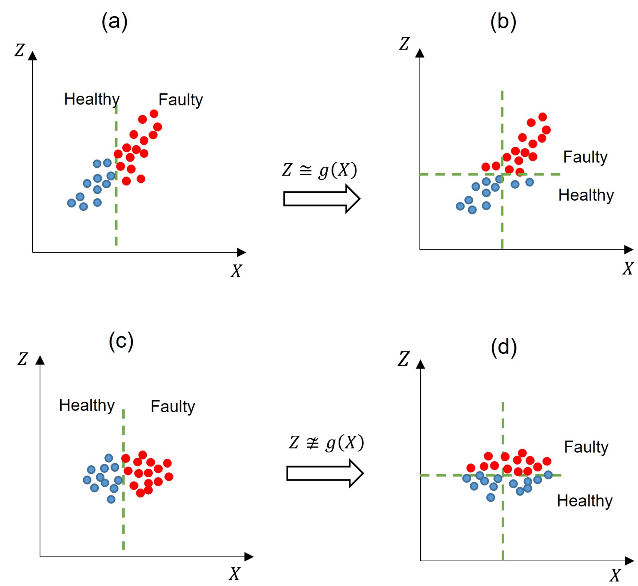


Figure 4. Illustration of switching the labeling variable from the symptom domain (X) into the test signal (Z) domain. (top) successful switching when a correlation $Z = g(X)$ exists (bottom) very different labelling when there is no correlation.

tion $f(.)$ defined to trace the symptom.

$$[y_1, ..., y_n]^T = f([x_1, ..., x_n]^T) \tag{4}$$

where x_i is the i^th sample of the variable X and $[y_1, \ldots, y_n]$ are the labels assigned to each symptom sample. There could be m labels such that $y_i \in \{L_1, \ldots, L_m\}$ with $m < n$.

2. For each sample x_i there will be a corresponding sample z_i in Z domain that is collected at the same time instant as x_i. Assume there is a strong correlation between X and Z then, one can copy the labels from X and apply to Z elements using the time stamp connection between X and Z.

$$[y_1, ..., y_n]^T \rightarrow [z_1, ..., z_n]^T \tag{5}$$

3. Train a support vector machine (SVM) algorithm using training data Z and their associated Y labels.

4. Analyze the classification performance on the same training set Z by feeding it back into the trained SVM to estimate the label $\hat{y}_i$ for each sample z_i,

$$\hat{y}_i = SVM(z_i). \tag{6}$$

5. Calculate a deviation metric to measure the success of SVM training process. There could be different metrics, as a simple example the following deviation metric

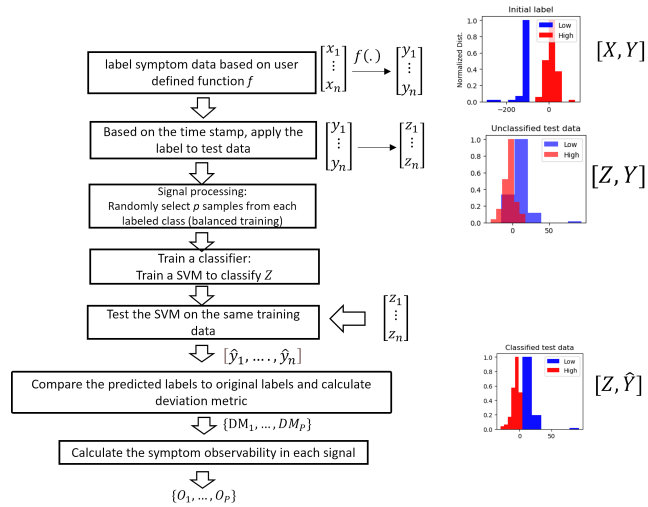


Figure 5. Major steps of the proposed label propagation algorithm.

is used here:

$$DM_j = \sum_{i=1}^{n} u(|\hat{y}_i - y_i|)/n \tag{7}$$

where, n is the number of samples in Z and $u(.)$ is the Heaviside step function. When an estimated label matches the original label, i.e $\hat{y}_i = y_i$, then $u(|\hat{y}_i - y_i|) = 0$ and the deviation metric approaches zero. Finally, to sort test signals based on the strength of the correlation, an observability, O_j, is associated with each test signal, calculated as:

$$O_j = DM_j^{-1} / \sum_{i=1}^{p} DM_j^{-1}, \qquad DM_j \neq 0 \tag{8}$$

where P is the number of test signals being analyzed and compared to the selected symptom. Higher observability of a test signal indicates that it has a better correlation with the selected symptom. A flowchart of the designed algorithm is shown in Figure 5.

The label propagation and data classification could be applied into a r-dimensional test data in general. In other words, the test vector in Eq. (5) could be in a $n \times r$ matrix $[Z_2; Z_3; \ldots; Z_r]$. Using higher dimensions of the data classification helps to visualize interactions between more variables (i.e. multivariate interactions) and the symptom at the same time, with a cost of increased computation time. Results in section 2.2 shows an example of a 2-dimensional classification.

2.1. Label propagation results

The signal abstraction method is realized with a structure shown in Figure 6 to detect the observabilities and use it to select diagnostically important signals in the fuel control system for a fleet of connected vehicles. As shown, the analysis starts with the user applying filters to select a populations of vehicles. For example, the filters could be applied to select a list of vehicles knowing the identification number (”VIN”), required model years (”MY”), and other production factors (”RPO”). Then, the user selects test signals ($[z_1, z_2, ...]$) necessary for the analysis. The user also designs the labeling function ($f(.)$ in Eq. (4)). Then, signals and labeled symptom data enter the reasoning machine for label propagation and observability detection. Depending on the user preferences, 1-D or 2-D classification results are generated and presented.

The signal abstraction system of Figure 6 is validated on the fuel control system of a fleet of vehicles with gasoline direct injection engines. The direct injection fuel system is one of the most complicated subsystems in modern vehicles. A simplified schematic of its components and their arrangement are shown in Figure 7. As shown, the fuel pressure increases at two stages; once at the low-pressure tank pump and then at the high-pressure pump before reaching the injectors. There is a check valve between the low pressure and high-pressure side that is integrated to the system to avoid fuel back flow. A malfunction in the check valve, such as slow response time at closing, could cause high pressure pulsations to be observed at the low-pressure side that could damage the low-pressure pump at extreme cases. Even with a check valve with a fast response, small pulsations from the high-pressure pump side could be observed at the low-pressure side. In addition to that, the final pressure at the high-pressure pump outlet is dependent on its input pressure, which is fed by the low-pressure pump. These physical couplings between high pressure and low-pressure sections of the fuel system is used here to illustrate the usage of the signal abstraction method.

The results of 1-D label propagation tested on the fuel system with (selected test) signals listed on Table (1) are shown in Figure 8 for the case where error at the high-pressure fuel line (ΔP_{HP}) is used as the symptom, which is expected to be zero for a perfect fuel controller. For this example, only two labels ”low” and ”high” are generated based on the value of ΔP_{HP}. Then, the labels are propagated to other selected (test) signals to estimate their deviation metrics and sort them based on symptoms observability values. This means, one should expect the signals on top of the list to have the best correlation with the reference labeling signal (i.e. ΔP_{HP}). In the example presented in Figure 8, it was known that the variable ”$Angl\_Adj$” (an adjustment angle from the controller for the high pressure pump to correct the fuel pressure error) is well correlated to the labeling variable, i.e., $Angl\_adj = g(\Delta P_{HP})$ through the internal controller software design. The presented results also indicate high correlation detected by the label propagation method. Also, observed from Figure 8, one can see that the label propagation is successfully detecting nonlinear correlations for signals such as ”$I\_feedBack$” or ”$Deliv\_duration$”. Figure 8 also reveals the internal connection between high pressure and low pressure sides of the fuel system; whenever the low pressure pump error (Err_press_LP) is less than 0.3, the high pressure pump error ΔP_{HP} is high, that matches the physical connection between the two pumps.

Table 1. Description of test signals used for root cause identification

- ΔP_{HP}: Error of of the high pressure fuel controller (ΔP_{HP} = desired pressure – actual pressure)
- $Angl\_adj$: Adjustment angle calculated by the controller based on the fuel-rail pressure error (ΔP_{HP})
- $Deliv\_duration$: Duration of the actuation signal applied to the fuel pump
- $I\_feedBack$: Measured current applied to the fuel pump
- Err_press_LP: Error of of the low pressure fuel controller
- $Controller\_Iterm$: High pressure loop controller integral term
- Eng_speed: Engine speed
- Inj_puls: Duration of the fuel injection
- $ActPress\_LP$: Measured fuel pressure in the low pressure loop
- $ActPress_HP$: Measured fuel pressure in the high pressure loop
- $Odometer$: Vehicle millage at the time of data collection
- $DesPress\_LP$: Desired fuel pressure in the low pressure loop

2.2. Label propagation results: 2-dimensional analysis

Higher dimensional (i.e. multivariate) root cause analysis reveals simultaneous interconnection of multiple signals with a symptom, a more comprehensive root cause analysis approach compared to a univariate analysis (Kirdar, Green, & Rathore, 2008). The results of a 2-D analysis example are shown in Figure 9 for the fuel system case study of this report. Results show the label propagation reveals the intercorrelation between three different signals (including the symptom variable that was selected to be the high pressure pump error, ΔP_{HP}, similar to the 1-D case). As plotted in Figure 9, with the 2-dimensional classification, it is easier to identify the separation edge between major regions corresponding to each label from ΔP_{HP} status (High, Low) simultaneously for all the selected test signals ($Angl\_adj$ and $I\_feedBack$). In a general case of r-dimensional analysis and for a control system with K test signals, the total number of cases to be analyzed (Γ) would be

$$\Gamma = \frac{K!}{r!(K-r)!} \tag{9}$$

with r being the dimension of classification. For example,

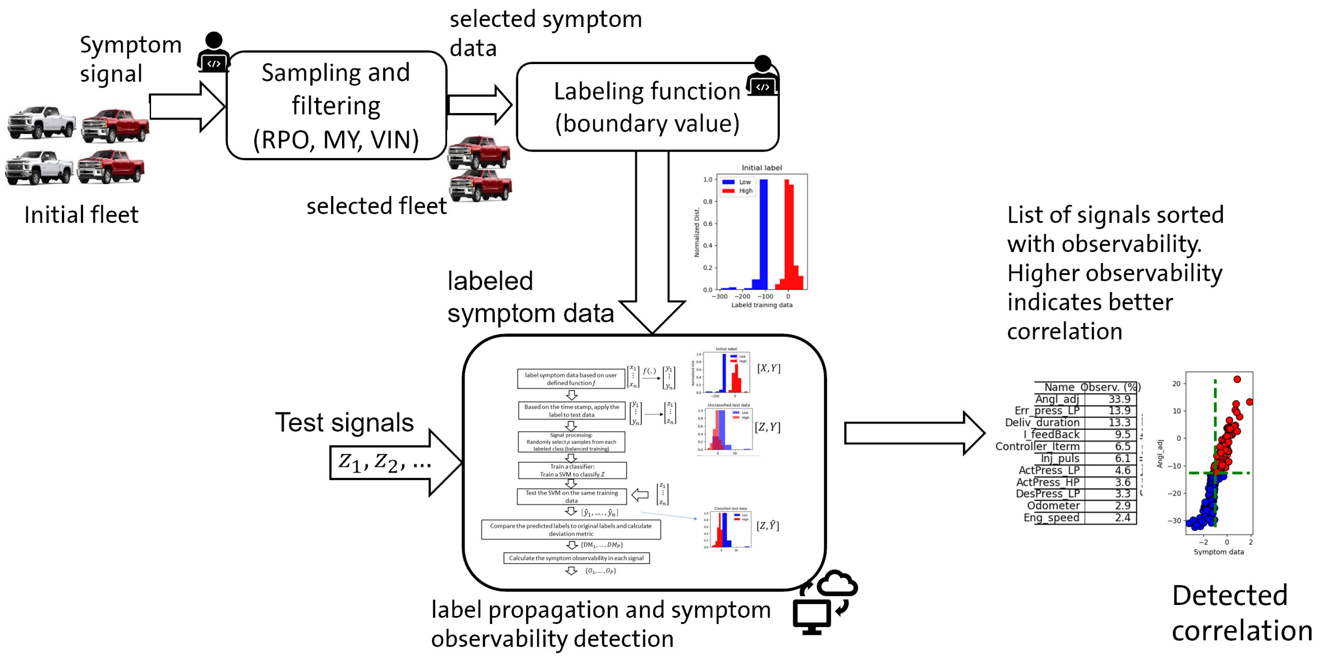


Figure 6. Architecture of implemented reasoning machine for label propagation and signal abstraction for the fuel system case study

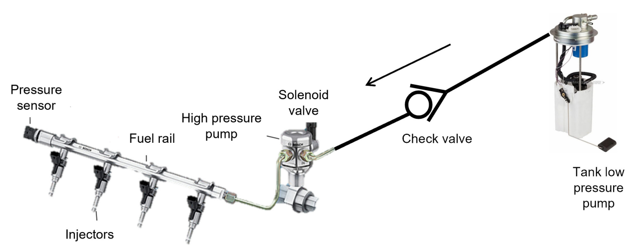


Figure 7. Major components of fuel system in a direct injection gasoline engine.

if $K = 10$, then for $r = [1, 2, 3]$ one need to analyze $\Gamma = [10, 45, 120]$ combinations of test signals with a selected symptom.

3. COMPARISON OF THE SVM-BASED LABEL PROPAGATION TO A LINEAR REGRESSION

The proposed label propagation method in section 2 is compared to a linear regression fit between the selected symptom (i.e. ΔP_{HP}) and each test signal. Deviation metrics (Eq. (7)) for the two classification results are shown in Table 2. Deviation metric indicates how the classification variable could be switched from the symptom into a test signal. Therefore, $DM = 0$ means no matter which variable (the symptom or the test signal) is used for the classification, the results would be the same. In another words, $DM = 0$ indicated perfect correlation between a test signal and the symptom variable. Table 2 compares the comparison between linear regression and label propagation with SVM. If DM is lower, that means the selected classification method was more successful to detect an existing correlation. For example, for the test signal "$Angl\_adj$", the SVM based label propagation classification results show a 70% better match compared to the linear regression. The DM difference, δDM, in Table 2 is defined as:

$$\delta DM = \frac{DM_{linearRegress} - DM_{SVM}}{DM_{linearRegress}} * 100 \quad (10)$$

The calculated DM differences in Table 2 suggest, for most of the test signals, existing relations could be revealed better with a general purpose classifier such as SVM that is suggested in this work, without any need for a known correlation kernel.

4. CONCLUSION

A signal abstraction methodology was proposed in this paper based on label propagation. The label, that was generated based on a symptom of a malfunction, was traced into a list of test signals for detection of existing correlations without needing the correlation kernel. It was suggested that test signals that show a high correlation with a symptom carry more diagnostics information and should be selected for building a root causing hypothesis. The proposed methodology was successfully tested for detection of existing relations in the fuel control system of a fleet of 5000 vehicles and was able to detect both nonlinear and linear relations between the controller

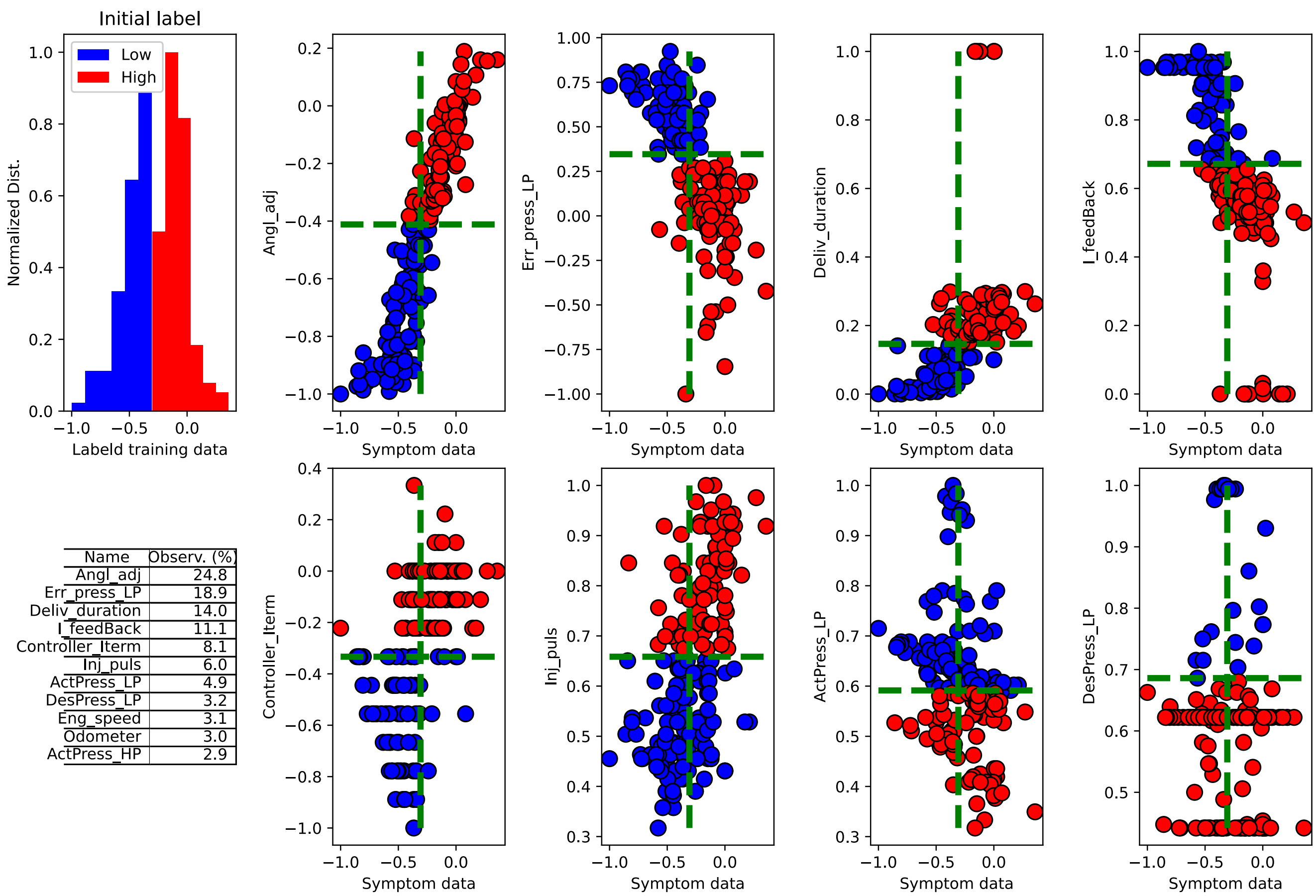


Figure 8. Results of label propagation and correlation detection for an analysis with high pressure pump error selected as the symptom (only 8 top observable signals plotted). The vertical dashed lines indicate the original separation edge in symptom domain and the horizontal lines show the separation edge in test signal domain after label propagation. All values are scaled.

Table 2. Comparision of DM between linear regression and nonlinear label propagation with SVM classifier.

Test signal name	DM_{LG}	DM_{SMV}	$\delta DM(\%)$
$Angl\_adj$	0.1	0.03	70.0
$Deliv\_duration$	0.12	0.12	0.0
$I\_feedBack$	0.125	0.12	4.0
Err_press_LP	0.13	0.115	11.5
$Controller\_Iterm$	0.19	0.185	2.6
Eng_speed	0.235	0.3	-27.7
Inj_puls	0.265	0.26	1.9
$ActPress\_LP$	0.315	0.365	-15.9
$ActPress\_HP$	0.43	0.43	0.0
$Odometer$	0.465	0.445	4.3
$DesPress\_LP$	0.495	0.49	1.0

error (selected as the symptom) and selected test signals.

REFERENCES

Chioua, M., Bauer, M., Chen, S.-L., Schlake, J. C., Sand, G., Schmidt, W., & Thornhill, N. F. (2016). Plant-wide root cause identification using plant key performance indicators (kpis) with application to a paper machine. *Control Engineering Practice*, *49*, 149-158.

Choroszucha, R. B., Sun, J., & Butts, K. (2015). Closed-loop model order reduction and mpc for diesel engine air-path control. In *Proceedings of american control conference.*

Isermann, R. (2022). *Automotive control modeling and control of vehicles*. Springer.

Kirdar, A. O., Green, K. D., & Rathore, A. S. (2008). Application of multivariate data analysis for identification and successful resolution of a root cause for a bioprocessing application. *Biotechnology progress*, *24*(3), 720–726.

Komsiyska, L., Buchberger, T., Diehl, S., & Ehrensberger. (2021). Critical review of intelligent battery systems: Challenges, implementation, and potential for electric vehicles. *Energies*, *14*, 5989.

Moulin, P., & Chauvin, J. (2011). Modeling and control of the air system of a turbocharged gasoline engine. *Journal of Control Engineering Practice*, *19*(3), 287–297.

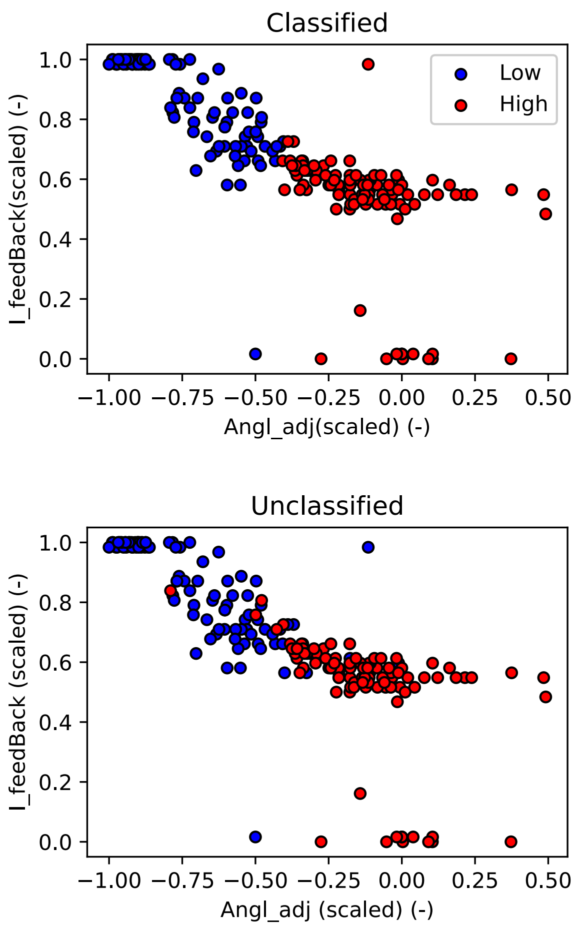


Figure 9. Results of 2D classification showing how the label propagation improves visualization of correlation between signals.

Naidu, D. S. (Ed.). (1988). *Singular perturbation methodology in control systems*. IET.

Naidu, D. S., & Calise, A. J. (2001). Singular perturbations and time scales in guidance and control of aerospace systems: A survey. *Journal of Guidance, Control, and Dynamics*, *24*(6), 1057-1078.

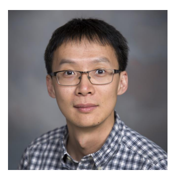
Salehi, R., & Stefanopoulou, A. (2020). Parameter set reduction and ensemble kalman filtering for engine model calibration. *Journal of Dynamic Systems, Measurement, and Control*, *142.1*, 287–297.

Sharma, R., Nesic, D., & Manzie, C. (2011). Model reduction of turbocharged (tc) spark ignition (si) engines. *IEEE Transactions Control System Technology*, *19*(2), 297–310.

Xiong, R., Sun, W., Yu, Q., & Sun, F. (2020). Research progress, challenges and prospects of fault diagnosis on battery system of electric vehicles. *Applied Energy*, *279*, 115855.

BIOGRAPHIES

Rasoul Salehi is a senior researcher at General Motors research and development. My major background is system modeling, identification, and control. Currently the focus of my work is on developing solutions for vehicle health management that includes detection, prediction and management of degradation in vehicle and its surrounding environment. Prior to joining GM, Rasoul was a research scientist at the University of Michigan in Ann Arbor.



Shiming Duan received the M.S. and Ph.D degrees in mechanical engineering from University of Michigan, Ann Arbor, MI, USA, in 2005 and 2011 respectively. He currently holds the staff researcher position in propulsion systems research lab, GM Global Research and Development Center, Warren, MI. His research interests include fault diagnostics and prognostics, big data analytics, machine learning, system identification, control of nonlinear systems, etc. He has published more than 10 peer review papers and holds 25+ patents or patent applications. He has been serving as an associate editor for Journal of Intelligent and Fuzzy Systems and served as panel for various international conferences and forums.