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Lifecycle Assurance Leadership for Multi-Plant ADAS and Restraint Product Deployment

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ABSTRACT

A number of plants are now simultaneously associated with the manufacture of advanced driver assistance module and airbag restraint controllers by auto parts suppliers. Each plant introduces a different variation in the calibration, testing, supplier management, and change management. To address this issue, this paper suggests the lifecycle assurance leadership as a managerial model, which links safety decisions integral to all stages up to concept, and field feedback. The model has six-dimension Lifecycle Assurance Index and a central assurance office where plant level leads are considered. We experimented the model in a year-long program in five plants which produced forward camera modules, front radar units and restraint controllers. The defect rate in the network decreased from 57.4 percent to 62.0 parts per million. Calibration escapes reduced by 71 percent and the time of audit findings reducing as much as from 41 to 17 days. There was a reduction of defect rate spread in plants by 38 percent. Regression analysis indicates that every one-unit increment in the index decreased the defects by 2.9 parts per million. Ramp up learning went up by a factor from 0.18 to 0.31. These findings show that leadership practice can be used to identify most of the quality difference between the plants.

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1. INTRODUCTION

Vehicle manufacturers have resorted to purchasing driver assistance sensors and restraint controllers' manufacturers that have multiple plants across locations. This part of change is explained by Industry 4.0 research. According to one review, new tools cause a transformation of factories as they apply the pull methods and technological advancement in new tools causes their push [1]. A second paper proposes four design principles to be used in connected factories that include interconnection, information transparency, technical assistance and decentralized decisions [2]. These principles assist a supplier to exchange data amongst plants. They fail to guide a leader to maintain stability of safety in those plants.

Driver-assistance safety work is different than a mechanical-part safety work. Koopman and Wagner explain that the task of safety of autonomous vehicles is not an engineering task but rather a multidisciplinary problem [3]. Wachenfeld and Winner demonstrate that driving

distance alone should be used to prove safety since the distance needed is so big that it proves impossible to drive [4]. Road mileage cannot thus be depended on by a supplier. It requires a lifecycle approach to join design proof, plant management and field statistics.

Additional challenges are restraint systems. An airbag controller needs to respond appropriately in a rare crash, and needs to remain silent in all other situations. Output will not be sufficient to validate this behavior of a plant. It has to be based on regulated procedures, measured test apparatus and regulated change management. When there is one product manufactured across five plants, a slight variation in such controls leads to unequal quality.

In this paper, leadership is taken as the missing link. Lifecycle assurance leadership implies that specific leaders are authorized to make decisions regarding safety evidence in each stage and within each plant. There are three aims of the study. The former is to establish a quantifiable measure of lifecycle assurance. The second objective will be to confirm that an increase in index scores reduces defect rates. The third objective is to determine whether the model can reduce the quality gap among the plants. The figure below (figure 1) displays lifecycle stages that the model includes.

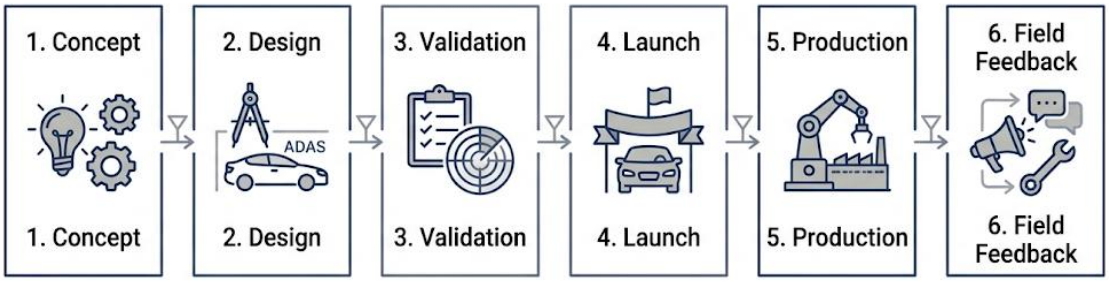


Figure 1. Stages of development of an ADAS and restraint product lifecycle, concept to field feedback, with a leadership gate at each stage

2. BACKGROUND

Scenario based testing is the primary avenue in testing driver assistance functions. An overview of this topic can construct a taxonomy of the methods and demonstrates the fitting of scenarios, test methods and formal verification [5]. The terms about scene, situation and scenario have been defined by Ulbrich and others in such a way that the engineers would think of them as a unit [6]. Such terms are then turned into generated test cases by ontology-based scene creation [7]. Another approach constructs libraries of test scenarios of connected and automated vehicles out of driving data [8]. Table 1 summarizes these and other streams and indicates the support of each one to the model.

Table 1. The streams of literature utilized to create the model, including the primary contribution of each stream and its application to this study

Literature stream	Main contribution	Use in this study	Source
Scenario based testing	Establishes functional, logical and concrete levels of the scenario	Structure for validation evidence per phase	[9]
Sampling efficiency	Makes use of importance sampling in reducing the assessment of rare events	Basis for risk weighted test coverage	[10]
Perception datasets	Offer the information of six cameras, a lidar, and five radars	Sensor volume reference	[11]
Digital twins and big data	Relate the physical production to the virtual models	Traceability and data sharing of plants	[12]
Quality 4.0	Checks large data issues in the manufacturing quality	Plant level analytics for the index	[13]

Literature stream	Main contribution	Use in this study	Source
Supply chain viability	Integrates agility, resilience and sustainability	Stability of suppliers when disrupted	[14]

The perception is at the heart of the product. An overview of autonomous driving practice reviews provide sensors, perception and planning, and it demonstrates that camera, radar, and lidar have various applications [15]. Learning based control introduces uncertainty and, a survey of deep learning in vehicle control enumerates open problems in safety and verification [16]. Some of the approaches to AI safety practicality solve this issue by inspecting and mitigating neural networks [17].

There are public datasets which demonstrate the size to which large perception evidence grew. The KITTI benchmark established an initial benchmark in vision tasks in driving [18]. Waymo Open Dataset contains twenty seconds long scenes counted 1,150 times in [19]. There are always products and plants to which a supplier has to handle evidence of this size.

In the factory side, digital twin research describes how to keep physical products and virtual models connected with each other via data [20]. Current work is not enough to be considered as leadership. It outlines tools and test technique, but leaves the decision of when evidence is adequate to undertake a launch in a particular plant, to whom it is allocated. This gap is filled in the next section.

3. LIFECYCLE ASSURANCE LEAERDHIP MODEL

The model consists of three sections. First is a gate structure which adheres to a lifecycle in Figure 1. The second section is the structure of governance that cuts across plants as shown in Figure 2. The third one is a Lifecycle Assurance Index.

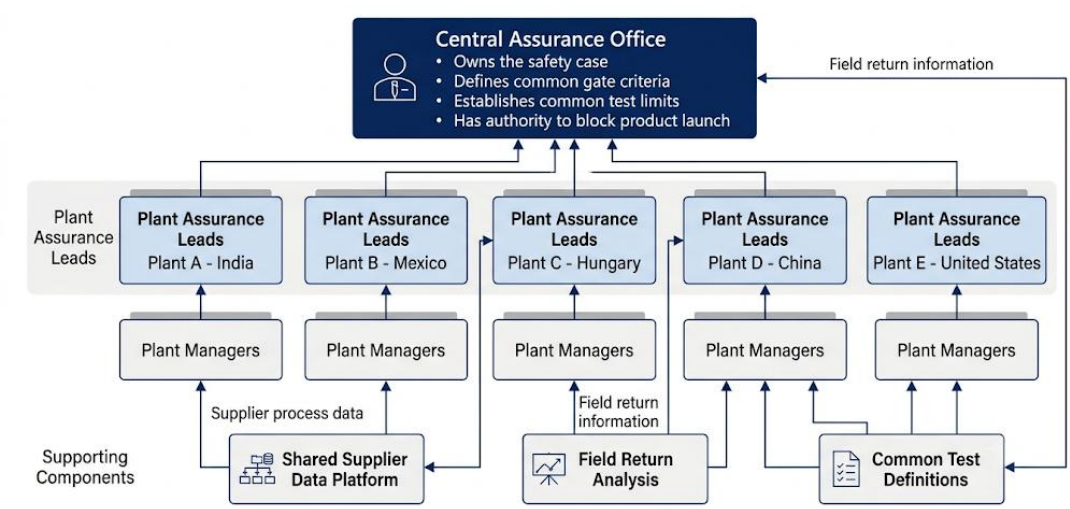


Figure 2. Governance architecture between the central assurance office, assurance leads at the plant, data feeds in supplier data and field analysis and returns

The safety case, the gate criteria and the common test limits are owned by a central assurance office. Plants also have an assurance lead, reporting to the plant manager and to the central office. The process data are sent to a common platform by suppliers. This design will enable the plant lead to halt a shipment. It provides the headquarters with the right to prevent a launch. This work is helped by shared test definitions, and the CommonRoad platform demonstrates how to achieve the comparability of sites with composable benchmarks [21]. Each of the leadership

decisions at the gates, the decision owner, and evidence basis are in Table 2.

Table 2. Each of the lifecycle gates of the assurance model has its leadership decisions, whether it is an owner or not, in addition to its evidence bases

Phase	Leadership decision	Decision owner	Evidence basis	Source
Concept	Formalize functional and hazard intended	Central safety lead	Analysis of hazard and risk	Internal gate criteria
Design	Design release and safety case to be validated	Engineering director	Twin based review of design and review of scenarios	[22]
Validation	Risk, accept test evidence and residual risk	Central assurance office	Results and analysis of sensor data and scenario results	Internal gate criteria
Launch	Start production in the plant	Plant assurance lead	Linked-equipment status/records of calibration	[23]
Production	Withhold or free freights	Plant manager	Part traceability and process data	[24]
Field	Closed or open correction	Quality director	Analysis of returns and comparison of plants	Internal gate criteria

Any gate has security within it. A comparison of methods of threat analysis and risk assessment of vehicles compares techniques which a gate can demand prior to release [25]. The threat analysis is hence examined by the central office at the design gate and review during the launch gate.

The index can rate every plant on six dimensions. These are the governance, design and safety case, process and supplier control, calibration and test assurance, field feedback and leadership capability. Each dimension has a score of 0 to 100 by an audit team. The score of plant p is added with equation (1) below:

$$\mathrm{LAI}_p = \sum_{k=1}^{6} w_k s_{pk} \qquad (1)$$

The s_{pk} denotes the score of plant p on dimension k. The weights are 0.20, 0.15, 0.20, 0.20, 0.15, and 0.10 in the order listed above. These weights are determined by a panel of twelve safety and quality leaders, and add up to one.

4. EXPERIMENTAL SETUP

It was conducted over a period of 24 months in five plants. It was the initial twelve months of the baseline. The initiative began in the 13th month. The vehicles manufactured a forward camera system, front radar system and driver airbag control system. Plant profiles are in table 3. The five plants had 11.0 million units shipped during the entire study.

Table 3. Five plants with region, volume, and volume share, assembly lines, shifts and products built

Plant	Region	Annual volume (thousand units)	Share of volume (%)	Assembly lines	Shifts	Products built
A	India	1,400	25.5	6	3	Camera, radar, restraint
B	Mexico	1,100	20.0	5	3	Camera, restraint
C	Hungary	900	16.4	4	2	Radar, restraint
D	China	1,300	23.6	6	3	Camera, radar, restraint
E	United States	800	14.5	3	2	Restraint
Total	Five regions	5,500	100.0	24	Not applicable	Three products

The overriding quality indicator is the rate of general defects per million parts. It is defined (like plant p in quarter t) by equation (2):

$$\text{PPM}_{pt} = \left(\frac{d_{pt}}{n_{pt}}\right) \times 1{,}000{,}000 \qquad (2)$$

The count d_{pt} consists of nonconforming units known as confirmed in final test or in customer plants. The quantity n_{pt} is the quantity of units shipped. The research also monitored first pass yield that according to Equation (3), is the product of the station yields.

$$\text{FPY} = y_1 \times y_2 \times \ldots \times y_m \qquad (3)$$

A small set of output indicators were used in the camera module test. This concept is an extension of direct perception studies which decode pictures into a limited number of driving affordances that engineers can test [26]. The radar test was also based on the same logic using the range and the angle indicators.

There were five actions in the program. A monthly review of the gates was conducted at the central office in each plant. Calibration limits were shared by all plants. The common platform was used to share process data between the suppliers. The target of a 14-day field return loop was imposed on the field return loop. There were several leaders of the plants who had attended a leadership course on gate decisions (38). The score of the index was done quarterly by an audit team.

5. RESULTS

Table 4 presents network outcomes of the baseline year and the program year. The rate of defect was reduced to 62.0 parts per million, compared to 145.7 previously, a reduction of 57.4 percent. First pass yield increased to 98.1 percent as against 96.2 percent. Calibration escapes decreased by 71.1 per cent and early field returns by 53.8 per cent. The findings of the audit were closed in 17 days rather than 41. The time dropped from 19 to 12 weeks to launch ramp time.

Table 4. The baseline year and program year network outcomes of seven quality and delivery measures expressed as percentages change

Measure	Baseline year	Program year	Change
Defect rate (parts per million)	145.7	62.0	57.4% lower
First pass yield (%)	96.2	98.1	1.9 points higher
Calibration escapes (per million units)	38	11	71.1% lower
Early field returns (per million units)	52	24	53.8% lower
Audit finding closure (days)	41	17	58.5% lower
Launch ramp to stable output (weeks)	19	12	36.8% lower
Engineering change cycle (days)	34	21	38.2% lower

The results of the plant level are presented in figure 3 and Table 5. Every plant improved. The range of changes in defect rates amounted to 53.7 percent in Plant E and 59.5 percent in Plant B. Plant B was the one with the greatest defect rate and increased by 30 index points. Plant E solely built restraint controllers and received the least index points, with 23.

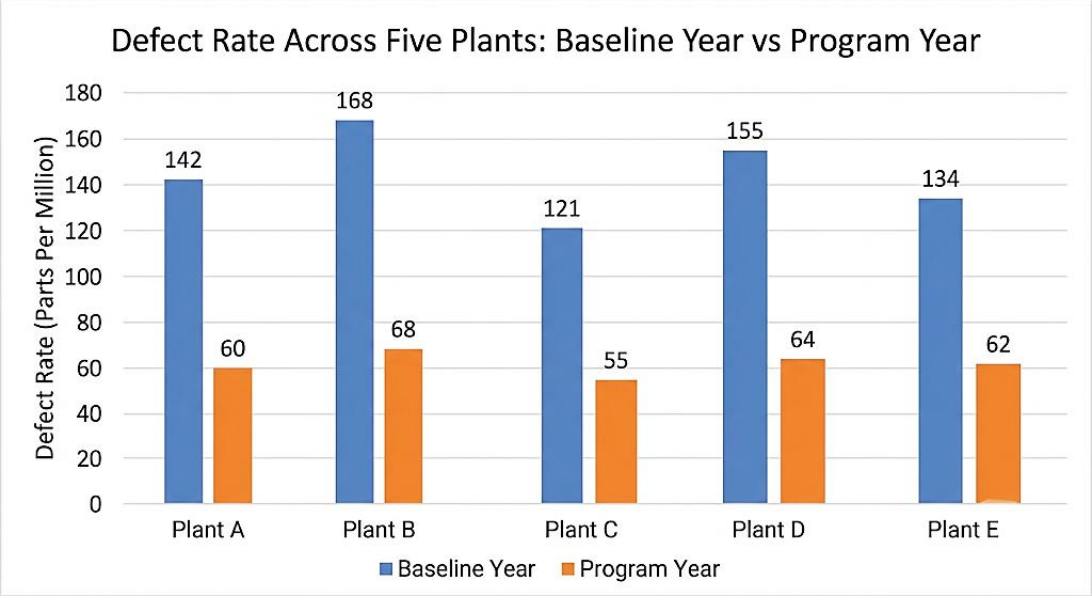


Figure 3. Parts per million defect rates in the five plants based on the five plants on the program year and the baseline year

Table 5. Lifecycle Assurance Index scores and rate of defects of plant level of the program year and the base year with percentage change

Plant	LAI baseline	LAI program	PPM baseline	PPM program	PPM change
A	58	86	142	60	57.7% lower
B	51	81	168	68	59.5% lower
C	64	88	121	55	54.5% lower
D	55	84	155	64	58.7% lower
E	60	83	134	62	53.7% lower
Mean	57.6	84.4	144.0	61.8	57.1% lower

The distance between plants was less. The spread calculated using equation (4) is the coefficient of variation that was given as the standard deviation/mean among plants.

$$\mathrm{CV}_t = \frac{\sigma_t}{\mu_t} \quad (4)$$

This coefficient dropped by 38 percent, to 0.078 in the program year as opposed to 0.127 in the base year. It was no longer clear that the plant that had the best baseline was out of reach of the others. The network defect rate by quarter is plotted in figure 4. The rate remained within the range of 145 during the four quarters. It dropped to 101 in the first program quarter that is a 29.4 percent decrease to the previous baseline quarter. It went to 33 in the eighth quarter that is 76.9 percent less as compared to the same quarter.

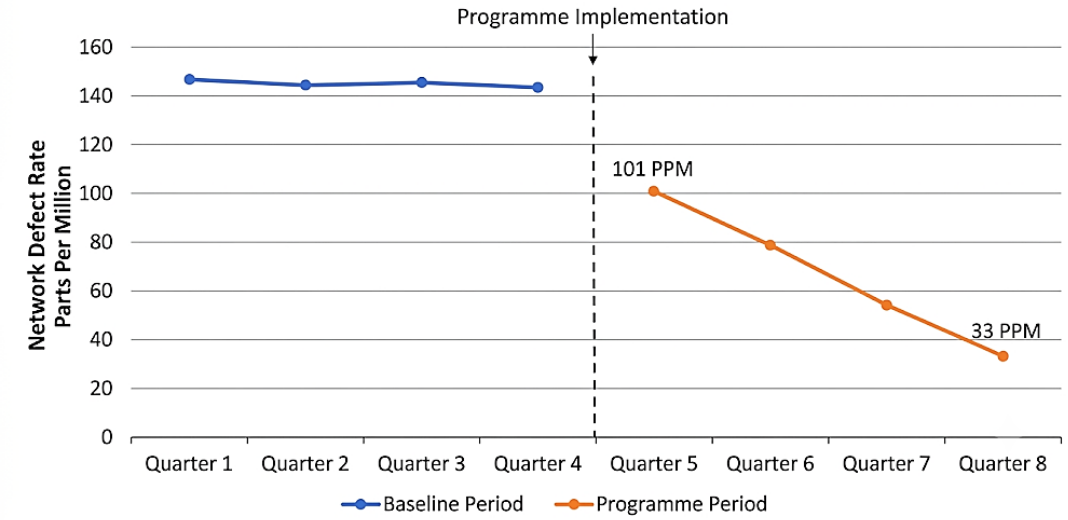


Figure 4. Network defect rate in eight successive quarters in parts per million and the program commences in the fifth quarter

Detection also improved. The probability of a defective unit passing through three consecutive controls is provided in equation (5) where c_j is the coverage of control j.

$$P_{esc} = (1 - c_1)(1 - c_2)(1 - c_3) \quad (5)$$

The three controls included in circuit test, functional and calibration test and final audit. The values of the baseline coverage were 0.88, 0.80, and 0.84 that provided an escape probability of 0.38 percent. Program values were 0.93, 0.88, and 0.92, which give 0.067 percent. The program, thus, reduced the escape probability by 5.7 times.

Equation (6) is used to fit a learning curve with D_n being the number of units that have been defected per thousand in week n after the launch and b is the learning exponent.

$$D_n = D_1 \times n^{-b} \quad (6)$$

The initial launch of radar variant provided D_1 = 9.4, b = 0.18. The program launch gave D_1 of 8.1 and b of 0.31. Week 12 shows that the program curve fitted gives 3.7 defects per thousand units vs 6.0 with the baseline curve. Both of these curves are presented in Figure 5.

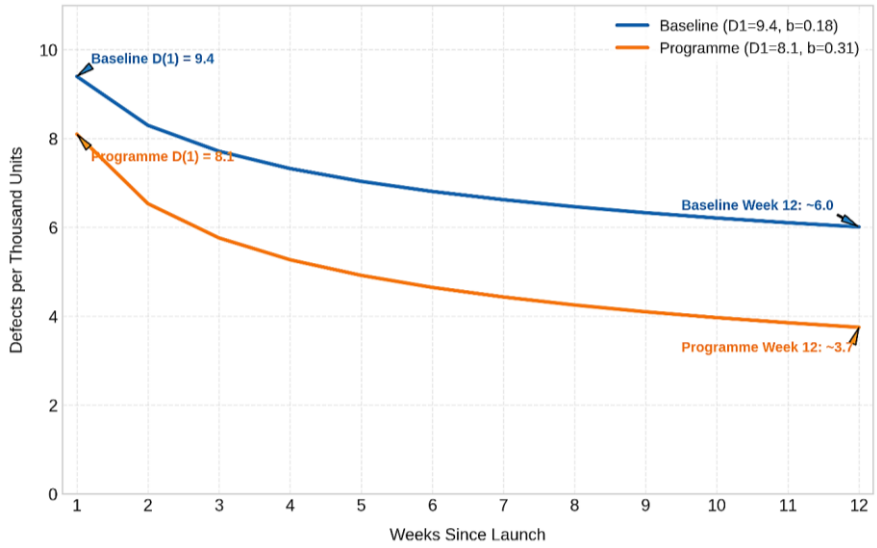


Figure 5. Baseline and program launch plotted fitted ramp up curves of defects per thousand units versus weeks since launch

The final test is associated between the index and the defect rate. Equation (7) also represents the quarterly defect rate as the regression of the index and production volume in threat units, based on 40 observations of the quarterly data of the plants.

$$\mathrm{PPM}_{pt} = \alpha + \beta \times \mathrm{LAI}_{pt} + \gamma \times \mathrm{VOL}_{pt} + \varepsilon_{pt} \quad (7)$$

The relationship of index score and defect rate is illustrated in Figure 6. Two models are reported in table 6. This is a slope of the pooled model of -2.9 parts per million per index point. The model with plant effects gives −2.4 and explains 83 percent of the variance. There is no apparent impact of volume in either model.

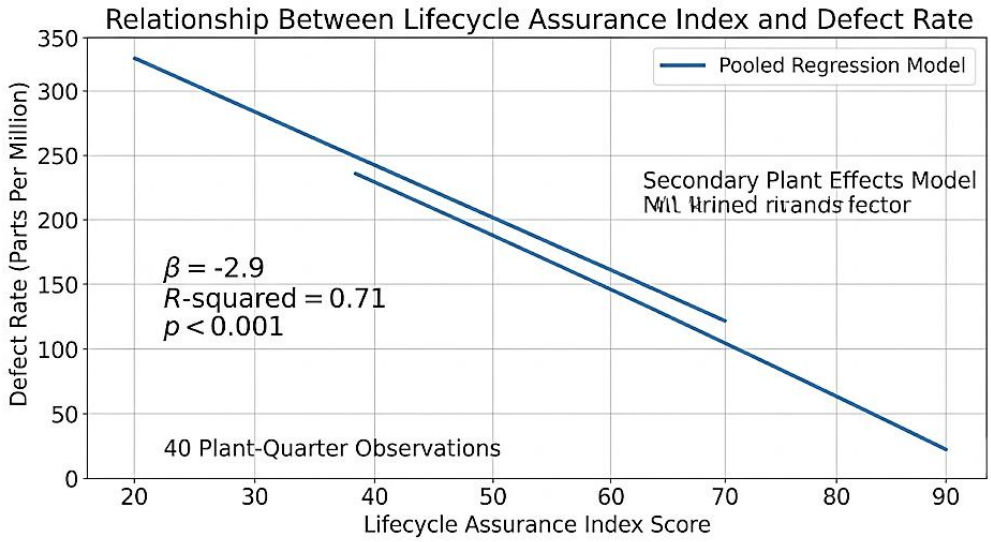


Figure 6. Plant quarter defect rate versus Lifecycle Assurance Index score with the estimated pooled regression line

Table 6. The pooled and plant effects model regression estimates of the rate of plant defects per quarter on Lifecycle Assurance Index and the production volume

Term	Model 1 pooled estimate (SE)	Model 1 p value	Model 2 plant effects estimate (SE)	Model 2 p value
Intercept	311.7 (18.6)	Below 0.001	Absorbed by plant effects	Not applicable
LAI score	−2.9 (0.35)	Below 0.001	−2.4 (0.39)	Below 0.001
Volume (thousand units)	0.011 (0.009)	0.24	0.006 (0.010)	0.55
R squared	0.71	Not applicable	0.83	Not applicable
Observations	40	Not applicable	40	Not applicable

6. DISCUSSION

The outcomes promote the three objectives. The index can be measured, it is connected with the defect rate, and the program reduced the discrepancy among plants. Table 6 has a large slope. A plant improving on a scale of 55 to 85 will move to 85 and this would mean that the plant would have fewer defects averaging 30 points under the pooled model representing 72 defects per million. That figure is similar to the 83.7-point drop in the network rate.

Leadership has revealed the reason why the gain was not even among the five plants. Plant E was most robust on baseline governance and had the least gain. Plant B was the weakest and had the biggest gain. This trend indicates that in areas where there was ambiguous authority, leadership

decisions are the most important. The gates allowed each plant led to have a clear right to halt a shipment and the central office to have a clear right to halt a launch.

There are limitations in the study. These findings are based on an experimental program data and require to be validated using real plant data. There is a small sample consisting of five plants. Audit grades are ordinal and the weights of those in charge of the panel can change the order. The authors did not determine the influence of the leadership training independent of the influence of the common calibration limits. Further work should verify the model on additional plants, additional levels to the suppliers, as well as on formal safety criteria in the audit score.

7. CONCLUSION

Lifecycle assurance of driver assistance and restraint product multi plant deployment was proposed in this paper. The model is a combination of a gate structure, a central assurance office and a six dimension index. In five plants the network fault rate was reduced by 57.4 percent, and the inter-plant spread was reduced by 38 per cent and ramp up learning was enhanced. Every unit (index point) reduced the number of defects by 2.9 parts per million in the shared model. The suppliers can implement the model through naming gate owners, scoring plants with the same index, and one platform of sharing process data. This is followed with a field trial, live plant records and weights audit.

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