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A Review of Recent Trends in Machine Diagnosis and Prognosis Algorithms

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Abstract

The machine diagnosis represents the fault condition monitoring system i.e. discrete or continuous in nature. The monitoring systems may include preset limit indicators such as green for good, yellow for warning and red for failure to notify low levels of fluid or pressure measurements. The machine prognosis represents the set of activities performed based on diagnostic information to maintain its intended operating condition before complete failure. In the automotive assembly plants, the avoidance of complete failure i.e. sudden breakdowns is desired since it causes economical misfortune to the companies. This paper intends to review and summarize various techniques, models, and its applications. In this paper, we also intend to review various BIW assembly processes. The critical robotic assembly failure modes are identified and FMEA table has been developed. Formulate a failure prediction methodology based on actual plant data exclusively for robotic body shop assembly process by formulating various diagnosis and prognosis prediction algorithms. Also, develop a methodology on how to apply some of the techniques for body shop assembly process in an automotive assembly plant.

Keywords – Markov process; time series; artificial neural networks; ARMA; genetic algorithm; FMEA; BIW; robotic welding; failure modes

1. Introduction

The US automotive industry has seen unprecedented worst market condition in the recent years. According to the Harbour report 2008, even though the US car companies were able to improve hours per vehicle (HPV) target year after year, which is now close to 20 hours per vehicle, but their profit margin, is not. The average labor cost per vehicle reduced from $1,800 to $1,000 due to continuous improvements in product, process and methods. But, the profit margin per vehicle is not increasing. Actually, the domestic auto makers are losing money from $400 to $1,400 per unit vehicle sold.

It is becoming very critical for the US automakers to increase plant throughput to sustain in the market place. A typical automotive body shop consists of about 700+ robots working in sync with other automated machines. The robots perform various processes such as welding, sealing, stud welding, inspection, loading and unloading of parts from weld fixtures, power and free conveyors, etc. It has become very critical for the body shop to continuously monitor the performance of these robots, automated machines, welding equipments, and conveyors and take proactive action.

2. Diagnostic and Prognostic Algorithms

The data acquisition techniques are used to collect and storage data of a physical machine. The signal processing usually analyses the waveform and multi-dimension data. The time- domain analysis is based on time waveform itself. The time-domain analysis is done by AR (autoregressive), ARMA (autoregressive moving average), and ARIMA (autoregressive integrated moving averages) models. The frequency - domain analysis is based on the transformed signal in the Frequency domain. The most widely used spectrum analysis is Fast Fourier Transformation (FFT). The time-frequency analysis, investigates both time and frequency domain for non-stationary waveform signals. The other one is wavelet transform analysis. The data containing large variables use multivariate analysis techniques such as principal component analysis (PCA) and independent component analysis (ICA). The AR models are used to analyze machine signal trends. The hidden Markov models (HMM) are used for event and condition monitoring together. The diagnostic mapping process is called pattern recognition.

The fault diagnostic techniques are categorized by three types: statistical approaches, artificial intelligent approaches, and model based approaches. The Statistical process control (SPC), Cluster analysis, HMM, Support Vector Machine (SVM) techniques are commonly known as statistical approaches. The Artificial Intelligence (AI) such as artificial neural network (ANN), fuzzy logic systems (FLS), fuzzy neural networks (FNN) and Genetic algorithms (GA) are some of the fault diagnostic techniques. The model based techniques utilize physical and explicit mathematical models of the monitoring machine. Based on this model, residual generation methods such as Kalman filter (Bayesian estimator of the current mean), parameter estimation, and parity relations are used to obtain signals, called residuals, which indicate fault presence in the machine. This approach is only effective if the model is accurate and it becomes so complex for large systems [1].

2.1 The Markov Process

The Markov process, named after the Russian mathematician Andrey Markov, is a mathematical model for the random evolution of a memoryless system, that is, one for which the likelihood of a given future state, at any given moment, depends only on its present state, and not on any past states. Over the years, the Markov processes has been successfully used by researchers to model past failure state or predict future state of processes or machines in aerospace, automotive and defense industries. The cutting tool wear monitoring and prediction of useful life was modeled using hidden Markov model (HMM), self organizing map (SOP) and dynamic HMM, and continuous HMM [2-6]. There are lot of research literatures published on bearing diagnosis and prognosis. A strategy to optimize bearing maintenance schedule was proposed with the application of condition-based monitoring techniques [7]. A robust condition based maintenance algorithm was developed for gearbox of Westland and SH-60 helicopters and remaining useful life prediction (RUL) using HMM techniques [8-10]. The diagnosis of pump systems was studied by Yang et al. [11] using a new model AR-HSMM (Auto-regressive Hidden Semi-Markov Model).

The maintenance strategy has evolved over the years. There are so many buzzwords used by the industries like, condition-based maintenance (CBM), reliability center maintenance (RCM), etc. A real-time health prognosis and dynamic preventive maintenance (PM) policy was developed for equipment under aging Markovian deterioration [12]. Guo and Yang [13] used Markov analysis technique to calculate reliability measures for safety systems that involve several typical reliability related factors. The structural parallel system with multiple failures was studied using Markov chain-line sampling method [14].

Another important aspect of maintenance is keeping accurate and optimum number of spares in inventory. The Markov process and the matrix-geometric approach was used to develop a cost model to obtain the optimal values of the number of spares and the number of servers while maintaining a minimum specified level of system availability [15]. Love et al. [16] proposed a method to decide, on failure to repair or renew based on the semi-Markov decision process. Welte [17] developed a new state diagrams in maintenance modeling when the inspection is non-periodic. Wu et al. [18] developed a simple formula to calculate availability and reliability of repairable systems using the Markov process.

The value of maintenance has intrinsic value and should be considered for optimal maintenance strategies [19]. Under the suitable cost structure, buffer size plays a role in optimal average-cost policy proved by the Markov decision process [20]. The Markov chain model was developed for analyzing activity based failure costs of quality in a batch manufacturing system [21]. Another cost factor is number of repair personal in the plant. Wu and Zhou [22] studied a repairable conseculive-k-out-of-n:G system with one repairman utilizing reliability theory incorporating fuzzy states. The difference between fuzzy reliability and conventional reliability compared.

Over the years, machine or processes diagnosis and prognosis, modeling is developed using Markov process for various applications. However, these techniques can be used only after the machine is installed. The machine development process itself must be integrated in to the product cycle to develop cost effective machines that have proper sensors, signals, preventive algorithms, self correcting its mistakes, requiring no or minimum maintenance for the intended life cycle.

2. 2 AR-ARMA-ARIMA Model

The time series-forecasting models forecast future events based on known past events and forecast future data points before they are measured. The time series analyses are often divided into two classes: Frequency-domain methods and Time-domain methods. The former based on spectral analysis and recently wavelet analyses and time series analyses regarded as model-free analyses well suited to exploratory investigations. The time-domain methods have a model-free subset consists of the examination of auto-correlation and cross-correlation analysis. The autocorrelation analysis examines serial dependence; whereas, the spectral analyses examine cyclic behavior which need not be related to seasonality.

The Box–Jenkins methodology, named after the statisticians George Box and Gwilym Jenkins, applies ARMA or ARIMA models to find the best fit of a time series to past values of this time series, in order to make forecasts. The time series model data can have many forms and represent different stochastic processes. When modeling variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearly on previous data points. Combinations of these ideas produce autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. The autoregressive fractionally integrated moving average (ARFIMA) model generalizes the former three. The ARMA model is used to successfully to monitor and forecast past, present and future condition of the machine by various researches in automotive and aeronautical fields.

The power consumption of active suspension of automotive system is predicted [23] using novel pseudo-linear method for the estimation of fractionally integrated ARMA. Hu and Liu [24] used AR (1) and ARMA (2, 1) models to predict automobile body shop assembly process variation. The steam turbine rotor failure forecasted by [25] using vibration signals and applying ARMA model. The condition based maintenance forecast for aeroengine performance parameters analyzed using ARMA model [26]. A simple and fast softwired tool wear state at every wear condition monitoring is developed using ARMA model [27]. A method to predict the future conditions of machines based on one-step-ahead prediction of time-series forecasting techniques and regression trees is proposed by Tran et.al [28].

The merits and demerits are analyzed by Aryal et al. [44] who proposed a hybrid ARIMA and Neural networks model to time series forecasting. The model outperformed ARFIMA and ANN used separately by using each model's unique features to capture different patterns in the data. Chang and Wu [45] compared two kinds of ARMA-autocorrelation computation merits, namely the recursive approach and the direct approach. The tube sealing method using fractal characteristics of ARMA is studied by [29]. Li et al. [30] proposed a simulation of blind identification with ARMA model and its application to machine fault diagnosis. Wang et al. [31] proposed a precise method to analyze the generalized time-varying series (or signal) whose mean, variance, autoregressive and moving average coefficients vary with time. The ARMA model is the best modeling tool to monitor the system as proposed by various researchers. The ARMA methodology is used in meteorology, communication, automatic control, structure response analysis, fault diagnosis and other fields.

2.3 Artificial Intelligence (AI) algorithms

In Artificial Neural Network (ANN), the information processing algorithm is similar to human brain that process information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. The ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. In the literature, two popular AI techniques i.e. artificial neural networks (ANN) and expert systems (ES) are used for machine diagnosis. The other AI techniques include fuzzy logic systems (FLS), fuzzy-neural networks (FNN), neural-fuzzy systems (NFS), and evolutionary algorithms (EA).

Cao et al. [32] developed a new hydraulic valve fluid field model based on non-dimensional artificial neural networks (NDANNs) to provide an accurate and numerically efficient tool in an automatic transmission (AT) hydraulic control system design which is better method than computational fluid dynamics (CFD) technique, which is numerically inefficient and time consuming. The turbine, compressor and gear wear status studied by Parthasarathy et al. [33] who developed a neural network model which predict temperature faster in comparison with the original models for Honeywell turbine and compressor components. Wang et al. [34] evaluated the performance of recurrent neural networks (RNNs) and neuro-fuzzy (NF) systems predictors using two-benchmark gear wear data sets. Through comparison, it is found that if an NF system is properly trained, it performs better than RNNs in both forecasting accuracy and training efficiency. The artificial intelligence techniques have been applied to the machine diagnosis and have shown improved performance over conventional approaches.

The genetic algorithm popularized by John Holland in the early 1970s. The process of biological evolution inspires the genetic algorithm. The GA is a heuristic search technique inspired by evolutionary biology: mutation, selection, reproduction [inheritance] and recombination. The GA is one of several evolutionary techniques for optimization. The Genetic algorithms are used in financial, industrial design using parameterization, scheduling, net work design by construction, routing, time series prediction, signal processing, database mining, control systems, artificial life systems, chemistry- molecular confirmation.

Kamali et al. [35] proposed a layered approach based on Q-learning, a reinforcement learning technique, on top of genetic algorithm to determine the best weightings for optimal control and design problems. Levitin et al. [36] presented an algorithm for determining an optimal loading of elements in series-parallel systems. Lei et al. [37] proposed an early warning method based on a discrete event simulation that evaluates cost-effects of an arbitrary allocation of failure risks for a simulated 3-machine production system. Yang et al. [46] proposed an optimization procedure based on GA to search for the most cost-effective maintenance schedule, considering both production gains and maintenance expenses. Makis [38] considered a multivariate Bayesian process mean control problem for a finite production run under the assumption that the observations are values of independent, normally distributed vectors of random variables. Pan et al. [39] modeled repairable systems using hierarchical Bayes model that are a compromise between the bad-as-old and the good-as-new.

The aircraft rotor dynamic system is studied [40] using applied Continuous Wavelet Transform (CWT) that utilizes harmonic forcing satisfying combination resonance. Ohue et al. [41] performed health monitoring and evaluation of dynamic characteristics in gear sets using wavelet transform (WT) method. Pedregal and Carnero [42] setup a condition monitoring system for turbine using vibration data based on the state-space framework whose associated recursive algorithms (Kalman filter and Fixed interval smoothing) provide the basis for probability of failure estimation. Swanson [47] used Kalman filters method to track changes in features like vibration levels, mode frequencies, or other waveform signature features. The prognostic utility for the signature features are determined by the transitional failure experiments.

Qiu et al. [43] introduced enhanced and robust prognostic methods for rolling element bearing including a wavelet filter based method for weak signature enhancement for fault identification and Self Organizing Map (SOM) based method for performance degradation assessment. Shi et al. [48] proposed a new approach based on the fusion of the wavelet transform (WT) and envelope spectrum for detecting and localizing defects in rolling element bearings. Samanta et al. [49] studied Nome placer gold deposit using two conditional simulation algorithms: sequential Gaussian simulation (SGSIM) and Gaussian Markov random (GMR) model based simulation. Tsai et al. [50] modeled the degraded behavior of components in a mechatronic system by a dynamic reliability equation, and the effect of PM activities to reliability and failure rate of components based on age reduction model. The optimal activities-combination at each PM stage was decided by using GA in maximizing the system unit-cost life. Ghazali et al. [51] modeled the neural network to predict the exchange rate signals; the British Pound to Euro and the Japanese Yen to British Pound. In order to deal with a dynamic behavior which exists in time series signals, the functionality and architecture of the ordinary feedforward RPNN were extended to a novel recurrent neural network architecture called Dynamic Ridge Polynomial Neural Network (DRPNN). Simulation results indicate that the proposed DRPNN offers significant advantages over feedforward RPNN and Multilayer Perceptron including such increment in profit return, reduction in network complexity, faster learning, and smaller prediction error. Ciarelli et al. [52] proposed a new version of a Probabilistic Neural Network (PNN) aiming at executing automatic classification of economic activities comparing the PNN algorithm against other classifiers. This approach surpassed the other algorithms in many metrics typically well known in the literature for the multi-label categorization problems. De Souza et al. [53] presented an experimental evaluation of Data Correlated VG-RAM WNN (VG-RAM WNN-COR) on multi-label text categorization and compared its performance with that of standard VG-RAM WNN and ML-KNN categorizers using two data sets composed of textual descriptions of economic activities of companies categorized manually according to lawful Brazilian economic activities. The experimental results showed that VG-RAM WNN-COR has an overall better performance than VG-RAMWNN and ML-KNN on the two databases for the set of metrics considered. Samsudin et al. [54] proposed a GAGMDH model combining the modified Group Method Data Handling (GMDH) method and genetic algorithm (GA) to study yearly cancer death rate in Pennsylvania. The empirical results with a real data set clearly suggest that the GAGMDH model can improve the forecasting capability of the model compared with optimal simple combining forecasting methods and neural networks combining forecasting methods.

One must be very cautious when selecting which algorithm to use otherwise one might end up with wrong prediction.

3. The Automotive Assembly Process

The automotive assembly process consists of three major process areas. The sheet metal body called Body-In-White (BIW) vehicle is produced in the body shop. Then, the BIW vehicle is painted in the paint shop where customer desired color is applied by robots to prevent sheet metal corrosion. In the trim, chassis and final (TCF) shop, the painted bodies are assembled with various TCF components including the final testing. In this paper we will review only the body shop processes and failures. In the body shop, there are five major sheet metal assembly lines that produce BIW assemblies. They are: (a) Under Body Complete (UBC) line– consists of Dash, Engine Box, Ladder, Floor sub assemblies, (b) Body Side Aperture (BSA) complete line – consists of BSA inner sub assembly, BSA outer sub-assembly, (c) Body Framing line – consists of Toy-tab, Body framing and Respot, (d) Roof assembly line, and (e) the installation of hang on panels- consists of fenders, doors, hood and trunk or lift gate sub-assemblies.

The BIW assembly processes flow is shown in Figure: 1.

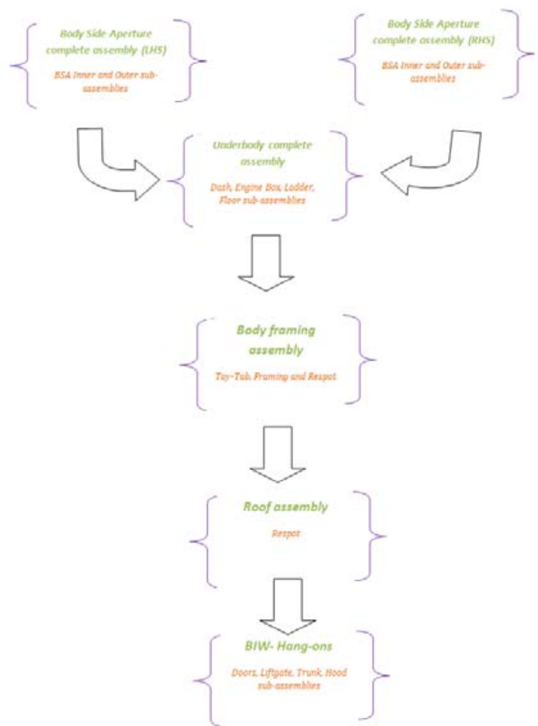

Figure: 1. BIW Assembly Process Flow

In Figure: 2, a typical weld assembly process station is shown with operator load, robot welding with material handling robots. The operator in operator station (OS) gets signal from production control system to load correct number of parts in proper assembly sequence in to geometry setting weld assembly fixture station #1 (WS1). In station #1, the part presence sensors read the number of parts and for proper shingling. After the parts load, the part sensors send signal to fixture clamps to close. After clamps close, the signal is sent to weld robots to initiate weld cycle operation. There are four weld robots (WR) inside the weld station #1, two on each side of the fixture. These robots in weld station #1 move from its home position to work position after receiving the signal. The work position signal is sent from robot to the servo weld gun which is mounted on axis 7 to start weld cycle. After the welding cycle is completed, the signal is sent from weld robots to weld fixture to open part clamps. After the clamps are opened, than the signal is sent to material handling robot to unload welded sub-assembly. The material handling robot (MHR) swings into work position from home position after receiving the signal. The robot end-effectors' clamps locate sub-assembly and close clamps and robot pickup the welded sub-assembly from station #1 and load on to the fixture in weld station #2 (WS2). The cycle continues in other stations in a similar fashion for all other automated robotic processes like, sealing, studding or quality inspection using camera vision.

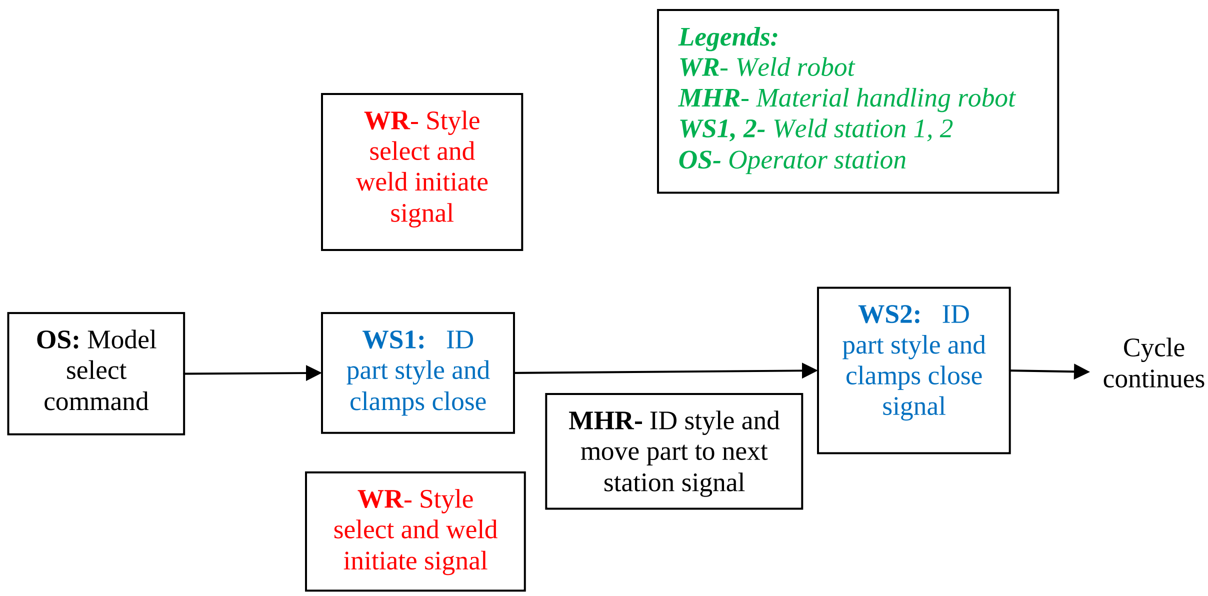

Figure: 2. Typical Weld Assembly Process Station

4. Automotive Assembly Failure Modes

The BIW vehicle assembly process failure modes are analyzed by a cross functional team during the design stages of manufacturing assembly process systems. The cross functional team consists of members from advanced manufacturing engineering, product engineering, plant assembly personal, sub-contract tooling vendors and various parts suppliers. This is a very critical step during initial stages of manufacturing process design. The Failure Mode and Effects Analysis (FMEA) is performed for each BIW assembly process. In the weld assembly process, there many failure modes present for example, the robot might fail to move, the weld gun might fail to weld, or the fixture clamps might fail to open or close etc.

The Failure Mode and Effects Analysis (FMEA) is a methodology designed to: Identify potential failure modes for a product or process. It assesses the risk priority number (RPN) associated with those failure modes based on Severity, Occurrence, Detection, and prioritizes issues for corrective action. Tumer and Stone [55] proposed the function–failure mode method to design new products or redesign existing ones with solutions for functions that eliminate or reduce the potential of a failure mode. This method is explained by a helicopter rotor blades using epicyclic transmission gear box design example. Bowles [56] suggested that the RPN approach should be dropped and entirely different prioritization techniques should be used. The recommendations are drop the detection and severity ranking. Instead these categories should be considered as nominal classifications (categorizations) for safety, operational, and cosmetic related failure mode effects.

In Figure 3, the various equipment and process failure modes for BIW assembly process are illustrated. As shown in Figure 3, tracking down the failure modes for each component function is very complex and it is very critical to trouble shoot the machine with minimal mean time to repair (MTTR).

The various failure modes are represented by a failure function:

$$\mathbf{Y = F(X)} \qquad \mathbf{(1)}$$

Y = Performance function

X = Vector of variables related to failure or reliability function

F = 1 means survival- no failure

F < 1 means failure has occurred- working

F = 0 means failure is impending or sudden failure.

The detailed explanation of failure modes: The robot dress package consists of pneumatic hoses and electrical wires that deliver power, air and water to the system. The compressed air is used to close clamps; the water is circulated to cool weld gun tips; the dress package is one of the critical items that should be monitored and maintained for the robotic operation. The individual components may also fail on their own due to their own premature life cycle.

The top of the diagram, show the overall failures due to the robot dress package failure mode ($X_{1,a\ \ldots f}$), the pneumatic clamps failure mode (X_2), and the sensor failure mode (X_3). The other equipment failures are: weld gun failure mode (X_4), welding fixture failure mode (X_5), sealing dispense failure mode (X_6) and lifter/transfer equipments failure mode (X_7) and lastly, the overall product mix failure mode depicted as (X_8).

Figure: 3 Critical failure modes in BIW assembly process

The Failure Mode and Effects Analysis (FMEA) is a methodology designed to: identify potential failure modes for a product or process. Assess the risk priority number (RPN) associated with those failure modes based on Severity, occurrence, detection, prioritizes issues for corrective action. The RPN number drived for various BIW process failures are shown in Table 1.

TABLE: 1. FMEA table for BIW Assembly Process

FMEA Number: FMEA Type: Process
FMEA Description:

Function Requirements	Potential Failure Mode	Potential Effect(s) of Failure	Sev	Class	Potential Cause(s)/ Mechanism(s) of Failure	Occur	Current Controls -Prevention	Current Controls -Detection	Detec	RPN	Recommended Action(s)	Responsibility	Target Completion Date	Action Results: Actions Taken	Sev	Occ	Det	RPN
1	2	3	4	5	6	7	8	9	10	11								
1. ROBOTIC PART UNLOAD FROM RACK USING VISION SYSTEM	a) Robot end effector crashes in rack	- Quality issues in build - Lost Production	7		Details on end of arm tooling out of location after crash	4	Master robot axis - control each axis to its intended position - EOAT Breakaway feature	Robot programmed path - Visual inspection of EOAT	4	112	MISBUILT. Manual Teach. Marked up Mastered part. Nest Fixture to quality. Develop SOP identifying all maintenance failure modes and recovery procedures			Develop and verify Failure modes/recovery procedure at the plant	7	2	2	28
2. ROBOT TO ROBOT PART HANDOFF	a. Robot and/or part out of position for welding	- Quality issues in build - Lost production	7		- Details on end of arm tooling is out of location	4	Gate line sequence - Time stamp - Extra spot on out side robots	- Vision or lack of part load to end effector - Part presence will not make	3	84	MISBUILT. ID welds with extra weld with a statement of purpose - CMM Check weld parts regularly			Process updated CMM check procedure in place	7	3	2	42
3. ROBOTIC (SERVO- GUN ON ROBOT ARM) WELDING	a. Minimum weld nugget diameter not met	- Quality issues in build - Lost Production	7		- Low water flow -	4	water flow meter calibrated for proper volume setting	Water flow meter signals low volume	1	28	QUALITY ISSUE: ID weld spot for manual repair			Process updated Weld destruct procedure in place	7	1	1	7
4. SERVO GUN (MOTOR) FAILURE	a. No Weld	- Quality issues in build - Lost Production	7		- Sheet metal quality issues - Too much force required to weld	4	- Weld gun calibration	-Control signal setup to warn	1	28	QUALITY ISSUE: ID weld spot for manual repair			Manual Process updated.	7	1	1	7
5. ROBOTIC (NOZZLE ON ROBOT ARM) SEALING DISPENSE	a. Small sealing bead diameter	- Quality issues in build - Lost Production	7		- Robot is too fast	3	Calibrate dispense equipment for proper temperature, volume and robot speed	Rerun to apply sealer again	1	21	DEVICE ISSUE: Recertify sealer bead with template sample			Template made available at the sealer station	7	1	1	7
6. SEALER/ADHESIVE EQUIPMENT FAULTS	a. No sealing material dispense	- Quality issues in build - Lost Production	7		- Sealer hardened during weekends	2	Purge sealer equipments per schedule at end and beginning of the shift and weekends	Post standard operating procedure	1	14	DEVICE ISSUE: Record sealer bead, volume, temperatures in the database for correct process parameters			Check sheet provided at the equipment set-up	7	1	1	7
7. PRODUCT MIX- Multi model mix	a. Wrong part loaded	- Quality issues in build - Lost Production	7		Details on end of arm tooling out of location after crash	4	Master robot axis - control each axis to its intended position - EOAT Breakaway feature	Robot programmed path - Visual inspection of EOAT	4	112	MISBUILT. Manual Teach. Marked up Mastered part. Nest Fixture to quality. Develop SOP identifying all maintenance failure modes and recovery procedures			Develop and verify Failure modes/recovery procedure at the plant	7	2	2	28

5. Summary and Research Directions

Several failure prediction mythologies are presented in this paper and the challenge is to properly selecting, applying and developing a new failure prediction model for the given application. Based on the study, a comprehensive forecast model will be developed exclusively for body shop robotic process to assist the automotive maintenance department. The actual automotive body shop failure data will be studied for suitability of various failure mode theories. The main focus of this research is to use actual plant failure data (variables) and develop comprehensive failure prediction model (dependency model) exclusively for BIW robotic assembly process. The future dissertation research also will develop a procedure to improve overall body shop plant maintenance policy. The automotive body shop assembly processes require continuous monitoring of the process equipments to achieve the production targets. The future research intends to bridge the gap between equipment failures and process failures by developing an appropriate diagnostic and prognostic algorithm exclusively for robotic automotive BIW assembly process.

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