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Artificial Intelligence for Predictive Maintenance of Armoured Fighting Vehicles Engine

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Abstract*_*Armoured Fighting Vehicles (AFVs) also called as Tanks play a critical role in modern warfare, providing mobility, protection and firepower on the battlefield. However, maintaining these complex machines and ensuring their operational readiness is a significant challenge for military organizations. Traditional maintenance practices are often reactive, resulting in unexpected failures, increased downtime, and operational inefficiencies. This paper focuses on the application of Artificial Intelligence (AI) for predictive maintenance of Armoured Fighting Vehicles. By harnessing the power of AI algorithms and advanced data analytics, predictive maintenance aims to anticipate and address potential equipment failures before they occur. This proactive approach enables military organizations to optimize resource allocation, improve operational planning and extend the lifespan of AFVs. The integration of AI in predictive maintenance involves collecting and analysing data from various sensors installed on the AFV engine. These sensors monitor key parameters, such as engine performance, temperature, vibration and fluid levels to detect anomalies and deviations from normal operating conditions. AI algorithms process this data, utilizing machine learning techniques to identify patterns, correlations, and potential failure indicators. The benefits of AI-based predictive maintenance for AFVs are multifaceted. Firstly, it enhances equipment readiness by reducing unexpected failures and maximizing operational availability. Secondly, it enables optimized resource allocation, ensuring that maintenance activities are scheduled efficiently, minimizing downtime, and improving overall operational efficiency. Thirdly, the predictive capabilities of AI help military planners in better decision-making allowing for improved mission planning and execution. However, the successful implementation of AI for predictive maintenance of AFV engine requires overcoming several challenges. These include data collection and integration from diverse sensors, ensuring data accuracy and quality, establishing robust communication infrastructure, and addressing cyber security concerns to protect sensitive vehicle data. This paper underscores the growing importance of AI in revolutionizing maintenance practices for Armoured Fighting Vehicles. By shifting from reactive maintenance to predictive strategies, military organizations can enhance their operational capabilities, reduce costs, and ensure the optimal performance and longevity of their AFV fleet.

Keywords: Armoured Fighting Vehicles, Predictive Maintenance, Artificial Intelligence, Data Analytics, Machine Learning, and Operational Readiness.

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I. INTRODUCTION

Armoured Fighting Vehicles (AFV) or Tanks have long been a symbol of power and dominance on the battlefield. These armoured vehicles have played a significant role in shaping the outcome of wars throughout history. From their humble beginnings in World War I to their highly advanced and sophisticated designs in the present day, tanks have proven to be an integral part of modern warfare. The concept of armoured vehicles was first introduced during World War I as a response to the stalemate of trench warfare. The British Mark I tank, introduced in 1916, was the world's first operational tank and set the stage for future developments. Early tanks were slow, mechanically unreliable, and lacked the advanced features of their modern counterparts. Over the years, tanks have undergone remarkable technological advancements. Improved armour protection, enhanced mobility, and advanced weaponry have transformed these armoured beasts into highly formidable war machines. Modern tanks feature composite and reactive armour, providing superior protection against anti-tank weapons. They are equipped with sophisticated fire control systems, thermal imagers, and advanced sensors, allowing for enhanced situational awareness and accurate targeting. The primary purpose of tanks is to provide firepower and support to ground forces. They are armed with a variety of weapons, including main cannons, machine guns, and anti-aircraft missiles. Main cannons can penetrate heavily armoured vehicles and fortified positions, while machine guns are effective against infantry and light vehicles. Tanks are versatile assets capable of engaging targets at various ranges and adapting to changing battlefield conditions. One of the defining features of tanks is their exceptional mobility. They are powered by powerful engines that allow them to traverse difficult terrains, including mud, snow, and rough landscapes. Tanks can operate on both roads and off-road, enabling them to swiftly move across the battlefield and seize key positions. Their ability to cross obstacles such as trenches and water bodies grants them a significant advantage in combat. Tanks play a pivotal role in modern warfare due to their strategic importance. They provide armoured protection to infantry forces, enabling them to advance under heavy fire. Tanks are also instrumental in breaching enemy defensive lines, conducting offensive operations, and supporting urban warfare. Their presence on the battlefield often serves as a deterrent to enemy forces and can change the dynamics of a conflict.

Maintaining these complex machines and ensuring their operational readiness is a significant challenge for military organizations. Traditional maintenance practices are often reactive, resulting in unexpected failures, increased downtime, and operational inefficiencies. The sudden or unexpected failure during war is catastrophic and may lead to defeat and thus requirement of Predictive Maintenance.

II. WHY PREDICTIVE MAINTENANCE

Predictive maintenance, enabled by advanced data analytics and sensor technologies, has several implications for military strategy, doctrine, and force structure. Here are some key implications [1]:

1. **Enhanced Equipment Readiness**. Predictive maintenance allows military organizations to monitor the health and performance of their equipment in real-time. By analysing data from sensors and predictive algorithms, potential failures or maintenance needs can be identified before they occur. This leads to increased equipment availability, reduced downtime, and improved overall readiness.
2. **Improved Operational Planning**. With accurate predictions about equipment maintenance requirements, military planners can better schedule and allocate resources for maintenance activities. This enables more efficient planning of **operational** missions, exercises, and deployments, reducing the risk of unexpected equipment failures during critical operations.
3. **Optimized Resource Allocation**. Predictive maintenance helps military organizations optimize their resource allocation. By **identifying** equipment issues in advance, maintenance activities can be scheduled proactively, ensuring that personnel, spare parts, and maintenance facilities are efficiently utilized. This leads to cost savings and improved utilization of limited resources.
4. **Extended Equipment Lifespan**. By proactively identifying and **addressing** potential maintenance issues, predictive maintenance can extend the lifespan of military equipment. This reduces the need for premature replacements and costly acquisitions, allowing for the more efficient allocation of budgetary resources.
5. **Enhanced Force Availability.** Predictive maintenance ensures that military forces have the necessary equipment available when required. This reduces the risk of equipment shortages or failures during critical missions, improving force availability and operational effectiveness.
6. **Data-Driven Decision Making**. Predictive maintenance generates a wealth of data about equipment performance and maintenance requirements. This data can be leveraged for informed decision-making at various levels, from tactical to strategic. It provides valuable insights into equipment reliability, maintenance trends, and resource allocation optimization.
7. **Shift in Maintenance Culture**. Predictive maintenance requires a shift in maintenance culture, emphasizing proactive and data-driven approaches. Military organizations need to develop the necessary skill sets, training programs, and organizational structures to effectively implement and manage predictive maintenance practices.
8. **Collaboration and Partnership**. Predictive maintenance often involves collaboration and partnerships with industry and technology providers. Military organizations may need to engage with external stakeholders to access specialized expertise, advanced analytics tools, and sensor technologies. This requires building partnerships and fostering collaboration with relevant industry players.

In summary, predictive maintenance has significant implications for military strategy, doctrine, and force structure. It improves equipment readiness, enables better operational planning, optimizes resource allocation, extends equipment lifespan, enhances force availability, facilitates data-driven decision-making, and necessitates a shift in maintenance culture. By embracing predictive maintenance practices, military organizations can enhance their operational capabilities and achieve cost savings while maintaining a high level of readiness. Predictive maintenance requires data which can be historical, sensors and weather condition and once sufficient data is available then AI models can predict equipment failure [3]. Present AFVs have only basic sensors which give engine oil temperature, Coolant temperature which gives input to the driver who ensures that the equipment does not fail due to overheating. An engine failure during operations will be catastrophic.

III. METHODOLOGY

Military College of Electronics and Mechanical Engineering (MCEME) based in Hyderabad has large number of tanks which they use for maintenance training of Electronics and Mechanical Engineering (EME) technicians. EME is a Corps of Indian Army which is responsible for repair of all equipment of Indian Army. Thus all the technicians of EME get trained in MCEME. The author while being the commandant of the college did an experiment of fitting sensors in the tank and taking their reading. The data is limited as Tanks consume large quantity of Diesel for a km of driving. Thus these reading could be taken during restricted usage especially during driver training. Help of nearby armoured units were also taken during their driving training. Details of Armoured Fighting Vehicles or Tanks are not being covered in this thesis as they are confidential in nature. The aim being only to validate as to how AI could be used in predictive maintenance of tanks. For developing AI model certain parameters have to be continuously monitored and thus there is a requirement of fitting large number of sensors for supply of continuous stream of data from engine which can be analysed to predict Remaining Useful Life (RUL) of an engine [4]. The entire sys would consist of various sensors like Oil Pressure Sensor, Engine vibration Sensor, Torque sensor, Coolant temp sensor, Fuel consumption sensor, Exhaust sensor, Acoustic Sensor and data logger which would be employed on the AFV as part of remote diagnostics mechanism [5-10]. The sensors would be of compact size, so that it can be mounted easily on various assembly/sub system of the AFV, without hampering the design and overall functioning of the tank.

The figure 1 depicts the type of sensors required to be fitted on the tank for statistical analysis leading to predictive maintenance. Ideally all the sensors should be fitted on each and every tank and reading obtained continuously over long distance. As the sensors are expensive, it was decided to take reading of three sensors and see if they have any relationship with engine hours. The tank engine running is always measured in number of hours due to static running and km covered is also converted to number of hours. Two sensors i.e. oil pressure sensor and coolant sensor were already fitted in the tank. For this experiment Oil Pressure sensor, Coolant Temp sensors were selected along with a strap on Vibration acceleration sensor. The Vibration acceleration sensor was fitted on the Tank under test and after completion of test, the same was removed and fitted in the next tank. Fuel consumption is heavy during running of tank, hence limited readings were taken during driver training.

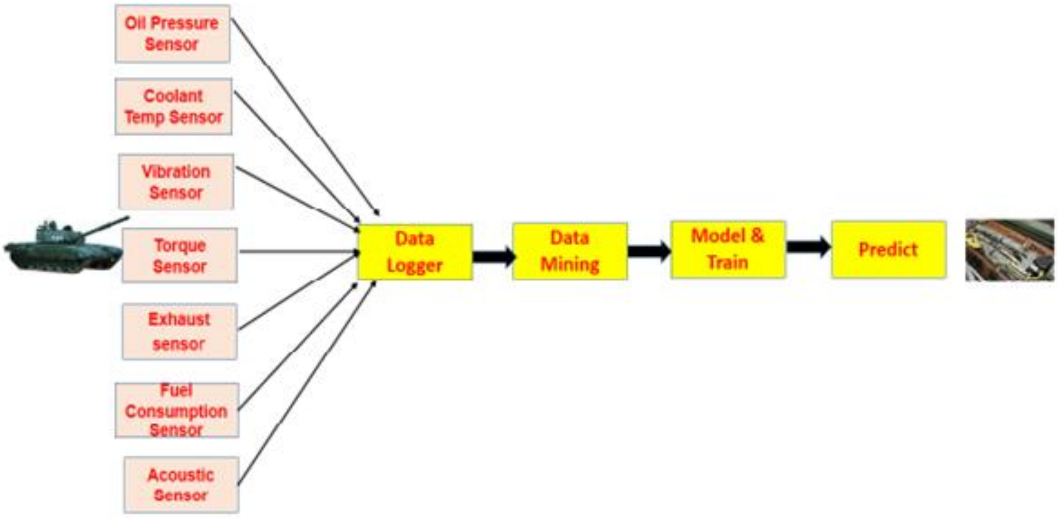

Fig 1 –Predictive Maintenance of Armoured Fighting Vehicle Engine

A. Basis for Selection of Sensors.

1. **Oil Pressure Sensor**. Inside any diesel engine, oil plays three important roles; lubricating, cooling and cleaning. The oil pressure is an indication of the health of the engine. For engine components to work smoothly, oil pressure must be within prescribed limits. Oil Pressure involves several main elements to include oil pump, lubricant and distance it travels to reach the various parts. It is measure of force pushing the lubricant through oil pump as well as the distances it must cover i.e. the length of pipes, joints and filters it must pass through, among other parts, which reduce this force. This sensor indicates level between the min and max range which shows lubricant process is smooth. If it is not within prescribed limit, it implies that the Oil pump is faulty and needs corrective maintenance. This is not feasible during battle and thus the importance of predictive maintenance. The data can be obtained through the sensor already placed in the sys, as depicted in Fig 2.

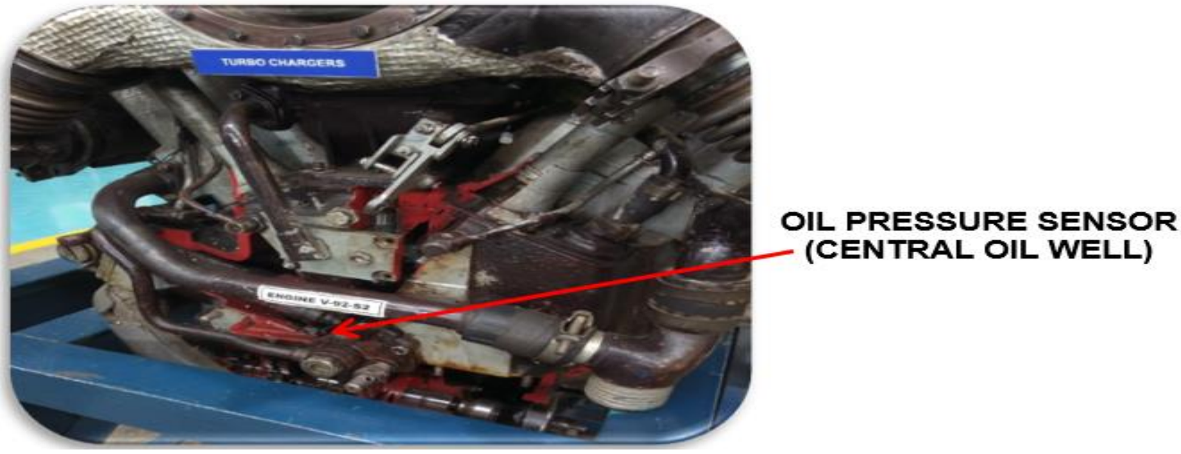

Fig 2 – Oil Pressure Sensor in Armoured Fighting Vehicle (AFV)

2. **Coolant Temp Sensor**.Overheating is one of the major fault observed in the AFV engines, which occurs mainly due to faulty gasket, blocked ferrules, insufficient compression etc. Coolant temp has effect on volumetric efficiency. High coolant temperature decrease cooling. It also has effect on NO_x emissions and minor effect on volumetric percentages of O_2, CO_2 and CO. This sensor is used to measure the temp of the engine which will help in monitoring the coolant temp, so as to make sure the engine is running at the optimum temp. If the temp is high than max value, it means engine is overheating.

If the coolant temperature is not within range then it implies that the coolant could be leaking or faulty water pump or faulty water pump gasket or broken thermostat. If temp indication is less than min, even after engine has warmed up, means the display is faulty. Thus in both cases corrective maintenance is required to be performed which takes time and is not feasible during battle. Thus the importance of predictive maintenance. The data can be obtained through the sensor already placed in the sys, as depicted in Fig 3.

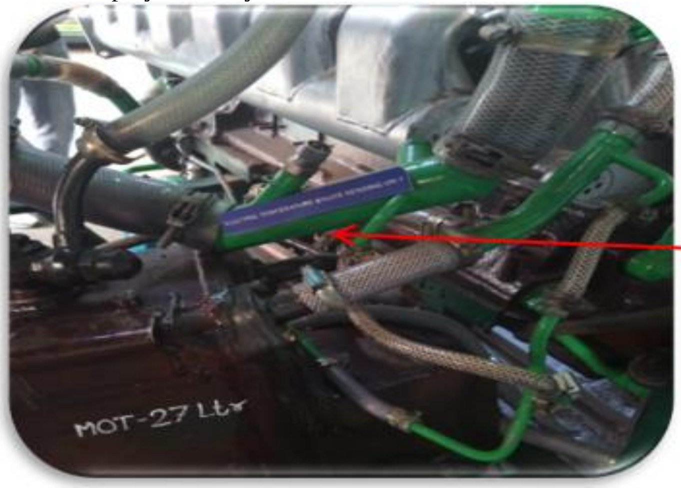

Fig 3 –Engine Temperature Sensor

3. **Engine Vibration Sensor**. Vibration plays a very important role in efficient function of an engine. Vibration can cause reduction in engine power by interfering with the functioning of engine. Torsional vibration of the crankshaft leads to drastic reduction in engine power. This vibration is mostly caused by the large amount of oscillating torque on the crankshaft due to move of piston back and forth in the cylinder. As the engine gets older, the vibration increase due to loose engine parts. The vibration produced by lesser run engines is less as compared to engines with higher run engines. Due to heavy noise of the engine the vibration noise gets merged to engine noise and thus it is not possible to pin point the reason for loss of engine power. Thus the importance of predictive maintenance. The infinite uptime sensor, being a magnetic one was fitted on the upper crankcase bolt, close to the engine to obtain accurate readings

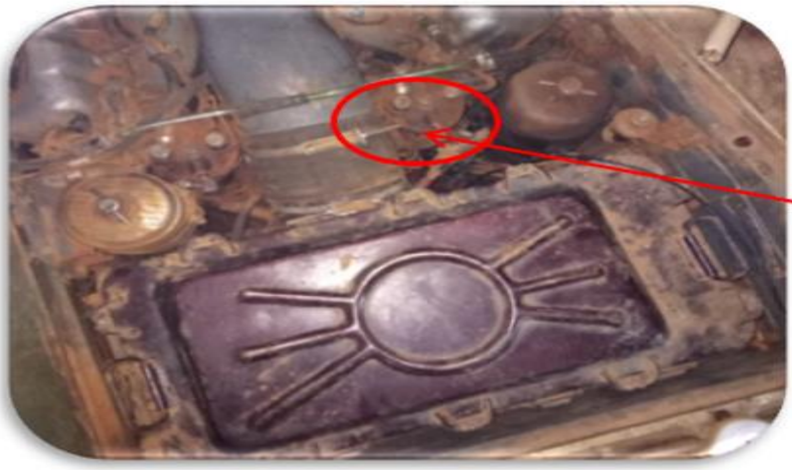

Fig 4 - Engine Vibration Sensor

B. Relationship Between Oil Pressure And Health Of Engine. The oil pressure in an engine is a critical factor that directly affects the health and performance of the engine. It plays a vital role in lubricating the various moving parts within the engine, reducing friction, and carrying away heat. The relationship between oil pressure and the health of the engine can be summarized as follows:

1. **Lubrication**. Adequate oil pressure ensures proper lubrication of the engine components. The engine oil forms a thin film between moving parts, such as the pistons, crankshaft, camshaft, and bearings. This lubrication reduces friction, prevents metal-to-metal contact, and minimizes wear and tear.

Cooling.Engine oil also helps in dissipating heat generated by the moving parts. It absorbs heat from components like the pistons and cylinder walls and carries it away to the oil pan, where it can be dissipated. Sufficient oil pressure ensures that the oil reaches all the necessary areas, effectively cooling the engine. Inadequate oil pressure can result in poor heat dissipation, leading to overheating and potential damage to the engine.

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2. **Seal Integrity**.Proper oil pressure helps maintain the integrity of gaskets and seals within the engine. The oil pressure assists in keeping the seals properly lubricated and prevents oil leaks. If the oil pressure is too low, it can lead to seal degradation, causing oil leaks and potential contamination of other engine systems.

3. **Oil Circulation.** The oil pump is responsible for circulating the engine oil throughout the system. It draws oil from the oil pan and sends it to the necessary areas under pressure. Insufficient oil pressure can indicate a problem with the oil pump or a blockage in the oil passages, hindering proper oil circulation. This can result in inadequate lubrication and cooling, leading to engine damage.

C. Data Set. A large number of data set is required for application of AI and meaningful prediction. The minimal data set even for normal distribution is thirty. Data generated from various sensor fitted into the tanks are in Table 1. Each of the Tank were run for only ten minutes and fifteen readings taken. The mean of those fifteen readings have been recorded in the table. The complete exercise was done over a week. The registered number of tanks have been replaced with ser number to ensure confidentiality.

Table1. Dataset for Predictive Model

S. No	Engine Hours	Vibration accelerometer (M/S^2)	Coolant Temp In Celsius	Oil Pressure (Kg/Cm^2)
1	118	235	65	9.8
2	118	214	65	9.8
3	122	208	65	9.2
4	162	240	58	8.8
5	162	231	58	8.8
6	234	261	60	10
7	260	270	60	10
8	296	269	62	9.2
9	306	266	70	9.4
10	324	266	70	8.6
11	324	257	70	8.6
12	344	260	70	8.7
13	380	309	72	8.7
14	380	299	72	8.7
15	517	287	80	8.4
16	560	322	75	8.2
17	863	305	70	8.2
18	863	312	70	8.2
19	961	428	75	8.2
20	1041	385	78	7.8
21	1041	374	78	7.8
22	1087	440	80	7.8
23	1087	426	80	7.8
24	1141	428	81	7.7
25	1152	429	81	7.7
26	1255	431	82	7.6
27	1257	435	82	7.5
28	1288	437	84	7.5
29	1412	442	83	7.4
30	1428	448	85	7.4
31	1573	457	85	7.3
32	1587	457	87	7.4
33	1623	458	86	7.3
34	1652	462	87	7.2
35	1674	465	87	7.2

IV. CORRELATION AND REGRESSION

The correlation factor, also known as the correlation coefficient, measures the strength and direction of the linear relationship between two variables. It is denoted by the symbol "r" and ranges between -1 and +1. A correlation coefficient of +1 indicates a perfect positive linear relationship, meaning that as one variable increases, the other variable also increases proportionally. A correlation coefficient of -1 indicates a perfect negative linear relationship, meaning that as one variable increases, the other variable decreases proportionally. A correlation coefficient of 0 indicates no linear relationship between the variables. The correlation coefficient is calculated using statistical methods and can help determine the degree to which two variables are related. However, it only measures linear relationships and may not capture other types of relationships, such as nonlinear or causal relationships. The Correlation between the Engine hours with Vibration, Coolant temperature and Oil Pressure were checked and are as under:-

1. Correlation between Engine hours and Vibration – (0.9656)
2. Correlation between Engine hours and Coolant Temperature –(0.772)
3. Correlation between Engine hours and Oil Pressure – (-0.9215)

A. Analysis of Correlation Factor.

1. **Correlation Between Engine Hours and Vibration**. A correlation coefficient of 0.9656 indicates a strong positive correlation between the two sets of data. The value of 0.9656 represents a high degree of linear association between the variables. In simpler terms, a correlation of 0.9656 suggests that there is a strong tendency for the two sets of data to move together in a positive direction. As one variable increases, the other variable is likely to increase as well, and vice versa. The closer the correlation coefficient is to 1, the stronger the positive relationship between the variables.

2. **Correlation Between Engine hours and Coolent Temperature**. A correlation coefficient of 0.772 indicates a strong positive relationship between the two sets of data. It suggests that there is a strong tendency for the variables to move together in a consistent pattern. In simpler terms, when one variable increases, the other variable is likely to increase as well, and when one variable decreases, the other variable is likely to decrease too.

The magnitude of 0.772 indicates that the relationship is fairly strong, meaning that the variables are related and tend to change in a similar direction.

3. **Correlation between Engine hours and Oil Pressure.** A correlation coefficient of -0.9215 indicates a very strong negative relationship between the two sets of data.It suggests that as one variable tends to increase, the other variable tends to decrease, and vice versa. In simpler terms, when one variable shows a tendency to go up, the other variable tends to go down, and when one variable shows a tendency to go down, the other variable tends to go up. The magnitude of -0.9215 indicates a close and highly reliable inverse relationship between the variables.

4. **It is important to understand that correlation does not imply causation.** While a high positive or negative correlation coefficient suggests a strong relationship, it does not provide information about the cause-and-effect relationship between the variables. Correlation measures the strength and direction of the linear association, but it does not reveal the underlying reasons or mechanisms behind the relationship for which one has to look at regression analysis[11,12].

B. Regression Analysis between Engine Hours and Vibration. The data collected from 35 x Tanks with Vibration was plotted against the engine hrs run and fwg graph was obs. The graph clearly indicates that there is increase in vibration readings in the older engines i.e in the rg of 400-450 m/s² vis-à-vis younger engines having oil pressure in the rg of 200-300m/s². A statistical analysis will further confirm if it is case of linear regression.

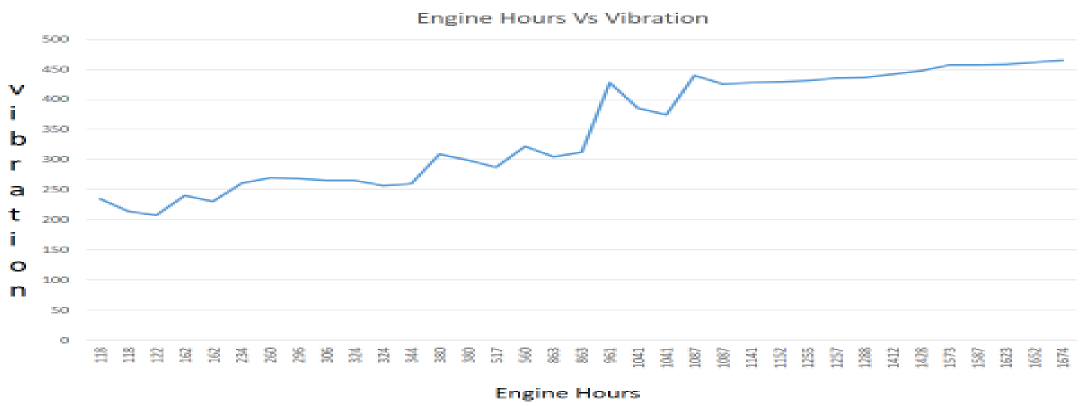

Chart1: Oil Pressure vs Engine Hrs Analysis

Statistical Analysis.

Regression Statistics								
Multiple R	0.965522177							
R Square	0.932233074							
Adjusted R Square	0.93017953							
Standard Error	23.81545891							
Observations	35							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	257477.075	257477.075	453.9632094	7.33714E-21			
Residual	33	18716.81074	567.1760831					
Total	34	276193.8857						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	216.647206	7.399940735	29.27688393	3.4401E-25	201.5919134	231.7024986	201.5919134	231.7024986
X Variable 1	0.161945572	0.00760079	21.3064124	7.33714E-21	0.146481648	0.177409496	0.146481648	0.177409496

1. **Multiple R.** The multiple correlation coefficient is 0.9655, indicating a strong positive relationship between the variables.
2. **R Square**. The coefficient of determination (R-squared) is 0.9322, which means that approximately 93.22% of the variance in the dependent variable can be explained by the independent variable(s) in the model.
3. **Adjusted R Square**. The adjusted R-squared value is 0.9302. It takes into account the number of independent variables and provides a slightly more conservative estimate of the goodness of fit compared to R-squared.
4. **Standard Error.** The standard error is 23.8155, representing the average deviation of the observed values from the regression line. Smaller values indicate a better fit.
5. **ANOVA**. The ANOVA table breaks down the sources of variation in the data.

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- **Regression**. With 1 degree of freedom (df), the regression explains a significant amount of the total variation, as indicated by the large F-statistic of 453.96. The associated p-value (7.33714E-21) is very small, suggesting that the relationship between the variables is statistically significant.
- **Residual**. The residual or error variation, representing the unexplained variability, has 33 degrees of freedom.

6. Coefficients

- **Intercept**. The intercept coefficient is 216.6472. This represents the estimated value of the dependent variable when the independent variable(s) are zero.
- **Engine Hrs**. The coefficient for "Engine hrs" is 0.1619. This indicates the estimated change in the dependent variable for a one-unit increase in the independent variable.
- For both coefficients, the standard error represents the average variability in their estimates. The t-statistic assesses the significance of each coefficient, with higher absolute values indicating greater significance. The p-values for both coefficients are very small, suggesting that they are statistically significant.
- The lower and upper 95% values represent the confidence intervals for each coefficient. The intervals indicate the range within which the true population values are likely to fall with 95% confidence.
- In summary, based on the provided regression statistics, there is a strong positive relationship between the variables. The regression model explains approximately 93.22% of the variance in the dependent variable. Both coefficients are statistically significant, suggesting that they have a significant impact on the dependent variable. The intercept indicates the expected value of the dependent variable when the independent variable(s) are zero, and the coefficient for Engine Hours represents the estimated change in the dependent variable for a one-unit increase in the independent variable. Thus engine vibration is an important factor towards the predictive model

C. Regression Analysis Between Engine Hours and Coolent Temp. The data collected from 35 x Tanks with Coolant Temp was plotted against the engine hrs run and fwg was observed. There is a sinosidal variation in temp as the engine hours increases but it clearly indicates that there is increase in Coolant temp, In the older engines i.e in the rg of 80-87 degree centigrate vis-à-vis younger engines having Coolant Temp in the rg of 65-70 degree cent. Further statistical analysis will be carried out to confirm the linearity.

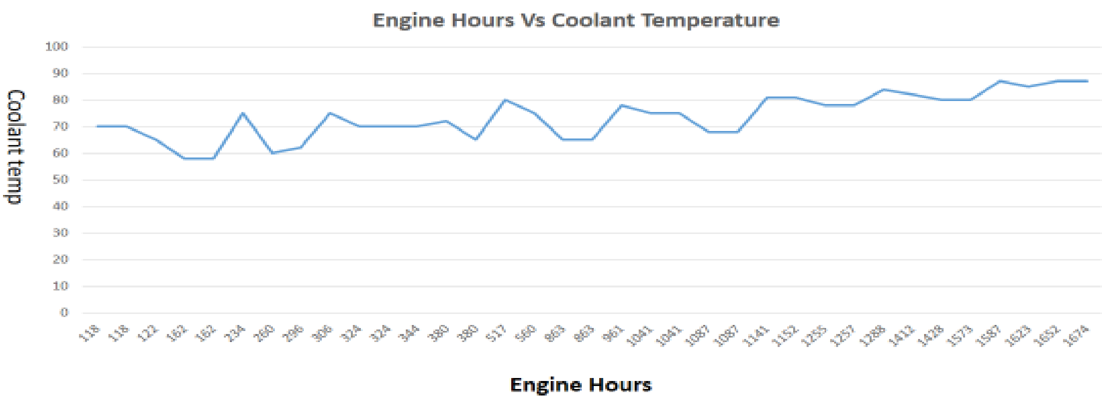

Chart 2: Coolent Temp vs Engine Hrs Analysis

Statistical Analysis

Regression Statistics								
Multiple R	0.77185525							
R Square	0.595760526							
Adjusted R Square	0.583510845							
Standard Error	5.398948136							
Observations	35							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	1417.637705	1417.637705	48.63477877	5.66669E-08			
Residual	33	961.905152	29.14864097					
Total	34	2379.542857						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	63.86916361	1.677561469	38.07262195	7.55002E-29	60.45613914	67.28218809	60.45613914	67.28218809
Engine Hours	0.012016623	0.001723094	6.973863977	5.66669E-08	0.008510962	0.015522284	0.008510962	0.015522284

1. **Multiple R.** The multiple correlation coefficient (R) is 0.7719. It represents the strength and direction of the linear relationship between the predictor variables and the response variable. In this case, it indicates a relatively strong positive correlation.

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2. **R Square.** The coefficient of determination (R^2) is 0.5958, which means that approximately 59.6% of the variability in the response variable can be explained by the predictor variable(s) included in the regression model. This suggests a moderate level of explanatory power..
3. **Adjusted R Square**: The adjusted R^2 accounts for the number of predictors and the sample size. It is 0.5835, indicating that about 58.4% of the response variable's variability is explained by the predictor variable(s), considering the model's complexity and the number of observations.
4. **Standard Error**: The standard error is a measure of the variability in the residuals or the average distance between the observed and predicted values. In this case, it is 5.3989, suggesting that the average prediction error is approximately 5.3989 units
5. **ANOVA**: The ANOVA table breaks down the sources of variation in the data.

- **Regression**: The regression model has 1 degree of freedom (df), explaining 1417.64 units of sum of squares (SS) and a mean square (MS) of 1417.64. The F-statistic is 48.63, indicating the overall significance of the regression model. The p-value associated with the F-statistic is very small (5.67E-08), indicating that the regression model is statistically significant.
- **Residua**l. **The** residual (error) has 33 degrees of freedom, explaining 961.91 units of sum of squares, and a mean square of 29.15. The total sum of squares is 2379.54, accounting for all the variation in the response variable.

6. **Coefficients**.

- **Intercept**: The intercept is estimated to be 63.8692, indicating the expected value of the response variable when all predictor variables are zero.
- (ii) **Engine Hr** The coefficient for the predictor variable "Engine Hours" is estimated to be 0.0120. It suggests that, on average, for each unit increase in "Engine Hours," the response variable is expected to increase by 0.0120 units.

The lower and upper 95% values represent the confidence intervals for each coefficient. The intervals indicate the range within which the true population values are likely to fall with 95% confidence. The graph of Engine hours Vs Coolant Temp indicate a linear relationship. The regression model explains approximately 59.57% of the variance in the dependent variable. Both coefficients are statistically significant, suggesting that they have a significant impact on the dependent variable. The intercept indicates the expected value of the dependent variable when the independent variable(s) are zero, and the coefficient for "Engine Hours" represents the estimated change in the dependent variable for a one-unit increase in the independent variable. Thus Coolant Temp is an important factor towards the predictive model.

D. Regression Analysis Between Engine Hours and Oil Pressure. The data collected from 35 x Tanks with varied engine hrs was plotted against the engine hrs run and fwg graph was obs. The graph clearly indicates that there is downfall in the oil pressure readings in the older engines i.e in the rg of 7 - 8.5 Kg/cm2 vis-à-vis younger engines having oil pressure in the rg of 8.5 - 10Kg/cm2.

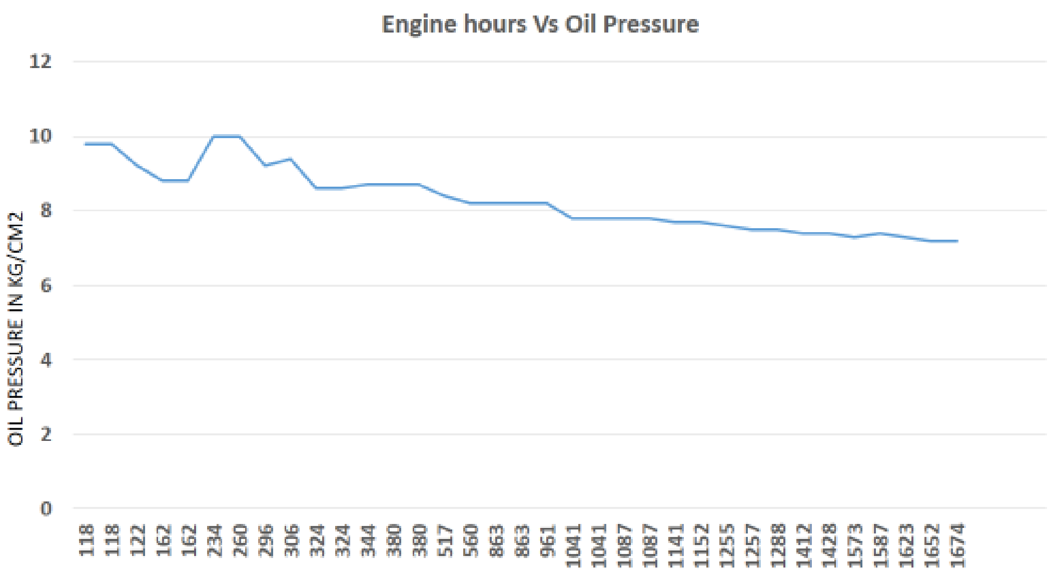

Chart 3: Oil Pressure vs Engine Hrs Analysis

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Statistical Analysis.

Regression Statistics								
Multiple R	0.921520971							
R Square	0.849200899							
Adjusted R Square	0.84463123							
Standard Error	0.3356204							
Observations	35							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	20.93255954	20.9325595	185.8341964	4.13323E-15			
Residual	33	3.717154744	0.11264105					
Total	34	24.64971429						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	9.475711586	0.10428399	90.8644905	3.46815E-41	9.263544214	9.687878958	9.263544214	9.687878958
Engine Hours	-0.001460195	0.000107114	-13.632102	4.13323E-15	-0.001678121	-0.001242269	-0.001678121	-0.001242269

1. **Multiple R.** The multiple correlation coefficient is 0.9215, indicating a strong positive relationship between the variables.
2. **R Square**. The coefficient of determination (R-squared) is 0.8492, which means that approximately 84.92% of the variance in the dependent variable can be explained by the independent variable(s) in the model.
3. **Adjusted R Square.** The adjusted R-squared value is 0.8446. It takes into account the number of independent variables and provides a slightly more conservative estimate of the goodness of fit compared to R-squared.
4. **Standard Error.** The standard error is 0.3356, representing the average deviation of the observed values from the regression line. Smaller values indicate a better fit.
5. **ANOVA.** The ANOVA table breaks down the sources of variation in the data.

- **Regression.** With 1 degree of freedom (df), the regression explains a significant amount of the total variation, as indicated by the large F-statistic of 185.83. The associated p-value (4.13323E-15) is very small, suggesting that the relationship between the variables is statistically significant.
- **Residual.** The residual or error variation, representing the unexplained variability, has 33 degrees of freedom.

6. **Coefficients**.

- **Intercept**. The intercept coefficient is 9.4757. This represents the estimated value of the dependent variable when the independent variable(s) are zero.
- **Engine Hours**. The coefficient for the independent variable "Engine Hours" is -0.0015. This indicates the estimated change in the dependent variable for a one-unit increase in the independent variable.
- For both coefficients, the standard error represents the average variability in their estimates. The t-statistic assesses the significance of each coefficient, with higher absolute values indicating greater significance. The p-values for both coefficients are very small, suggesting that they are statistically significant. The lower and upper 95% values represent the confidence intervals for each coefficient. The intervals indicate the range within which the true population values are likely to fall with 95% confidence. Based on the above regression statistics, there is a strong negative relationship between the variables. The regression model explains approximately 84.92% of the variance in the dependent variable. Both coefficients are statistically significant, suggesting that they have a significant impact on the dependent variable. The intercept indicates the expected value of the dependent variable when the independent variable(s) are zero, and the coefficient for "Engine Hours" represents the estimated change in the dependent variable for a one-unit increase in the independent variable. Considering the impact of oil pressure, it is an imp parameter towards the predictive model

V. MULTIPLE REGRESSION

The available data of 35 tank suggest that the relationship between various variables form a linear regression model and hence machine learning algoritham can be implemented. In the instant case only three sensors were fitted whereas there are seven type of sensors which can be fitted onto the tank and their relationship with engine hours and relationship between themselves should be evaluated. This will be a multiple regression issue and may not be a linear regression issue [13-15]. This can be undertaken as a project by Indian Army as sufficient funds will be required to fit the tanks with all the sensors. The data of 35 Tanks is very insufficient to accuratly predict the model. About 1000 tanks reading at various km/hrs leading to minimum 10000 data points need to be taken for developing a predictive model. [16-19] No effort was undertaken to write the software in Python for development of predictive maint software as it was beyond the scope of this paper. The maj steps involved in designing the predictive model are as enumerated below:-

1. **Data Collection**. Gather historical data relevant to the prediction task. This includes the data from log book and sensors. The data should cover a sufficient time span and be representative of the patterns the AI has to learn.
2. **Data Preprocessing**. Clean and preprocess the data to remove **any** inconsistencies, missing values, or outliers.
3. **Feature Selection/Extraction**. Select the most relevant **features** that are likely to influence the future values. This reduces the dimensionality of the data and focusing on the most important factors for prediction.
4. **Model Selection**. In this case as the data is linear we will choose regression models (linear regression, polynomial regression) for predictive analytics

5. **Training**. The preprocessed data will be split into training and validation sets. The training set will be used to train the AI model by fitting the historical data to the desired output. The model learns the patterns and relationships between the input features and the corresponding target values.
6. **Model Evaluation**. After the training of model, the performance of the trained model will be assesed using the validation set. Various metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), will be calculated to check the accuracy and goodness of fit of the model.
7. **Future Value Prediction**. Once the model is trained and optimized, predictions will be made on new, unseen data.
8. **Model Monitoring and Updating**. Continuously monitor the performance of the predictive model as new data becomes available. If the model's performance deteriorates over time, retrain it with updated data or consider reevaluating the model architecture and feature selection to improve its accuracy.

VI. SUMMARY OF RECOMMENDATIONS

Predictive maintenance for tank engines involves utilizing data and advanced analytics to anticipate and prevent potential issues before they lead to failures or breakdowns. Here is a summary of recommendations for implementing predictive maintenance for AFV engines:-

1. **Sensor Fitment.** Max tanks should be fitted with Oil Pressure Sensor, Engine vibration Sensor, Torque sensor, Coolant temp sensor, Fuel consumption sensor, Exhaust sensor, Acoustic Sensor and data logger so that the data could be collected.
2. **Data Collection**. Collect comprehensive and relevant data from **sensors** and historical maintenance records. Include parameters such as engine temperature, oil pressure, fuel consumption, RPM, vibration levels, and other critical performance indicators.
3. **Condition Monitoring**. Implement real-time condition monitoring to continuously assess the health of the tank engine. Utilize sensors and Internet of Things (IoT) devices to monitor key performance parameters, detect anomalies, and identify potential failures.
4. **Data Analysis.** Apply machine learning and data analytics techniques to analyse the collected data. Train predictive **models** to identify patterns, correlations, and anomalies that could indicate potential engine failures or performance degradation.
5. **Predictive Analytics.** Use predictive analytics algorithms to forecast potential engine failures or maintenance needs. Generate alerts, notifications, or recommendations based on predefined thresholds or patterns of abnormal behaviour to enable proactive maintenance actions.
6. **Maintenance Planning**. Develop maintenance schedules based on predictive insights. Optimize maintenance intervals and plan proactive repairs or component replacements before failures occur. Consider factors such as engine usage, environmental conditions, and manufacturer recommendations.
7. **Integration with Fleet Management Systems**. Integrate the predictive maintenance system with existing fleet management systems to streamline workflows, enable remote monitoring, and track maintenance histories. This integration facilitates efficient scheduling, resource allocation, and tracking of maintenance tasks across the tank fleet.
8. **Continuous Improvement.** Continuously refine the predictive maintenance system by incorporating feedback and lessons learned from previous maintenance actions. Monitor the effectiveness of predictions and adjust algorithms or models as needed to improve accuracy and reduce false alarms.
9. **OEM Collaboration**. Collaborate with Original Equipment Manufacturer (OEM) to leverage their expertise and access specialized tools or algorithms for predictive maintenance. Engage in knowledge sharing and collaborate on data collection strategies and best practices.
10. **Training and Expertise.** Invest in training and up skilling maintenance personnel to effectively use the predictive maintenance system and interpret its outputs. Develop a cross-functional team with expertise in data analytics, engineering, and tank technology to manage and optimize the predictive maintenance program. Implementing these recommendations enables tank operators to improve the reliability, performance, and lifespan of tank engines. Predictive maintenance helps minimize downtime, maintenance costs, and the risk of unexpected engine failures, ensuring the tanks are ready for critical operations.

VII. LITERATURE SURVEY

Singh, Sharma (2021). IoT based systems are now used for fleet tracking, fault and error detection, analyzing driver behavior and many other operational needs. The IoT protocols allow us monitoring and controlling remotely, over an existing network which results in improving accuracy, efficiency and security of the system. This paper describes the developments and evolution of Internet of Things in the automotive sector to provide diagnostic system which is intelligent diagnostic system based on IoT. [7]

Tosun, Aydin, Bilgili. (2016). This study deals with usage of linear regression (LR) and artificial neural network (ANN) modelling to predict engine performance; torque and exhaust emissions, carbon monoxide, oxides of nitrogen (CO, NOx) of a naturally aspirated diesel engine fuelled with standard diesel. Experimental work was conducted to obtain data to train and test the models. Back propagation algorithm was used as a learning algorithm of ANN in the multi-layered feed forward networks. Engine speed and fuel properties, cetane number, lower heating value and density were used as input parameters in order to predict performance and emission parameters. It was shown that while linear regression modelling approach was not very accurate to predict desired parameters, more accurate results were obtained with the usage of ANN. [13]

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Safavi, Hamid, Fallah (2021). Autonomous vehicles are already on the road in modern cities' thanks to the state-of-the-art machine learning algorithms and controllers. While great progress has been made, state-of-the-art algorithms still fail at times and some of these failures are due to the faults in sensors. It is therefore important that automated cars foresee problems ahead as early as possible. This paper proposes a fault detection, isolation, and identification and prediction architecture for an autonomous vehicles**.** [17]

Fabio, Mario, Luca, Marianna, **Francesco** (**2022**), With advancement of sensor and network technology, it is very effective to incorporate sensors such as vibration, temperature, pressure, voltage, and other electrical and mechanical parameters to monitor the vehicle. With availability of data, it is possible to prevent potential failures and estimate the remaining useful life of the equipment by statistical models and artificial intelligence (AI) techniques. This paper presents statistical inference approaches, stochastic methods, and AI techniques for predictive maintenance in the automotive sector. [18]

Gong, Simon, Guu. (2022). The necessity of vehicle fault detection in autonomous applications is very important. Various machine learning algorithms, which can be applied to the failure prediction of vehicle transmission system, engine operation have been discussed. The paper discusses three main AI algorithms, such as supervised learning, unsupervised learning, and reinforcement learning, and then summarises which artificial intelligence algorithm architectures are suitable for each system failure condition. [2]

VIII. CONCLUSION

The application of Artificial Intelligence (AI) for predictive maintenance of Armoured Fighting Vehicles (AFVs) holds great promise for military organizations. By leveraging AI algorithms and advanced data analytics, predictive maintenance enables proactive identification and mitigation of potential equipment failures. This approach enhances AFV readiness, optimizes resource allocation, and extends the lifespan of these critical assets. The integration of AI in predictive maintenance involves collecting and analysing data from various sensors installed on AFVs. Through machine learning techniques, AI algorithms can identify patterns and indicators of impending failures, allowing maintenance activities to be scheduled proactively. This reduces unexpected downtime, increases operational availability, and improves overall efficiency. By adopting AI-based predictive maintenance, military organizations can make informed decisions regarding AFV operations and resource allocation. Mission planning becomes more effective, as potential equipment failures are identified in advance, mitigating risks and ensuring optimal operational performance. However, the implementation of AI for predictive maintenance of AFVs comes with challenges. Ensuring accurate data collection, integration from diverse sensors, robust communication infrastructure, and addressing cyber security concerns are critical factors that must be addressed. Despite these challenges, the benefits of AI-based predictive maintenance for AFVs outweigh the hurdles. By embracing this approach, military organizations can optimize maintenance practices, reduce costs, and enhance their overall operational capabilities. AFVs can operate at peak performance, ensuring the readiness and effectiveness of armed forces on the battlefield.

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Dr. Suresh Chandra Padhy, a senior Academician with administrative and Governance experience has taken over as the President (Vice Chancellor) of Poornima University, Jaipur (Rajasthan) from May 2019. Dr. Padhy began his academic career as a Lecturer (Assistant Professor) in Sri Balaji Group of Institutes at Pune in 1998, rising to become the Director (Academics) of the entire group of Institutes in the year 2003 and continued upto 2014. From 2014 onwards he was appointed as Director of Balaji Institute of International Business under the aegis of Sri Balaji Society, Pune till he joined with Poornima University in 2019. Dr. Suresh Chandra Padhy has completed his Post Graduate Diploma in Management PGDM (Marketing & International Business) from Symbiosis Institute of Management Studies, Pune as well as Post Graduate Diploma in Foreign Trade from the same Institute. He completed his MBA from Periyar University, Tamilnadu. He has also completed his Doctoral Studies from Dy. Patil University, Mumbai in 2014. Before joining the Academics, he has served in the prestigious Indian Army for 7 years where he has undertaken all kind of office/administrative duties in both peace and field areas including the border and uncongenial climatic conditional areas. He has also worked as Head – HR of CG CoreEl Logic Systems Ltd (a start-up), at Pune for a short term where he has undertaken the entire gamut of HR and its operations. He has many journal papers to his credit which is published in various national and international journals. He has also organised and contributed to several seminars, conferences and training sessions during his academic career.