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DEVELOPMENT AND IMPLEMENTATION OF RELIABILITY CENTERED MAINTENANCE (RCM) SYSTEM USING ARTIFICIAL INTELLIGENCE

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Abstract

Global apparel manufacturing is becoming more competitive with each day. Effective and efficient utilization of resources has become vital for to survival. Cost optimization is the key to remain competitive and profitable in this scenario. Machine and equipment maintenance is one of the major factor contributing in the success or failure of any manufacturing organization. The issue of machine breakdown is very critical in apparel manufacturing which leads to delay in manufacturing and eventually results in various types of losses.

This research aims at reducing the downtime of the plant machinery by implementing a planned preventive maintenance program through the application of the Reliability Centred Maintenance using Artificial Intelligence. The traditional approach of planned preventive maintenance is based on the calendar which doesn't take due consideration of machine behaviour and failure patterns, hence it lacks reliability. Therefore, this research proposes a system which can learn the nature and frequency of defects on the bases of the machine types. Subsequently, a Reliability Centred Maintenance programme is devised ensuring improved availability of the machines, and resulting into reduced machine breakdown and failure.

The approach discussed in this research paper is based on the deep learning model to learn the defects and its analysis with help of a database created as per specific requirements of an apparel manufacturing environment. Initial data grasping of the machine breakdowns on floor was done to understand the nature of the problems. To understand the problem more accurately the nature of frequent machine breakdown as well as frequency of the breakdowns were recorded from thirteen sewing lines from three sewing floors. The machine breakdown data was collected for each of the sewing machines of different types from the selected lines of a sewing floor. The data was categorized as per the type of machine and number of machines. Month wise data related to machine breakdown occurrence, machine breakdown time and major defects frequency was collected before and after system implementation. A significant improvement was observed in all the aspects studied as approximately 29% reduction in machine breakdown, 35% reduction in defects occurrence and 15% reduction in the machine breakdown time was observed after system implementation. This approach also resulted in creating an environment of learning organisation which learns about itself as the system grows with the organization.

Keywords: Apparel manufacturing, Planned Preventive Maintenance (PPM), Reliability Centered Maintenance (RCM), Artificial Intelligence (AI), Machine learning, Failure pattern, Defect Analysis.

Introduction

Machinery and human resource are the key resources in apparel manufacturing, and maximum utilization of these resources is one of the prime goal of any organization. As these resources are vital for success, it is imperative to achieve the maximum utilization of available resources. Apparel manufacturing is a highly competitive, labour intensive field, hence there is severe competition among the vendors and service providers globally. This results in to an increased pressure on the apparel manufacturers to offer better prices, improved quality and shorter lead times . To achieve this kind of success, the availability of machine and equipment becomes vital and adequate maintenance of the equipment plays a critical role in ensuring the machine and equipment availability.

The absence of maintenance management system causes deterioration of equipment and machinery. Most of the organizations follow corrective maintenance only where maintenance activities are carried out at the time of breakdown of machines . Preventive maintenance is an approach that is regularly performed on a piece of equipment to reduce the likelihood of its failing and to enhance the resource availability. Preventive maintenance is performed while the equipment is still working so that it does not breakdown unexpectedly.

Reliability centered maintenance (RCM) is a maintenance strategy that is implemented to optimize the maintenance program of a facility. The final result of an RCM program is the implementation of a specific maintenance strategy on each of the assets of the facility. The maintenance strategies are optimized so that the productivity of the plant is maintained using cost-effective maintenance techniques. According to Moubray's definitions of IEC 60300-3-11, RCM is a systematic approach for identifying effective and efficient preventive maintenance tasks for items in accordance with a specific set of procedures and for establishing intervals between maintenance tasks.

Preserving system function, identification of failure modes that can affect the system function(s), prioritization of the failure modes, and finally selecting applicable and effective tasks to control the failure modes are the key principles of any RCM program.

The strength of RCM is that it produces extraordinarily robust and effective planned maintenance programmes, even in situations where the development team have access to little or no historical data. RCM has been applied with considerable success for more than 20 years . According to Campbell, if RCM is correctly applied, it can reduce the amount of routine maintenance work by a significant margin . Smith also states that the benefits and advantages of using RCM are several, and have an impact on operations, safety, logistics, configuration, and administration .

The traditional approach of RCM as used for many years in the industry has also a major challenge that it does not give prediction on what can go wrong with machine in the current working environment of the machine or does not give clear indication at what point in the life cycle of the machine one should plan maintenance to enhance the reliability of the machine. This limitation of the traditional approach of RCM can be minimized by using an artificial intelligent solution that can learn the modes of failure and that shall be able to give prediction on what type of maintenance can be done.

Background

The research was conducted on around 400 machines at an apparel manufacturing set-up which was following “Run to Breakdown” type of maintenance approach. However apart from this run to breakdown type of maintenance approach, the maintenance department was also involved in few basic maintenance activities such as oil change and machine cleaning at regular intervals. This was documented on a regular basis in a register. Lack of an appropriate standard preventive maintenance plan resulted into higher machine breakdown and over loading of maintenance personnel. In absence of any maintenance plan, the maintenance personnel were usually landed up in helpless situation and often in fire-fighting mode. Many a times, this situation severely affected the output due to line imbalance and creation of bottle-necks in the process. The work could only be resumed when the machine is corrected. The frequent breakdown effected the continuity of the production process and thus compromised on product quality.

In view of same, it was decided to develop a planned maintenance programme that could ensure the proper functioning and availability of the machines to avoid or control the situation of frequent unplanned breakdowns. As a solution to this problem, a reliable centered maintenance plan to reduce the risk of machine breakdown and increase the reliability of the machine was devised. The machine breakdown data was collected for four months prior and post the system implementation.

Research Objective

The key research objective includes development of a reliability centered maintenance plan to be executed based on the failure patterns and probability of failure of the machines. And the failure probabilities to be determined by the machine learning using artificial intelligence. Eventually the risk of sudden breakdown to be minimized by enhancing the reliability through adopting a robust preventive maintenance plan.

Materials and Methods

Initial data grasping of the machine breakdowns on floor was done to understand the nature of the problems. To understand the problem more accurately the nature of frequent machine breakdown as well as frequency of the breakdowns were recorded from thirteen sewing lines from three sewing floors. The machine breakdown data was collected for each of the sewing machines of the selected lines for seven days. The data was categorized as per the type of machine and number of machines. Other related data such as make of the machine, technical specifications (Model no., type and RPM), year of installation and the floor or line to which a particular machine belongs, were also documented in the prescribed format. Refer **Table 1** for the format of data collection for machine breakdown.

Table 1 : Machine Breakdown Data Collection

Sl. No.	Date	Floor	Line	Machine Type	Machine code	Breakdown reported	Maintenance action started	Maintenance action completed	Total repair time	Total breakdown time
1										
2										
3										
4										
5										

The analysis of the data collected helped in getting insights of the criticality of the machine breakdowns pertaining to the machine type. This has also guided on the approach to be adopted to devise a preventive maintenance plan.

Developing Database of Failure Modes

To develop an effective RCM Programme, the main challenge was to understand various modes of failure a machine can undergo in the operating environment. These failure modes also depend on the various factors including machine environment, machine maintenance procedure followed and the work content. The failure modes of the machine do not only change with the type of machine but also the nature of work machine is operational in.

The database of the machine failure modes enables to understand the machine failures specific to the machine type, make and model. This also helps in creating a deep learning curve for the factory to understand machine behavior in a better manner and eventually developing a maintenance strategy according to the failure modes. This data of the machine failure analysis can also be used to train a machine learning module which can be used to make maintenance plan and that module can be able to predict the type of maintenance that can be done on the machine or can build a maintenance plan for the machine so that the machine failure rate can be decreased.

Development of Machine Learning Model

With help the failure mode database, a machine learning model based on machine algorithm was developed to learn types of failures that a machine could undergo in the real factory environment. This machine learning model was capable of learning different field of the database and used the type of maintenance as target variable. This model was built using the random forest classification technique which is a supervised classification algorithm. The random forest classification technique has some key benefits including high accuracy, ability to handle the missing value in the dataset, and ability to classify categorical values. Further, in a situation of more trees in the forest, random forest classifier won't ever fit the model. In this model of maintenance, trained data comes from the central failure analysis database which is then used to predict the type of maintenance. And the predicted type of maintenance can be used to reduce the risk of machine failure and reduce the down time of the plant due to machine breakdown.

The methodology adopted in developing the process flow of the maintenance is shown in **Figure 1**. As indicated the very first step was creation of machine library followed by generation of failure analysis database. The same database was linked to the planned preventive maintenance schedule and the standard operating procedures (SOP) for each of the maintenance activity. Then all these details were connected with the local host. It enabled the automatic recording and retrieval of machine failures and maintenance actions for preventive as well as corrective maintenance activities. Using the algorithm, it was also ensured that the real-time data of maintenance activities should automatically incorporated in the failure analysis database.

Figure 1 : Process flow of Maintenance Activities

The process flow of the maintenance activities as depicted in **Figure 2** has been divided into two types of protocols, 1. Planned maintenance, and 2. Corrective maintenance. In case of planned maintenance shown in Figure 2 the structure of the maintenance task is predefined. The maintenance person follows the "Job Work" standard task and gathers the condition data of the machine. The machine learning algorithm checks the service date for the service date data base. Secondly, the machine is capable of generating maintenance task list, which helps to tell the task to be performed by the maintenance person. Then, the machine helps to generate the equipment inventory list, which adds to create the list of equipment required by the maintenance person to correct or maintain the machine. Accordingly, the machine will notify the person to issue the Job work, i.e. to allocate the operator to the machine for the maintenance task. As soon as the operator receives the notification for correcting the machine, the operator will either accept or deny the task proposal.

If the operator accepts the task, he will perform the instructed maintenance tasks given by the machine learning algorithm, and then provides the current machine conditional parameters to the machine itself. If the operator denies the task proposal by the machine algorithm, he has to report and comment the reason for not performing the particular task.

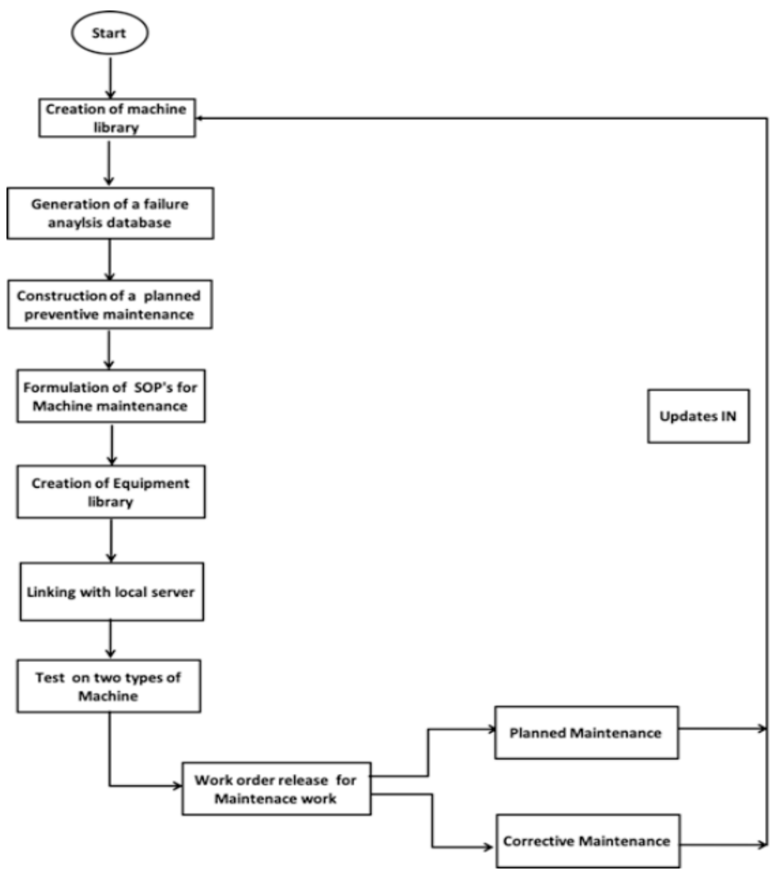

Figure 2 : Planned Maintenance Process

In the corrective maintenance process, the structure of the maintenance task is not predefined. As illustrated in **Figure 3** the maintenance person goes to emergency call when the machine breakdown occurs and collects the maintenance task information. When a machine breaks down happens on the factory floor then the available maintenance person get the information to attend the machine. As soon as the operator receives the notification for correcting the machine, the operator will either accept or deny the task proposal.

If the operator accepts the task, he will perform the maintenance tasks and then provides the maintenance data about the failure in the standard maintenance format and returns the information in the system. If the operator denies the task proposal by the machine algorithm, he has to report and comment the reason for not performing the particular task.

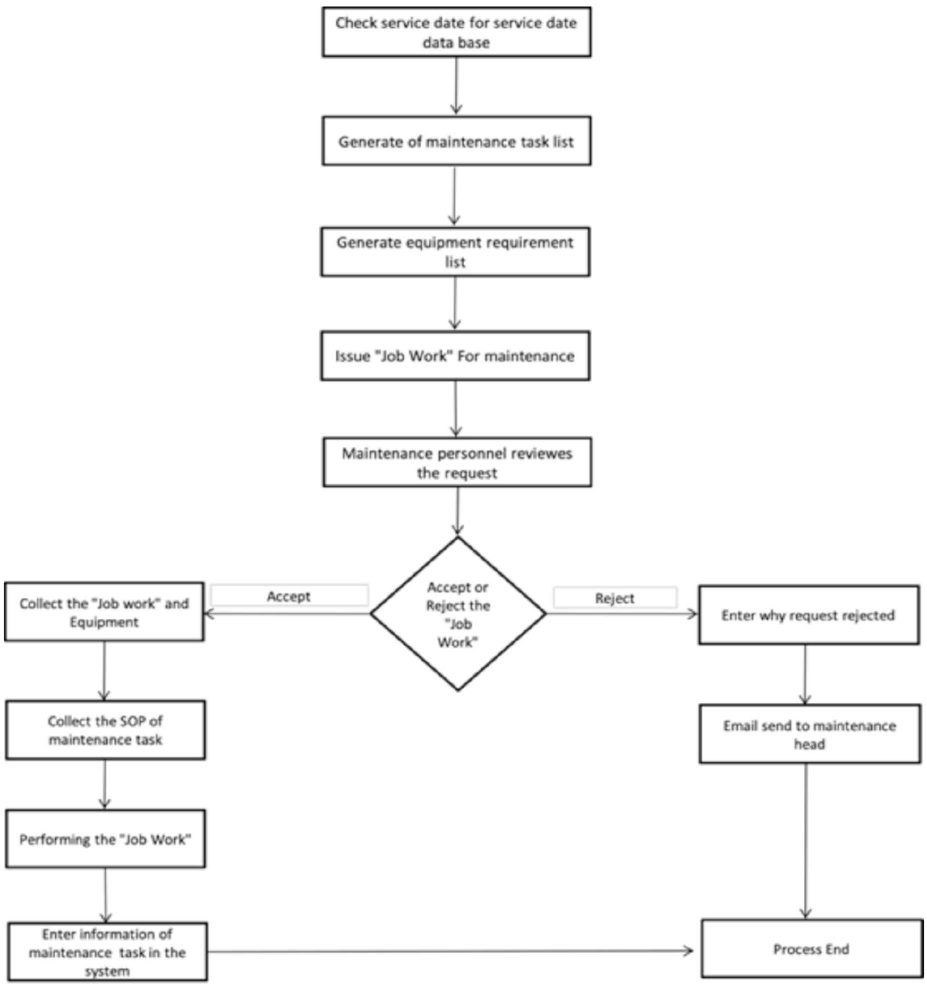

Figure 3 : Corrective Maintenance Process

Results & Discussion

The trial of the artificial intelligence based reliability centered maintenance management system was conducted on few sewing machines including Single Needle Lock Stitch (SNLS), Double Needle Lock Stitch (DNLS), Single Needle Chain Stitch (SNCS), Over lock, Flat lock, and Cutting machine. The month wise data related to machine breakdown frequency and machine breakdown time was recorded for four months prior to the system implementation and 4 months after the system implementation. Apart from it, top five sewing defects were identified and defect occurrence data was also recorded to confirm the improvements.

Month wise machine breakdown frequency values before and after implementation of the suggested system for different machine types have been indicated in the **Table 2**. It can be noticed from the **Figure 4** that there are improvements in the machine breakdown frequencies of the last four months when the system was implemented.

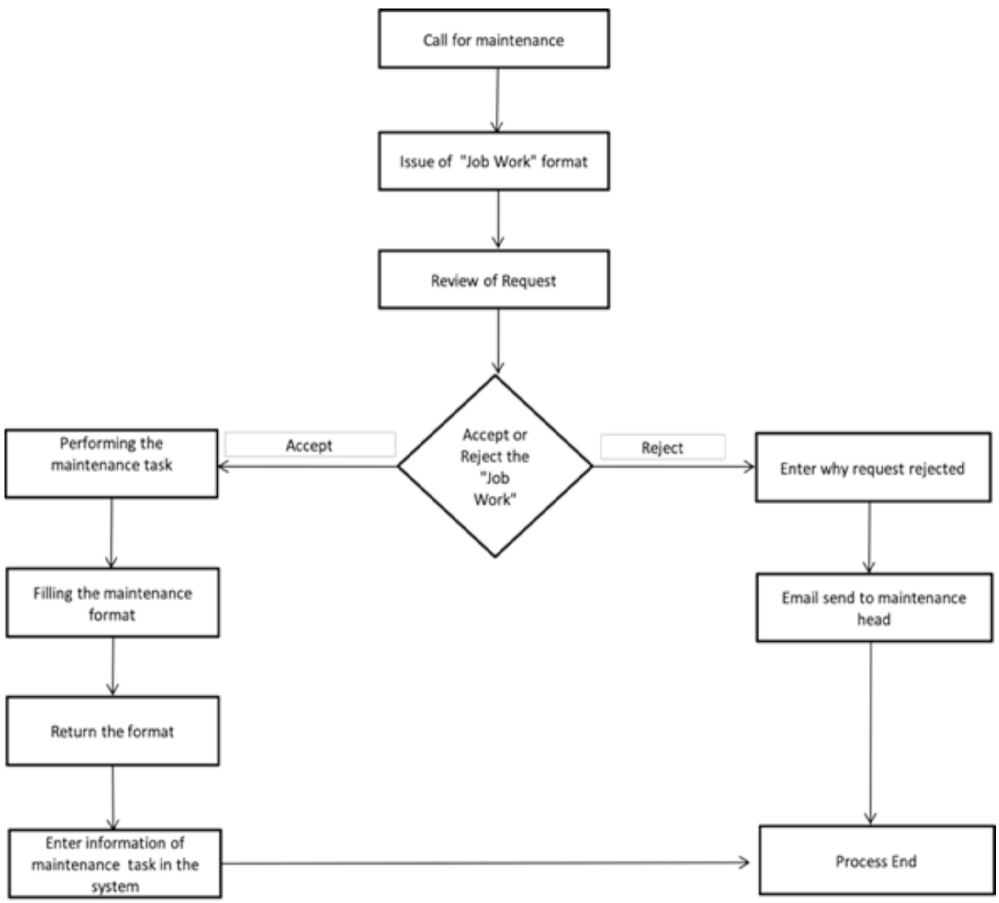

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Table 2: Month wise Machine Breakdown Frequency

Machine Type	Before System implementation				After System implementation			
	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18	Jan-19	Feb-19	Mar-19
SNLS	140	117	121	128	109	98	105	97
DNLS	29	37	42	36	38	31	32	31
SNCS	14	18	10	11	8	10	2	5
Over lock	57	62	48	55	53	49	42	46
Flat lock	25	27	28	23	21	18	20	21
Cutting M/C	40	27	38	33	25	12	15	8

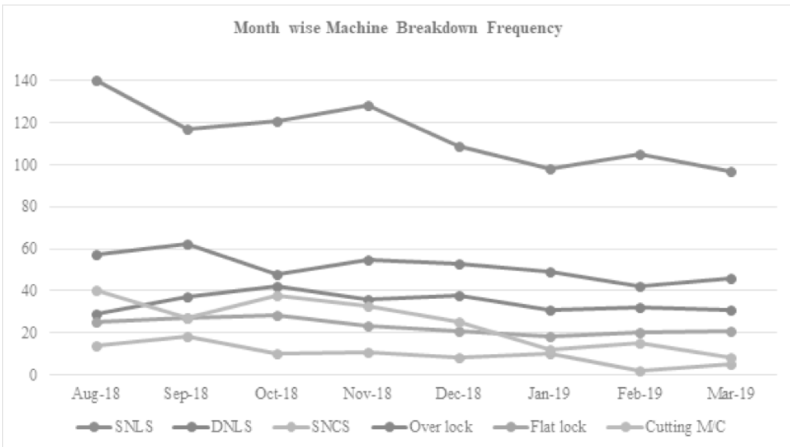

Figure 4: Month wise Machine Breakdown Frequency

As indicated in **Table 3**, the average machine breakdown with approximately 29% reduction over all the machine categories studied was observed. The range of improvement in the machine breakdown was observed between 8.33% to 56.52%.

Table 3: Average Machine Breakdown

Machine Type	Before System implementation	After System implementation	% improvement
SNLS	126.5	102.25	19.17%
DNLS	36	33	8.33%
SNCS	13.25	6.25	52.83%
Over lock	55.5	47.5	14.41%
Flat lock	25.75	20	22.33%
Cutting M/C	34.5	15	56.52%

Top five sewing defects were identified from the past data of the sewing process, and studied to check for the improvements. Defect occurrence frequency for these top five defects has been mentioned in **Table 4.** The defects were observed on monthly basis prior and post the system implementation.

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Table 4 : Month wise Defects Occurrence

Defect Type	Before System implementation				After System implementation			
	Aug-18	**Sep-18**	**Oct-18**	**Nov-18**	**Dec-18**	**Jan-19**	**Feb-19**	**Mar-19**
Thread breakage	22%	24%	21.68%	18.30%	17.20%	13.70%	11.10%	9.7%
Needle breakage	10.20%	9.60%	9.37%	8.89%	8.20%	7.95%	7.29%	7.14%
Skip stitch	8%	7.30%	7.18%	6.23%	6.40%	5.99%	5.80%	5.82%
Shuttle Damage	3%	3.25%	3.15%	3.00%	2.87%	2.35%	1.80%	1.62%
Alignment of feed dog	2.30%	1.80%	2.00%	1.60%	1.00%	0.80%	0.33%	0.21%

It can be observed from **Figure 5** that there is a reduction in the defect occurrence over four-month post system implementation. The highest improvement was witnessed in the machine thread breakage where thread breakdown level was dropped to approximately 10% from a higher level of 25%.

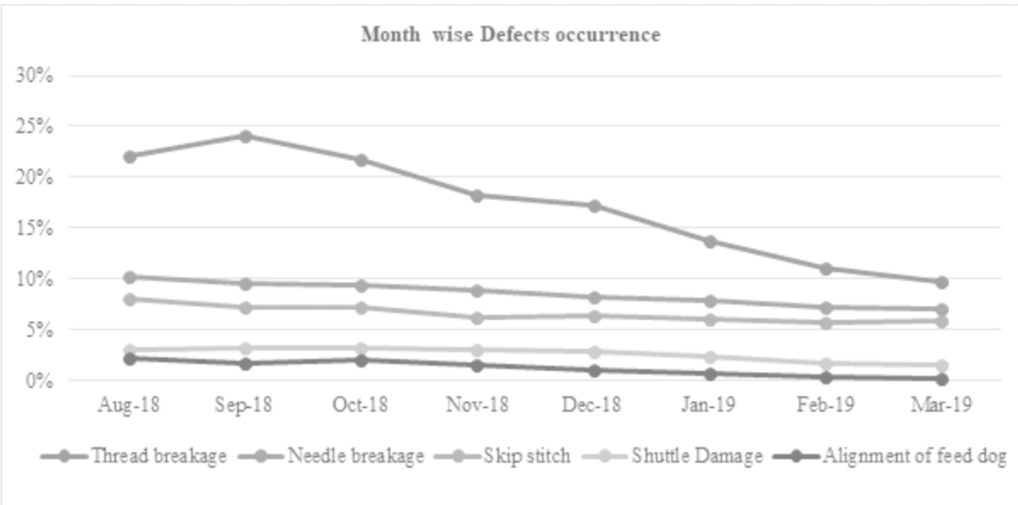

Figure 5 : Month wise Defects Occurrence

Month wise machine breakdown time in minutes was recorded before and after system implementation for each of the machine categories selected. The average values of monthly machine breakdown time (in minute) have been illustrated in table 5 and figure 6.

Table 6 : Average Machine Breakdown Time

Machine Type	Number of machines	Total Average Machine Breakdown time (Before System implementation) (in Minutes)	Average Monthly Breakdown per Machine (Before System implementation) (in Minutes)	Average Machine Breakdown time (After System implementation) (in Minutes)	Average Monthly Breakdown per Machine (After System implementation) (in Minutes)	% improvement
SNLS	350	6200	17.71	4837.5	13.82	21.98%
DNLS	10	438	43.80	320.75	32.08	26.77%
SNCS	10	197.25	19.73	192.25	19.23	2.53%
Over lock	20	192.75	9.64	161	8.05	16.47%
Flat lock	5	163.25	32.65	144	28.80	11.79%
Cutting M/C	4	85	21.25	73.5	18.38	13.53%

It can be observed from **Figure 6**, that there is an improvement in machine breakdown (in terms of reduction in average breakdown time per machine) for each of the machine type category. It may be noted **Table 6** that single needle chain stitch (SNCS) machine category did not witness a great improvement as the reduction in average breakdown time was only 2.53%. For rest of the machine categories, the reduction in average monthly breakdown time ranged between 11.79% and 26.77% post system implementation.

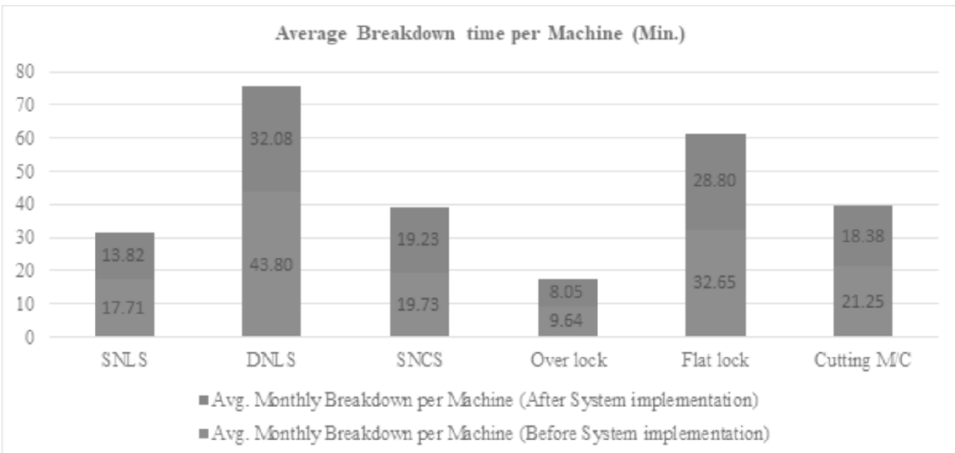

Figure 6 : Average Breakdown Time per Machine

As discussed, it can be observed from the initial data analysis that the results of implementing such an artificial intelligence based maintenance system are really promising. However, the detailed results of the research are yet to be received because the database of failure analysis needs time to become stronger and robust (through incorporation of data of the failures) to support the maintenance department in decision making. In order to achieve the full potential of the mechanism developed, a substantial failure data (for at least needs 8 months of failure data) is required. The other finding of the research was that this approach created an environment of learning organisation which learns about itself as the system grows with the organization.

Conclusion

As discussed in the previous section, significant improvements were observed in all the aspects studied as approximately 29% reduction in machine breakdown, 35% reduction in defects occurrence and 15% reduction in the machine breakdown time after system implementation was noticed. The conducted research was innovative in many aspects. The maintenance practices in apparel manufacturing in India are generally not given due attention, also it is primarily focuses on hit and trial basis with no or minimal records of the failures and its nature. As a result, the maintenance activities are carried out on ad-hoc basic, which lead to losses in terms multi-fold including loss in value, delivery time-lines, product quality, time, human efforts, and eventually the loss of image of the organization. This research has brought a new scientific direction in the area of reliability centered maintenance, and intervention of artificial intelligence can enable for informed logical decisions ensuring equipment availability.

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