Enhancing Reliability of Power Systems through *IIoT* – Survey and Proposal

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***Abstract* - This article presents an idea of achieving reliability through Industrial Internet of Things (IIoT) for industrial power systems. It proposes hybrid approach for predictive and corrective maintenance. It discusses the self-corrective maintenance (SCM) paradigm as hybrid approach for industrial power systems along with condition-based maintenance approach utilizing IIoT to achieve it. As it is well known that industries pay huge penalty for the down time, and suffer to meet reliability demands for years. Study witnesses its cost in millions of dollars yearly for production disruptions. It can be prevented by proactively following the aggressive maintenance schedule. However, it often becomes expensive as part or service may not be utilized for its full life and failure may occur even in middle of maintenance cycle. On the other hand, condition-based maintenance (CBM) helps utilize the full life and prevents the downtime by predicting the failures ahead. This article reviews current maintenance practices followed by industry leaders and a proposal on self-corrective maintenance based on condition of restorable resources. It is about learning the condition of sub-systems by itself and taking corrective action when sub-system is not active. This concept helps reduce manual intervention to correct the problem as well as the maintenance cost. This research also covers the self-uncorrectable issues to be handled by proactively following CBM process through IIoT. This hybrid proposal could be a significant gear shift in maintenance direction for general industry as well as power systems. It can be termed as industry's 5th revolution or Industry 5.0.**

***Index Terms* - Corrective Maintenance (CM), Preventive Maintenance (PM), Reliability Centered Maintenance (RCM), Reliability, IIoT, Self-Corrective Maintenance (SCM) Condition Based Maintenance, CBM, Survey, Industry 5.0**

I. INTRODUCTION

The increasing demands of manufacturing industry makes industry to run round the clock. This leaves almost no space for unscheduled downtime. Unscheduled down time incurs high penalty in manufacturing cost. For reference, it can cost as much as $260,000 per hour for manufacturing as shown in a recent study [1]. In other words, it costs millions of dollars for manufacturing industry every day worldwide. As per IEEE survey, rate of failure is three times higher without preventive maintenance in electrical component context. Corporations are working together to fight this battle and devising many ways to reduce or eliminate this disruption.

Research discussed in [2] presents common maintenance strategies pitfalls in every detail. Preventive Maintenance (PM) costs significantly while Corrective Maintenance (CM) penalize in terms of downtime. Reliability Centered Maintenance (RCM) is another step ahead in maintenance. RCM focusses on the probability of the functional performance of the item with stated conditions. However, it doesn't guarantee the full utilization of life and failures within predicted period.

The traditional maintenance methods [3] prevent failure to a good extent but that costs industries a huge sum. It is a phenomenon of being pro-active and replacing or servicing the part in regular interval or predicted interval per RCM methodology. In any case, life of a part or service is not completely utilized that leads to the wastage of part life and other unpredictable failure may go undetected and can still cause downtime. In last few decades, industry practices are moving towards intelligent solutions such as condition-based maintenance (CBM). US army [4] is first to adopt this paradigm and extensively working on making failproof military fleets. Condition-based Maintenance is academic term for condition aware maintenance where maintenance is performed only when part or condition warrants maintenance as opposed to at regular or predicted interval.

CBM is a process to identify where failure starts to occur and decide to complete maintenance at a point before part losses its expected performance.

This strategy allows utilization of full life of the part and detects unpredicted failures before they occur. It is capable of detecting future failing conditions. In turn, it reduces the maintenance as well as production cost manifold which increases the productivity significantly.

The key to the Condition Based Maintenance (CBM) [4] is its real-time prediction ability. The prediction ability is measured on how accurately and quickly a condition can be predicted before actual failure occurs. The fault prediction technique used is directly proportional to the performance of the maintenance algorithm. Statistics and Artificial intelligence are highly involved areas in the prediction study. The prediction techniques are used to study the properties to determine the life of the system or part. The design of maintenance systems with a robust and efficient prediction techniques can facilitate the operator to take the corrective action before failure actually occurs.

Figure 1 shows the stages involved in condition-based maintenance process. Data collection comprise of data collections through various sensors like ultrasonic sensors, infrared sensors, vibration sensors, current and voltage monitoring etc. Over the time, this data grow significantly and all data may not be usable.

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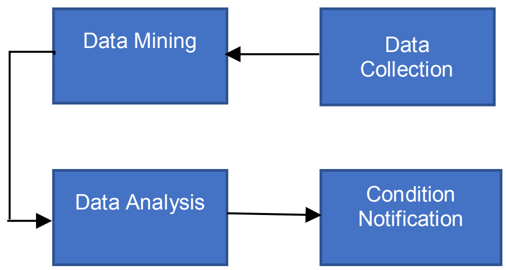

Figure 1: Four Step Process of CBM [5]

So, in second step of the model, relevant data is extracted using various data mining techniques. This step provides the required data for next steps. Next and key step is to apply appropriate prediction algorithm to understand the fault behavior. This is the layer where Statistics, Artificial Intelligence, Machine learning prediction capability plays a great role. This modular architecture can help to use best available module in the industry depending upon expertise once standardized. Someone may be expert in any of these layers and altogether gives a best product in the industry. Final step is to notifying the results. There may be various notification methods as discussed in [1], namely emails, mobile applications, web services, databases for further analysis etc. The main goal of this maintenance solution is to achieve three main objectives, increase revenue, reduce maintenance cost and mitigate risk in worst case scenarios.

According to an independent survey by US Department of Energy, predictive maintenance has huge saving as listed below [6].

- Return on investment: 10 times
- Reduction in maintenance cost: 25%-30%
- Breakdown reduction: 70%-75%
- Reduction in downtime: 35%-45%
- Increase in production: 20%-25%

II. MAINTENANCE STRATEGIES

In study [2], authors presented the comprehensive definition of legacy maintenance terms and statistical representation of terms used in each strategy. In brief, corrective maintenance is done after failure occurred while preventive maintenance is done periodically to prevent the problem from occurring. Reliability Centered Maintenance is tied to reliability of the functional performance which is determined based on probability density function (PDF) [2], reliability [2] and many other factors as discussed in [2]. RCM determines maintenance schedule based on all these factors. Authors in [2] advocated RCM is much better than corrective and preventive maintenance in terms of reliability, usefulness of the part life and performance which indeed is. However, static nature of predicated life in RCM puts it behind CBM. CBM falls into continuous monitoring category where ongoing condition can be monitored and action can be taken depending on the severity of symptom. CBM can be better understood using P-F curve [5] shown in figure 2. CBM relies highly on equipment behavior. The equipment behavior can be described using P-F curve. In figure 2, point ‘P_0’ where failure starts occurring remains undetectable and point ‘P’ where potential failure symptoms get identifiable.

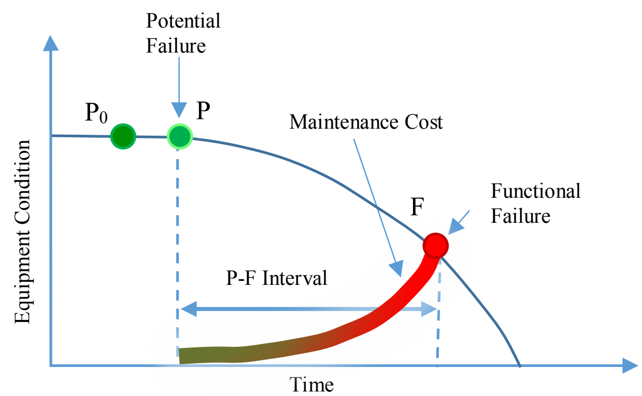

Figure 2: P-F Curve

Finally point ‘F’ where functional failure occurs. The time between ‘P’ and ‘F’ is called P-F interval as shown above between dotted lines by an arrow. Generally, maintenance cost increases from ‘P’ to ‘F’ as shown above. The term *Prognostic* [5] is often used in CBM which is a process of predicting future failure of any part by analyzing the system behavior, operating conditions and prior history. As per authors in [5], there are two biggest challenges in prognosis.

1) Predicting life before functional failure
2) Estimation of trust value or reliability

Given the advances in data analytics, achieving above two metrics are not difficult anymore. Vibration, Ultrasonic, Infrared, Voltage, Oil quality analysis are few highly used metrics for studying failure behaviors. Machine learning proved very promising in learning the fault behaviors recently. Researchers developed various highly efficient statistical, and artificial intelligent (AI) based models to learn the failure behavior and produced promising results. One of the such study is performed in [7] that uses various proven algorithms from Statistics and AI to accurately predict the auto tire pressure.

Below is a simple example of Artificial Neural Network (**ANN**) called linear predictor neural network used in [7]. It is a one of the simplest neural networks with few hidden layers. These are feedforward networks in nature so flow is unidirectional. They are capable of taking any input and produce output. Number of layers in hidden layer are application dependent but often low in number. During training of the model, input produces the output for the target. Then actual and generated output is compared to adjust the weight of the neurons. Eventually, a path from input to final output is established which has neurons with highest weights. Now this model is ready to take any input and provides desired results.

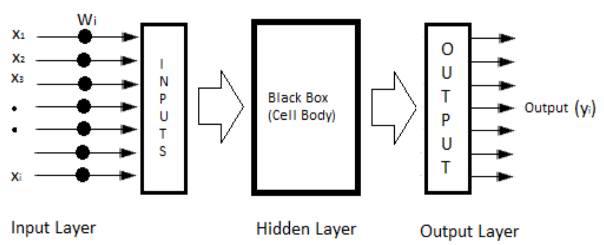

Figure 3: Linear Predictor Neural Network Architecture [7]

DNN (Deep Neural Network) is very popular term these days for deep learning in various domains. The working principle of DNNs is very similar to standard neural network explained earlier but it has complex design and multiple hidden layers. So, it can be said it is special type of artificial neural network with complex design and higher capability. It is heavily used in prediction for various disciplines. Such network can use feedback networks to feed the output back to input and get better results. They may use delay blocks to feedback outputs from previous iterations. Models could be liner or non-linear in nature. All these features make DNNs even more complex but more efficient and accurate to meet the better predicational requirements.

CBM is now gaining momentum and is viable solution for industrial maintenance needs. Industrial Internet of Things (IIoT) adds another wing to its efficiency and timeliness. IIoT reduced the physical intervention for data monitoring and analysis. Nowadays, all stages of CBM process can be automated and analyzed results can be communicated to responsible party via webservices, emails, texts, mobile applications etc. Many industry players started transitioning into it slowly as discussed in section 3.

III. CASE STUDY

Many manufacturers are following traditional maintenance paradigms today, the preventive maintenance (PM). It is the simplest way to maintain any system or equipment, though expensive. **The Lincoln Electric** is one of them using preventive maintenance to maintain their welders as stated in [8]. Their preference is to outsource the maintenance to the third party. The idea to outsource the work is to take advantage of experts of the field. Company's RASC a recently opened service center reconditioned more than 2300 welding machines and wire feeders incurring high maintenance cost. The Lincoln's preferred way to avoid downtime is to use rental machines when actual machine out for maintenance yet another cost to add up. There are various manufacturers across the industry follow this suit.

Recent trends are more focused on the predictive maintenance which is solely based on the condition-based maintenance theme. Manufacturing and Power Equipment industry leaders including Schneider-Electric, ABB, KUKA, MOTOMAN, FANUC, Duke Energy etc. started following the new paradigm either by providing in-house solutions or utilizing third party's rich solutions like one provided by SAP, NI, IBM etc..

Schneider-Electric [9] is one of the earlier ones to adopt the predictive maintenance policy. Operating conditions of a power equipment that can be monitored are temperature, operating time, opening and closing time of circuit breaker, temperature of connections and insulation condition of switchgear, motor starting time, number of operations, power, and insulation breakdown, also cable insulation breakdown. These inspections are mostly manual using measuring equipment so still there is significant cost involved but better than preventive maintenance. There are various assessments performed to study the equipment conditions as listed below.

- Power system assessments
- Thermographic inspections
- Online temperature monitoring
- Insulating fluid analysis
- Discharge monitoring
- Circuit monitor analysis
- Circuit breaker and motor control center monitoring

ABB is one of the leading robot manufacturer moved towards the predictive maintenance era. They offer the Internet of Things (IoT) based solutions in which they have their equipment connected to internet. Their equipment sends data periodically and it is analyzed to study the condition of equipment. An appropriate action is performed based on the study outcome. ABB's predictive maintenance program is called Life Expectancy Analysis Program (LEAP) [10].

MOTOMAN is another well-known robot manufacturer which provides many solutions to service their robots. They still follow the manual way to collect sample and analyze sample in their in-home laboratory. For example, company provides customer kit to collect grease sample [11] and send it to the factory for further analysis. Healthy grease is required for axes to function smoothly. Over the period, grease gets contaminated specially with iron content when axis drives are misaligned which reduces the drive life significantly. Timely grease change helps enhance product life and avoid unplanned downtime. Again, this involves manual intervention in all stages and incurs heavy cost on maintenance procedure which is big penalty of production cost.

SAP is a leading solution provider for many domains including IIoT (Industrial IoT) based predictive maintenance solution [12]. SAP HANA (SAP's maintenance solution) focuses on big data analytics on remotely collected data. Its framework is architected on physically connected devices in the factory floor while practicing industry security standards. SAP's world class integration center is one stop shop for all maintenance needs of the customers. It offers predictive maintenance solution with promise of below benefits:

- Increasing usability of product life by pro-actively analyzing the product condition
- Increasing profit margins by reducing operational cost
- Reducing maintenance and production cost
- Enhancing reliability and safety by detecting failures before they occur
- Boosting product quality by learning from the field failure patterns
- Most importantly offers service to suit the business needs by adopting different business models like performance based or pay-per-use or subscription.

FANUC is another world leader in CNC and Robot manufacturing. FANUC offers cloud based IIoT solution [13] for all its product line. FANUC is one of the first to offer cloud based solutions for intelligent and predictive maintenance. They collaborated with CISCO to meet industrial security needs. As stated in [14], FANUC ZDT saved up to $70 million by avoiding downtime in manufacturing factory floors. It is the game changer in the industry and offers wide range of predictive maintenance solutions which help reduce downtime as its name sounds i.e. Zero-Down Time (ZDT). FANUC hosts an in-house data center which collects data from the robots across the globe and a team consisting of people from across the globe writing algorithms to perform analysis. These in turn help determine the failure states or soon-to-be failed states of the equipment. As a result of this study, corrective action can be taken when appropriate time comes. This permits to use full equipment life and significantly avoids the unplanned downtime. Other benefits vouched by FANUC are improved cycle time, reducing energy consumption, extended robot life. However, this maintenance process requires manual maintenance at scheduled downtime per notification from FANUC data center that is helped by FANUC service technicians which still involves significant cost.

IBM is another big player in providing IoT based maintenance solutions. IBM's general purpose IoT solution is called MAXIMO [15]. It is designed to meet various maintenance requirements for various industries. For example, it has built-in feature for utilities such as transmission, power distribution, waste water treatment, vehicle fleet etc. For aviation industry, it can track critical maintenance of rotary or fixed wing aircraft and components. For oil and gas, it can manage critical equipment, facilities and infrastructure in single platform. Another great example is nuclear power. It can address safety and improve productivity etc.

Duke Energy [16] in collaboration with National Instrument (**NI**) did great paradigm shift from traditional failure monitoring to online monitoring. Duke stated that power generation industry faces huge problem in maintenance by deploying large fleet of maintenance engineers and technicians for manual maintenance. In 2010, Duke adapted to new technology to meet the demand of reliability for condition monitoring and maintenance which also helped in workforce optimizations company-wide. They deployed NI's **CompactRIO** system which connected company-wide assets to a centralized location. Later to expand technology, Duke partnered with EPRI (Electric Power Research Institute), OSISoft, Schneider Electric. They jointly developed "Smart Monitoring and Diagnostic" (Smart M & D) solution to meet this requirement. Smart M & D allowed to see notifications about issues prior to failure. That gave enough time to specialists to plan least disruptive window to fix issue. It was big initial investment as 50% of older machinery is used in power production on average in each plant. So, it was big decision to add on new equipment for data collections and transmission to data center. Eventually, it started paying back and could save 130% of associated cost by avoiding downtime in fourth year. On the way through this solution, there were many challenges Duke had to face. For example, training engineers with new technology, create trust on technology, convince management to invest significantly when not sure how far this can. Eventually, Duke was able to over all these hurdles and proved to be winner in adapting new maintenance paradigm.

IV. FUTURE DIRECTION

Various industry practices have been discussed including their respective benefits. Let us focus now on what are the disadvantages and how issues in those existing methods can be overcome and to what degree. Below are few parameters to look at.

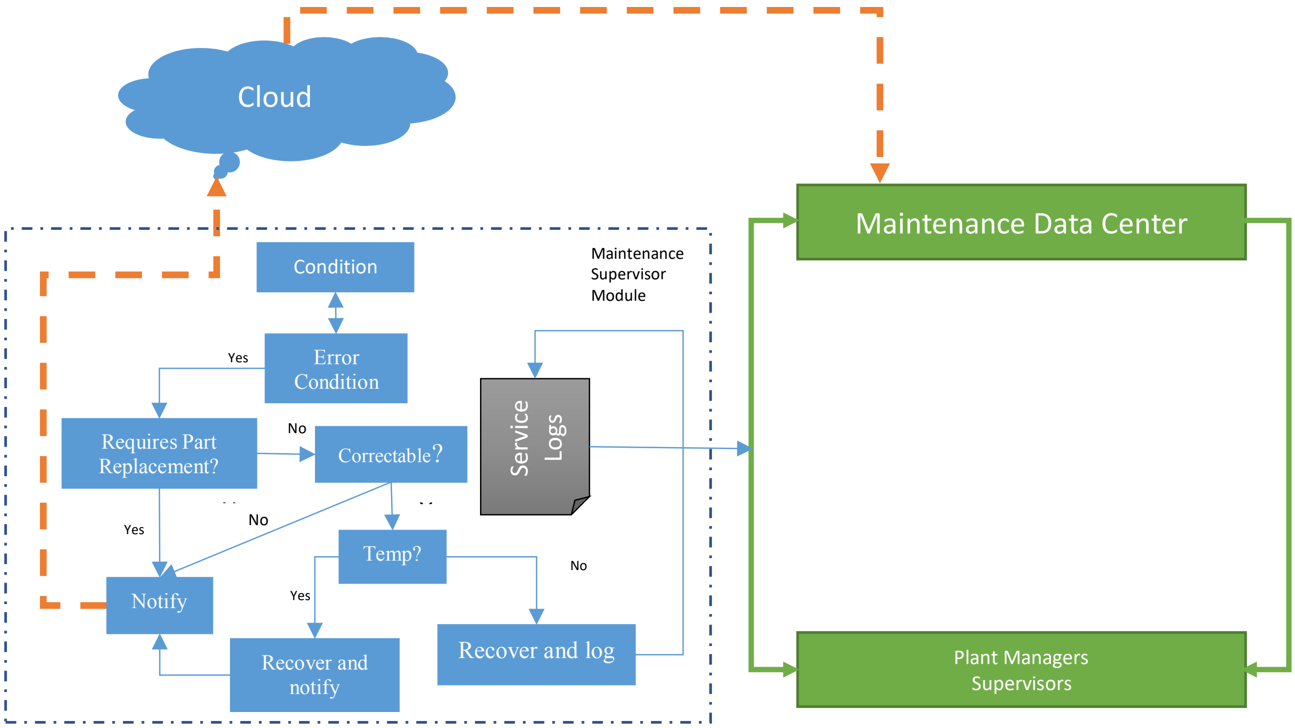

Figure 4: Self-Corrective Process for Maintenance

- Investment in infrastructure per equipment
- Training investment in staff
- Travel cost for onsite maintenance
- Man-hours involved in performing maintenance
- Investment in Data Center and its operating cost

SAP, IBM and FANUC's implementation of maintenance strategy adopted the model presented in [17]. It is proved to be very promising. This is the direction eventually manufacturers would have to follow to make maintenance more efficient and cost effective. Travel cost and man-hours can be reduced by applying new paradigms as discussed below. So, let's start with a question and if there is an answer, maybe partial if not full.

CAN EQUIPMENT FIX ITSELF?

Answer here is YES and NO because it all depends on the device and fault severity. Mechanical failures can't be self-corrected as they require replacement. Any part subject to wear and tear can't be self-corrected but still there are many error conditions can be self-corrected with required infrastructure. Some conditions can be corrected temporarily. In high production environment, if downtime can be avoided temporarily until actual fix is applied, is a big plus. This may be useful for devices where fault can be corrected or partially by some action to buy more time before system goes down completely. Below are few ideas those may come in category where self-correction may be applicable.

- Misbehaviors from unknown conditions in services running in devices
- System resource consumption issues
- Processes producing incremental errors
- Feedback loops
- Resettable systems
- Oil or Grease change

System designers are well aware of the conditions that can help recover their systems. So, idea is to implement the self-recovery methods in the system that can be performed without affecting production or operation or with minimal interruption. Figure 4 shows generic maintenance process flow for hybrid maintenance approach. SCM follows two-tier maintenance. Tier 1 is device level maintenance where self-corrective process applies and tier 2 maintenance where manual intervention is required. SCM is applicable only on self-corrective conditions. Some of the self-correct conditions are listed above. There could be wide range of self-corrective conditions depending upon the system design and could manufacturer specific.

MAINTENANCE SUPERVISOR MODULE

This paper proposes a design of maintenance supervisor module (MSM) that contains two sub-modules, Software Maintenance Supervisor (SMS) and Hardware

Maintenance Supervisor (HMS). MSM is included in every system that performs condition monitoring and isolates self-correcting conditions. MSM is also responsible for correcting conditions and notifying Maintenance Data Center and/or Plant Managers/Supervisors. Detection and correction is done in respective modules depending upon if failure is coming from software vs hardware. MSM is then notified about the condition state. Corresponding module checks if error condition is correctable. If it is correctable, it may be correctable temporarily or permanently. If temporarily correctable, it is corrected and notified to the data center and/or plant supervisors. If it is permanently correctable fault condition, then SMS or HMS corrects it and logs the issues for record purposes which is reported to concern authorities. In either case, equipment or system makes itself survive longer and gets enough time for problem to be corrected without incurring downtime. Permanent correction doesn't require any manual assistance that leads to high saving on man-hours and travel time. If there is high equipment population then it is a significant saving altogether. This helps in smooth operation of plants and even without noticing the issue in various cases. These two submodules monitor specific characteristic of the system and report to main module accordingly as shown in figure 5.

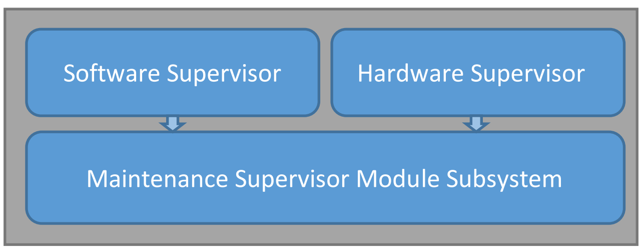

Figure 5: Maintenance Supervisor Module

A. *SOFTWARE MAINTENANCE SUPERVISOR*

This module is responsible for tracking software anomalies related to processes, memory, CPU cycles, and other computational results. This system verifies if output of algorithms is as expected. Is cycle time still in given limit? Is memory usage still not crossing prescribed limit? Is power consumption still in allowed limit? Is there any memory corruption? Is any system resource overutilized? Is there any other software failure? It also monitors the process behaviors if they behave as designed.

B. *HARDWARE MAINTENANCE SUPERVISOR*

On the other hand, hardware supervisor module is responsible for monitoring hardware related performance and failures. For example, sensor reading is still good. Check if any sensor stopped working due to hardware malfunction. Is any part overheating? Is there any vibration level increase in bearing or any other part? Is there any rotational damping increase? Is there any other hardware abnormality? This module tracks over hardware behavior and anomalies in the system or equipment.

This paradigm shift is about reducing human and machine interaction to get the task done. This could be part 5th industrial revolution i.e. Industry 5.0 [18]. Industry 5.0 is bringing machine intelligence with human intelligence.

V. CONCLUSION

In this article, we presented various case studies how manufacturers follow maintenance practices and widely used solutions by industry leaders in various domains. It also discusses industry-wide third-party solutions available in the market. However, many available solutions involve manual assistance to perform the maintenance operations after error condition detection. Manual maintenance incurs significant maintenance cost. Future direction is presented for reducing manual maintenance to reduce cost even further. With given infrastructure, maintenance can be automated to a certain degree to reduce maintenance cost and it is the future. This paradigm is termed as "Self-Corrective Maintenance". SCM is a 4th dimension of intelligent maintenance. Hence, reliability of power systems can be enhanced manifold utilizing hybrid self-corrective maintenance process (Hybrid-SCM). Hybrid-SCM can be part of 5th industrial revolution i.e. Industry 5.0.

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