INDUSTRIAL INTERNET OF THINGS (IIoT) - THE ENABLER FOR POWER STATION ASSET HEALTH MANAGEMENT

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ABSTRACT

Electricity power generation and transmission sector worldwide is experiencing the twin forces of fourth industrial revolution and the aging industrial assets comprising equipment and machinery. The technological advancements emanating from fourth industrial revolution which is also being referred as Industrial Internet of Things (IIoT) or Industrie 4.0 (its European equivalent) can enable significant improvements in the safety, reliability and availability of industrial assets. It also holds the promise of driving down the cost of asset operations and maintenance (O&M) along with managing environmental safety in power generation. Key enablers for achieving these goals are newer sensor technologies, massively scalable computing and storage capacity, fusion algorithms, machine learning techniques, and analytics software.

In this paper, we present the principles, techniques and a practical approach to building up an elastic, interoperable and reusable software centric architecture to monitor and diagnose the health of cyber-physical systems which make up the majority of conventional power plants with aging assets in India. This approach will also enable the integration of new smart assets thereby allowing them to coexist with the legacy assets. Our paper provides a practical approach to quickly detect impending faults in induction motors and pumps along with the usage of a real-time data infrastructure to speed up the multi-sensor data analysis. This approach is extensible in nature and can be applied to cover heterogenous assets in a power generation facility.

Keywords - asset health; condition monitoring; predictive maintenance, real-time data; plant O&M.

I. INTRODUCTION

Power generation industry is undergoing a period of rapid transformation with many industry experts predicting that electricity generation and transmission utilities will undergo more significant changes in the next ten years then they have in the past hundred. Environmental regulations, rapid adoption of renewable energy sources, changes in emission norms and emphasis on extending plant lifecycles, are forcing electricity power plant operators to carefully consider their strategies for:

a) More intelligent and efficient operations and maintenance (O&M).
b) On-demand sensor data collection and storage.
c) Simplifying the operational data processing and analysis.

Consequently, for new and aging assets it becomes all the more critical to:

a) Add new sensors to enable multi-point measurement and collection of statistically relevant data about asset health.
b) Transition from a time-based or reactive maintenance approach to real-time condition-based health management eventually leading to predictive maintenance (PdM).

c) Perform real-time sensor data analysis not just for controlling and tripping the machine for safety reasons, but also for gaining insight into its overall health and components' health by developing predictive models based on state-of-the-art machine learning methods [1].

Concurrently, Industrial Internet of Things (IIoT) is fast becoming the convergence point for operational technologies (OT) and information technologies (IT) aimed at building open-standards based reusable architectures for smart operations and maintenance (O&M) systems.

This above combination of asset owner/operator requirements, operating environment and the evolution of multiple technology stacks (e.g. wireless sensing, data processing, artificial intelligence and mobile computing) is leading to a more pragmatic solution which is rooted in at least 3 principles:

1. Massive amounts of real-time and historical data capture from heterogenous assets like boilers, circuit breakers, fans, feed pumps, motors, pipes, reactors, surge arrestors, transformers, turbines etc.
2. Application of statistical methods, machine learning algorithms and artificial intelligence techniques to gain valuable lead time before asset or component failures create unplanned downtime and impact electricity production.
3. Integration of many disparate operations and maintenance data sub-systems for critical assets into a unified real-time data infrastructure with north-bound and south-bound interfaces interoperable with a multitude of industrial protocols.

For concreteness, we consider the following use cases in this paper:

a) Sustainable energy mandates: are driving many electric utilities to integrate alternative energy sources such as solar, wind, and geothermal to their grid. Given the variable performance of alternative/renewable energy sources that are dependent upon weather conditions; coupled with the need to scale down generation from conventional power plants (coal or gas) during certain times of the day, operators will be required to maintain a diverse combination of power sources across their generation capacity to meet demand. To be able to perform this task reliably, plant operators will have to be constantly aware of the condition, availability and safety of all assets due to the varying nature of load on assets such as boilers, circuit breakers, fans, feed pumps, motors, pipes, reactors, surge arrestors, transformers, turbines etc.

b) Physical phenomenon impacting the performance and life of assets: including but not limited to (a) fouling of boilers/turbines/heat exchangers, (b) erosion and corrosion of boilers/ducts/piping/fans, (c) deterioration of electrostatic precipitator (ESP) due to leakages requires an ever-increasing visibility into the aging assets. Extending plant life through the use of more predictive maintenance strategies can buy electric utilities valuable time to consider various options while avoiding unplanned downtime. In addition, almost all life extension business cases can benefit from the use of real-time condition monitoring as opposed to engineering calculations alone.

To achieve all of the above, a holistic and systems approach is necessary for the purpose of early detection, diagnosis and remediation of impending faults in equipment, machinery and systems involved in power generation. Since these assets (comprising equipment, machinery and systems) span electrical, mechanical, structural and environmental engineering domains; the adoption of such an approach will also result in a much more comprehensive methodology for tracking the performance improvements following the retrofitting and maintenance (R&M) and tracking residual life of power plants.

For reference, figure 1 provides a view of the physical equipment and systems installed in a power plant, which when instrumented with sensors and connected to an industrial communications network become a network of cyber-physical objects. Having this view is important for the purpose of developing a hierarchy of data objects which can exchange information - both vertically and horizontally in the network.

Equipment and Machinery

- Boiler
- Boiler feed pump
- Circuit breakers
- Compressor
- Condensate extraction pump
- Conveyor motors
- Cooling tower
- Cooling water pump
- Forced draft fan
- Generator
- Heat exchanger
- Induced draft fan
- Induction motor
- Pipe
- Primary air fan

Equipment and Machinery

- Reactors, Surge arrestors
- Transformers
- Turbine

System and Sub-System

- Ash handling system
- Coal handling system
- Compressed air system
- Cooling water system
- Effluent treatment system
- Firefighting system
- Fuel oil system
- HVAC system
- Raw water intake system
- Water treatment system

To enable information exchange: physical objects have to be instrumented with sensors, embedded hardware and software, and communications protocols

Figure 1: Heterogenous elements of a power plant's cyber-physical system

Since the architectural barriers and technology price points are coming down rapidly, in this paper we discuss novel concepts, techniques and a pragmatic approach to designing and implementing the next generation machinery health management systems which can be consistently applied across: (a) new and old power plants, (b) smart and legacy assets. Section II discusses the practical considerations for organizing the discrete elements of a cyber-physical system from a power plant perspective, current challenges associated with incomplete sensor data, and complexity of interpretation of condition monitoring data. Section III presents a fusion architecture to overcome these challenges in a real-world implementation.

Considering the range of assets deployed and the spectrum of faults which can cause failures and/or degradation in performance, our thesis is grounded in the following practical principles:

1. Measure parameters by physical instrumentation in situations where it is economically and structurally feasible.
2. To detect onset of faults or anomalous behavior, analyze both upstream and downstream assets connected in the process chain.
3. Take into account the actual operating parameters across multiple assets in order to be able to derive meaningful conclusions such as in the case of cavitation in pumps described in subsequent sections.

II. THE EVOLUTION OF CONDITION MONITORING FOR CYBER-PHYSICAL SYSTEMS

For equipment and asset operators to be always aware and alerted about the health of various pieces of machinery deployed in their environments it is imperative they adopt a holistic approach to collecting, visualizing and analyzing the sensor data flowing from these sub-systems and systems. We discuss here the problems associated with the boiler feed-water pump and identify ways in which the failure modes of the pump interact with each other. We also identify the interaction between problems in the boiler feed pump and the malfunction in other systems of the power plant. The goal of this discussion is to highlight the need for a systemic architecture-based approach to condition monitoring instead of a sensor-specific (e.g. vibration) or a fault-based approach.

Let us assume that plant managers have determined that the boiler feed-water system is consuming more energy than it should, thereby reducing the cycle efficiency. We identify here the possible causes of this consumption related to the pump, the symptoms of these causes, potential methods of detecting these symptoms, and finally discuss root causes that may extend beyond the feed-water pump.

The boiler feed-water pump is located between the boiler and the deaerator. The pump may be driven by a dedicated electric motor and in some cases by a steam turbine. Figure 2 shows the major failure modes of centrifugal pump and heat exchanger.

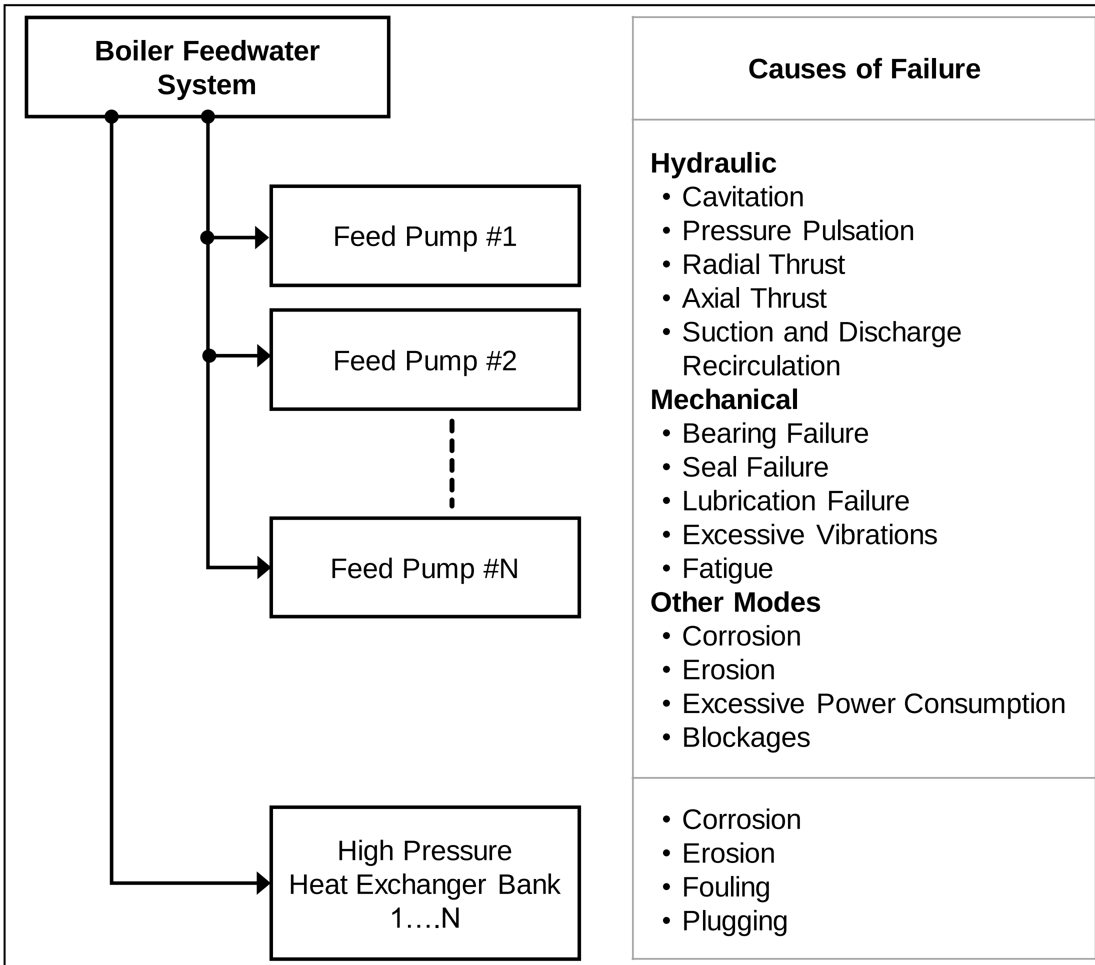

Figure 2: Asset hierarchy and failure causes for boiler feedwater system

Increased power consumption can result from abnormal behaviors/faults in either motor or pump or both. Here we first consider the role of various fault conditions in a motor that adversely affects the pump and consequently increases energy consumption. Assuming that the motor base is not level we examine the implications for pump. The non-level motor base will lead to a slight tilt of the motor axis which, because of the coupling to the pump, will cause additional radial stresses on the motor bearings. Over time, the outer race of the bearing will wear at the location of excess stress which can cause the air-gap of the motor to become eccentric. The eccentricity leads to further asymmetry in radial forces thus exacerbating the bearing problem. Bearings that do not run smoothly increase frictional losses and hence the power consumption (assuming constant load torque).

Traditionally, fishbone diagrams based on a tree structure have been utilized for fault analysis of induction motors or for that matter any rotating machinery. Recognizing the limitations of fishbone diagrams which neither represent faults that may reinforce or inhibit each other, nor can they capture faults that may have multiple causes or that lead to multiple effects, we consider a network structure technique that can capture the relationship between faults. Figure 3 shows the portion of such a network structure diagram for fault analysis of induction motors.

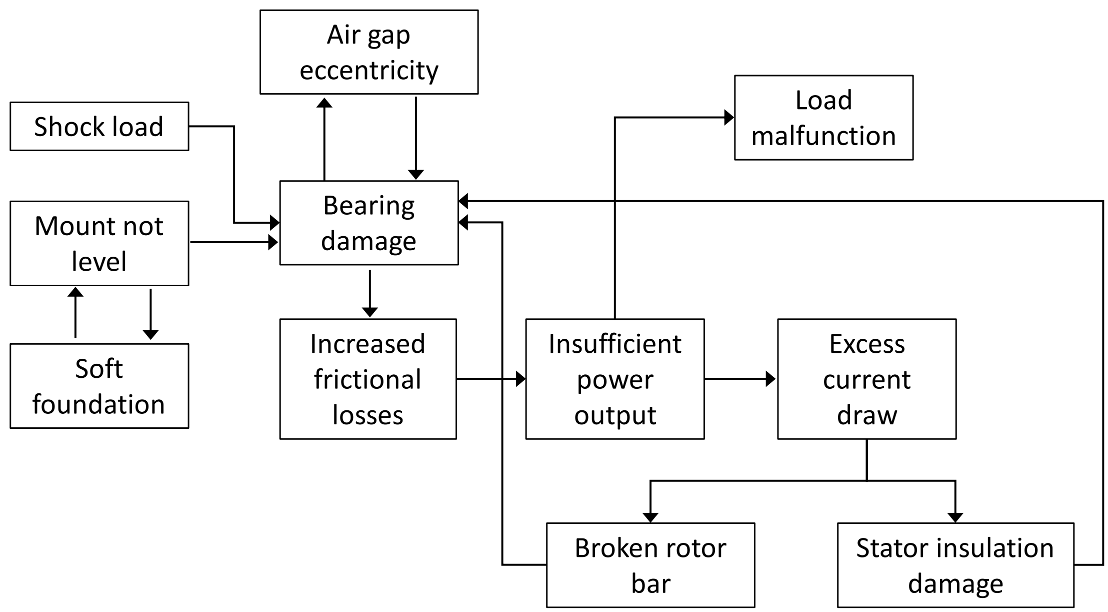

Figure 3: Cause-Effect network structure for motor failure

Since a network structure gives rise to multiple causes for a given effect and multiple effects for a given cause, the transition probabilities are necessary to allow the inference of likely causes from effects. For example, the interaction between bearing race problem with air-gap eccentricity also needs to specify the probability that the bearing issue will cause air-gap eccentricity and also the probability that the air-gap eccentricity will cause bearing problems. Note that these two probabilities may be different, and that they may depend upon the actual level of vibrations as well as the time elapsed since the vibrations increased. In another words, the process is non-stationary [2,3]. The practical application of this technique is in developing machine learning algorithms for fault diagnosis, assembling a library of faults that contains a catalog of faults as well as the connections between them to facilitate inferences.

Increased power consumption can also result from hydraulic instability or mechanical failures. Hydraulic instability can increase the power required to push the fluid into the boiler because problems such as cavitation, flow separation in the impeller and auto-oscillation can cause pressure pulsations in the flow resulting in backflow and re-circulation in the discharge [4]. Some of these problems can be detected by installing vibration sensors and acoustic sensors on the pump [5-7]. The data from these sensors can be processed by a variety of signal processing algorithms and classified by machine learning algorithms [8, 9]. We however note that vibrations can result from several other sources besides these [4]. Some of these alternate sources include line resonance (one of the blade passing frequencies match the acoustic modes of the inlet or discharge lines), blade flutter, blade excitation due to vortex shedding or due to rotor-stator interactions, unbalanced radial forces due to non-uniform casing and volute geometry, or circumferential non-uniformity in inlet flow, and unbalanced axial forces. Some of these have fairly well-defined frequencies while others are confounded with each other, making identification with a single sensor difficult. Another method to detect cavitation is to analyze the input voltage and current [10]. The other cause of increased power consumption, namely, mechanical failure, encompasses failure of the any of the following mechanical components: bearings, volute, shaft, impeller, or seals. Each of these can fail due to numerous causes and have several effects.

For example, Figure 4 shows the various causes contributing to impeller failure.

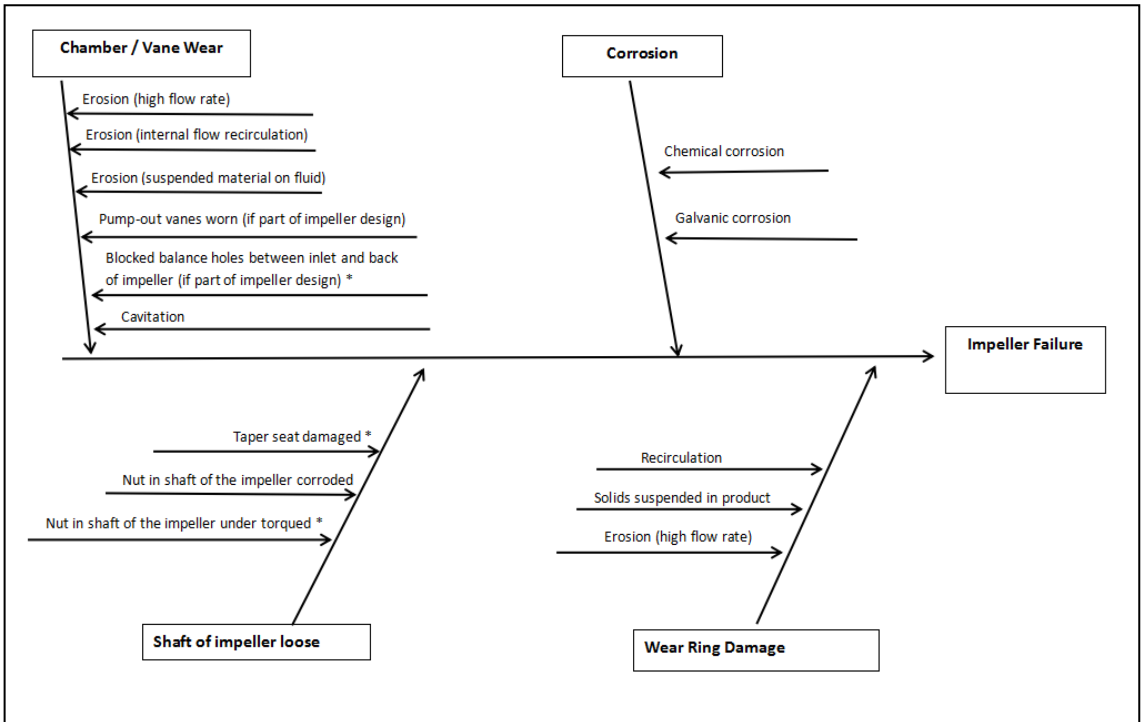

Figure 4: Causes of impeller failure

The above description illustrates the limitations of two most common approaches to condition monitoring: installing a sensor such as an accelerometer to measure vibrations (a sensor-based approach), and installing systems to detect specific faults such as cavitation (a fault-based approach). A sensor-based approach has two limitations: (1) it may pick up a wide range of conditions, some of which may be readily identified while others may defy explanation and may confound the analysis, (2) it may miss a set of problematic conditions, because those conditions do not produce symptoms that can be detected by the sensor. A multi-sensor fusion approach, that can be flexibly deployed can resolve these limitations. The fault-based approach also has limitations because machinery faults interact with each other; one fault may cause another which in turn may positively or negatively reinforce the first. Sensors that are meant to detect one fault may instead detect others that are confounded with the target fault. These limitations highlight the need for an open standards-based, flexible and interoperable system where the capability for fault detection (algorithms, statistical analysis etc.) can be added as new information and knowledge becomes available and as the need arises. For example, open data exchange protocols and the use of standards-based communications protocols enables heterogeneous condition monitoring systems such as handheld instruments, portable analyzers and permanently installed instruments to be integrated seamlessly into the database containing a library/ catalog of faults with known causes and effects that facilitate inferences to be drawn from petabyte-sized data sets. This flexibility and interoperability allows the library to be updated as we gain a better understanding of industrial machinery usage characteristics and how faults develop over time. Concurrently or as a consequence, fusion algorithms and models can also be periodically updated. Open protocols between each adjacent layer and uniform methods for import/export of data from/to a real-time data infrastructure removes barriers to data exchange and analysis.

We now discuss some of the systemic issues that can give rise to pump failures to highlight that root-cause analysis needs to look beyond the troubled asset. If we believe that the pump is cavitating, we need to understand why. As shown in figure 5, cavitation may be a result of (a) factors internal to the pump, (b) operating parameters of the pump, or (c) factors external to the pump. Internal factors include blade flutter which occurs when a compliant blade vibrates and results in unsteady flow, especially at the leading or trailing edges of the impeller blade. Note that the flutter itself may be a result of cavitation because a collapsing bubble near the blade can induce vibrations in the blade. Cavitation can also result from the operating conditions of the rotating stall due to low flow/ high pressure operation. External factors may include factors such as hotter condensate (which has a higher vapor pressure) and excess pressure losses in the suction line. Determining the root cause of the cavitation therefore requires fusion and analysis of multiple data streams. They must include information from sensors mounted on the pump, information regarding the operating conditions and finally information from other assets.

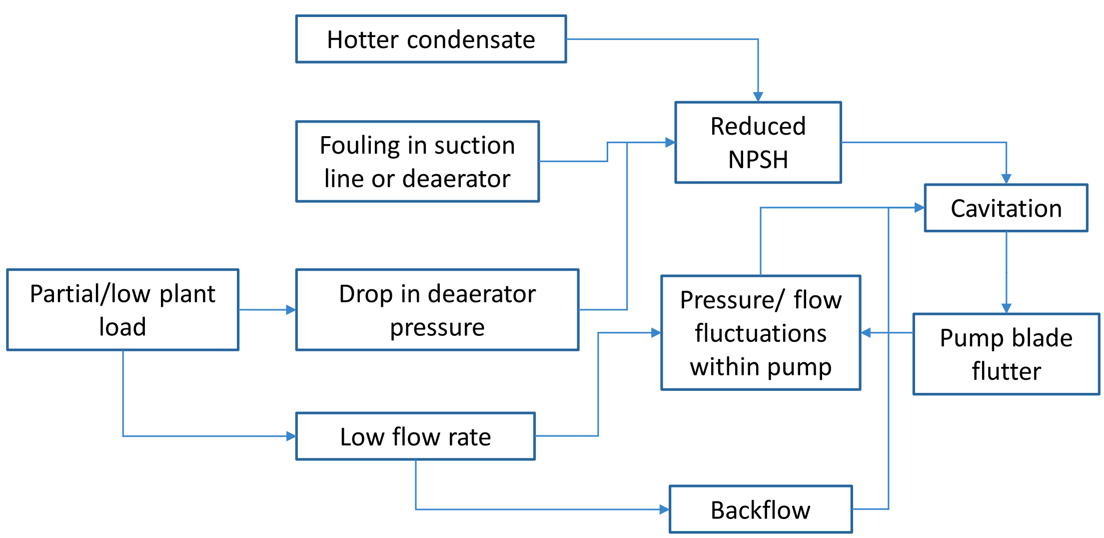

Figure 5: Cause-Effect network structure for cavitation

Consider again the boiler feed water system in Figure 2 where we show an asset hierarchy and their associated causes of failure which can be detected by multiple modes of sensing. Each sensor creates a data object which corresponds to an electrical or mechanical measurement in a larger pool of time-series data. Thus, in order to manage the health of a boiler feedwater system in the context of its process cycle, multiple sensors provide a more holistic coverage of failure modes and performance of individual assets. This method is visually represented in figure 6.

Consequently, the entire chain of assets that comprise a power plant operation can be monitored, analyzed and diagnosed in the context of a specific process. This also allows the plant personnel or control room personnel to drill-down into real-time data on individual assets in order to pinpoint sources of problems that may not be clearly identifiable when data is being viewed at a very coarse level in the asset hierarchy. The benefit of this approach is a more integrated view of system health across electrical and mechanical domains versus a siloed view restricted to a single domain and single database with limited or negligible connectivity to other domains and databases.

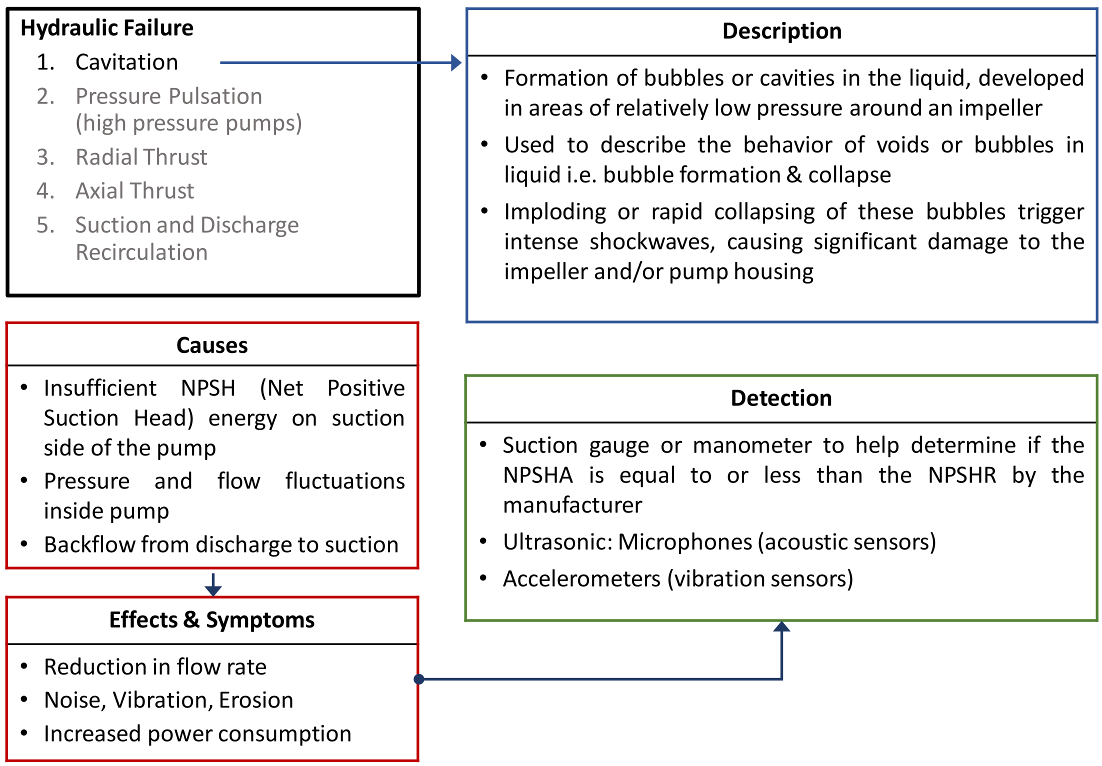

Figure 6: Detecting cavitation in centrifugal pumps

As power plant asset owners/operators begin to plan and implement advanced techniques such as predictive analytics to improve, optimize, and reduce overheads they can utilize the methodology represented in figures 1 through 6 which provides a framework to drill-down from the largest and most complex systems deployed in their plants to the various causes and affects which may affect the vast array of assets comprising equipment, machinery, sub-systems and components. In order to achieve the goals and objectives of predictive maintenance (PdM), we have applied the principles of Industrial Internet of Things (IIoT) and Industrie 4.0 to develop a fusion architecture which provides an evolutionary path for the power generation industry of India from its current state to a future state highly dependent on digital technologies, machine learning and artificial intelligence techniques.

III. FUSION ARCHITCTURE FOR CYBER-PHYSICAL SYSTEMS IN A POWER PLANT

This section describes an architecture-based approach that enables the implementation of an affordable, flexible, software centric and interoperable asset health management system. This architecture (figure 7) provides a solution to the multi-dimensional problem associated with analyzing and predicting the health of heterogenous assets across multiple fault modes under varied operating conditions (refer figures 1 through 5). As artificial intelligence tools and predictive maintenance applications are becoming available very rapidly, this architecture allows the end user to process millions of data streams in real-time as well as offline, to draw inferences from innumerable variables (vibration, acoustic, temperature, current, lubrication, viscosity, fouling, pressure, moisture, thermal stress etc.) embedded in petabyte-sized data volumes. Another significant benefit arising out of the software-centricity and abstractions inherent in this architecture is the ease of use, affordability, reduction in time and complexity of asset data collection, analysis, interpretation and action. For example, with a pool of time-series data, statistical approaches can be applied to predict equipment/machine failure by using the R scripting language to develop predictive modelling equations that can be run in real time to predict equipment/machine failure before it actually happens.

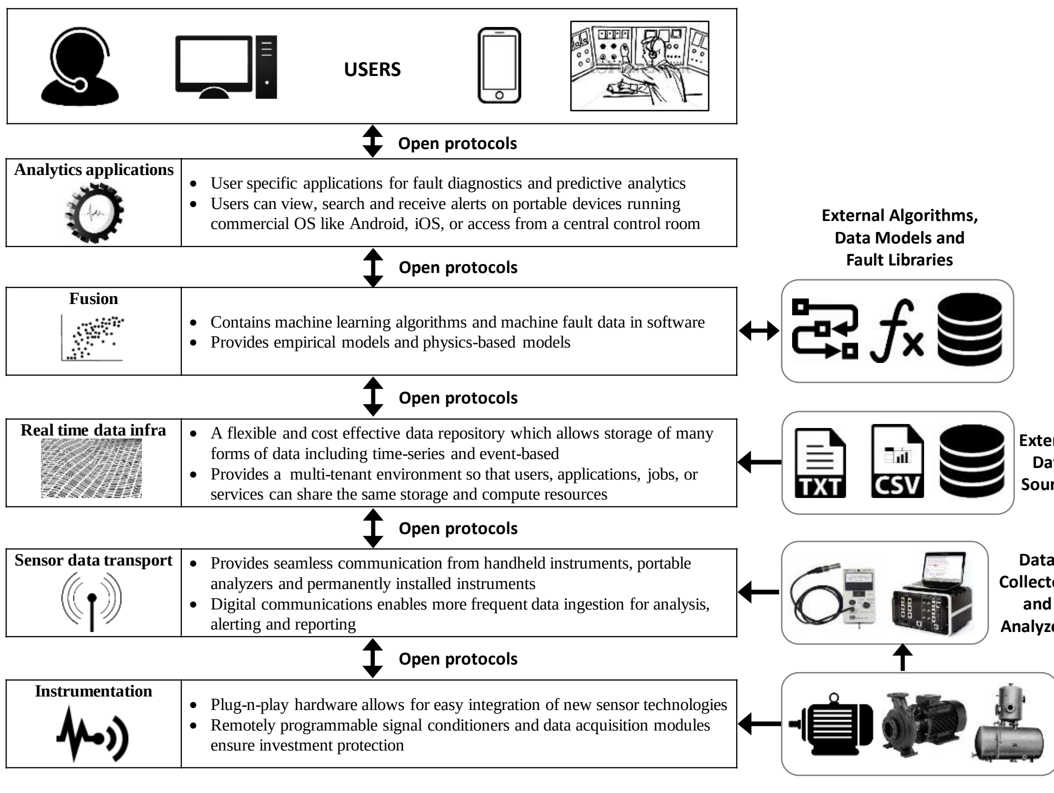

Figure 7: Fusion architecture for a power plant's cyber-physical system

From an implementation perspective, we can rapidly create and prototype a multivariate model to predict failures within a predefined window before equipment/machinery encounters anomalous behavior or actually fails. We recommend that end users adopt the data science process for predictive maintenance: prepare the dataset, visually explore it, partition the data for training and testing, validate the models using previously unseen data, and finally deploy the model.

From an information flow perspective, the lower layers are closest to the asset and collect data from equipment, machinery and systems and pass them on to high layers which integrate and synthesize information before passing them to even higher layers [3]. This aggregation enables the implementation of real-time predictive analytics to identify those early warning symptoms and precursor events that produce adverse operational consequences, create unsafe operating conditions, and/or result in unexpected equipment failures resulting in unplanned downtime.

Since the instrumentation and sensor data transport layers are closest to the asset, we have factored in the following technical requirements into the architecture:

1. The pre-trigger data or the data that occurs right before an event/trigger happens, is the most critical data to capture. If systems are continuously monitored, then one can capture both the pre-trigger and post-trigger event data.
2. If power plants have deployed the concept of gating acquisitions (meaning that data is stored only when certain thresholds are met regardless of other acquisition settings), then it doesn't make sense to capture data periodically on a machine that isn't running – software architecture needs to account for this 'silence'. If the user doesn't set up any type of gating, then data is collected regardless of machine state.
3. For machines running in steady state, taking periodic or event-based measurements is acceptable. But at some critical moments, such as the run-up or coast-down of rotating machinery, streaming transient data is more important.
4. In the case of electrical power protection systems such as circuit breakers, it is important to capture the surface temperature, contact temperature and contact resistance as the dielectric properties may change after a fault is cleared by the device.

IV. CONCLUSION

With increasing convergence of operational technologies (OT), information technologies (IT) and artificial intelligence (AI) techniques, the power generation and transmission sector of India can benefit from the next generation fusion architecture for improving the detection, diagnosis and prognosis of impending faults in rotating machinery, immovable machinery and electrical power systems by utilizing data science techniques for predictive maintenance (PdM).

We recommend an increasing level of scientific and technical collaboration between the asset owner/operators, academia and technology companies to gain a deeper understanding of combined fault conditions and how faults interact with each other. This will enable the development of predictive models which are much more precise in providing real-time early warning signs of abnormalities as well as predicting the time between maintenance (TBM).

Finally, multiple assets in the process cycle should be analyzed concurrently to localize the cause of abnormalities. This is necessary for the purpose of ensuring that similar faults are not repeated and even if they do, then remediation measures can be implemented and appropriate action taken. The most significant benefit arising of this methodology is the creation of an extensible database of known faults which can be continually updated as new knowledge is gained from operational data.

V. REFERENCES

[1] A. Coraddu, L. Oneto,. A. Ghio, S. Savio, M. Figari, D. Anguita, "Machine learning for wear forecasting of naval assets for condition-based maintenance applications," ESARS International Conference, 2015.

[2] E. Esfahani,, S. Wang; Sundararajan, V., "Multisensor Wireless System for Eccentricity and Bearing Fault Detection in Induction Motors," Mechatronics, IEEE/ASME Transactions on , vol.19, no.3, pp.818-826, June 2014.

[3] A. Kumar, V. Sundararajan, "An Architectural Approach to Industrial Machinery Health Management", Proceedings of the International Conference on Condition Monitoring (ICCM 2016), Gitam University, Vizag, India, Oct 26-27 2016.

[4] C. Brennen, "Hydrodynamics of Pumps", Cambridge University Press, 2011.

[5] M. Cudina, "Detection of Cavitation Phenomenon in a Centrifugal Pump Using Audible Sound," Mechancal Systems and Signal Processing (2003), Vol 16, no. 6, pp 1335-1347.

[6] L. Alfayez, D. Mba and G. Dyson, "The application of acoustic emission for detecting incipient cavitation and the best efficiency point of a 60 kW centrifugal pump: case study", NDT & E International, Volume 38, Issue 5, July 2005, Pages 354-358.

[7] J. Sikorska, M. Hodkiewicz, "Comparison of acoustic emission, vibration and dynamic pressure measurements for detecting change in flow conditions on a centrifugal pump", The Condition Monitoring and Diagnostic Engineering Management (COMADEM) International Congress.

[8] M.R. Nasiri, M.J. Mahjoob, H. Vahid-Alizadeh, "Vibration Signature Analysis for Detecting Cavitation in Centrifugal Pumps using Neural Networks", proceedings of the 2011 IEEE International Conference on Mechatronics, April 13-15, 2011, Instanbul, Turkey.

[9] V. Muralidharan, V. Sugumaran, "Feature extraction using wavelets and classification through decision tree algorithm for fault diagnosis of mono-block centrifugal pump", Measurement (2013), Vol 46, no. 1, pp 353-359.

[10] P. Harihara, A. Parlos, "Sensorless Detection of Cavitation in Centrifugal Pumps", Proceedings of IMECE2006 2006 ASME International Mechanical Engineering Congress and Exposition November 5-10, 2006, Chicago, Illinois, USA.