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REAL-TIME DIAGNOSTICS, PROGNOSTICS & HEALTH MANAGEMENT FOR LARGE-SCALE MANUFACTURING MAINTENANCE SYSTEMS

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ABSTRACT

Traditional technologies emphasize either experience or model-based approaches to the Diagnostics, Prognostics & Health Management (DPHM) problem. However, most of these methodologies often apply only to the narrow type of machines that they were developed for, and only support strategic level assessments as opposed to real-time tactical decisions. By enabling widespread integration of diagnostics and prognostics into our manufacturing business processes, we have reduced spacio-temporal uncertainties associated with future states and system performance and therefore enabled more informed and effective decisions on manufacturing activities. For large-scale systems, the usual approach is to aggregate multidimensional data into a single-dimensional stream. These methods are generally adequate to extract key performance indicators. However, they only point to observable effects of a failure and not to their root causes. An integrated framework for DPHM requires the availability of bidirectional cause-effect relationships that enable system-wide health management rather than just predicting what its future state would be. This paper summarizes best practices, benchmarks, and lessons learned from the design, development, deployment, and execution of DPHM systems into real-life applications in the automotive industry.

INTRODUCTION

Today's plant floor systems are approaching the state which e-commerce reached in the late 1990's [1, 2]. The power of pervasive data linking among heterogeneous systems is bringing the internet revolution into the four walls of the plant [3-6]. As it was the case with the world-wide-web, the initial lack of consistent data, communication, and security models across dissimilar systems was the bottleneck that prevented then, web services, and now, plant floor systems from realizing their full potential [1]. Fortunately, standards and applications already developed for the web including among others XML, HTTPS, OPC and web services [7-9] are now rapidly migrating into mainstream plant floor systems (PFS) applications. As a consequence, the broad real-time availability of PFS data sources [10, 11] and their subsequent integration in upper level systems have caused the advent and realization of e-Manufacturing [3] applications throughout every business function in modern plants.

The basis of an effective Prognostics and Health Management (PHM) implementation are in principle efficient and consistent diagnostics procedures [12]. However, that may not be enough [13]. For example, in the automotive manufacturing industry, maintenance diagnosis is mainly an *ad-hoc* process which is highly specialized for the specific type of system and even failure type under consideration [14, 15].

Typical and largely successful diagnostics methods and applications at General Motor's manufacturing plants include among others

- Electric Motor Monitoring,
- High Speed Video & Fiber Optic,
- Infrared Thermography,
- Laser Alignment,
- Lubrication & Oil Analysis,
- Ultrasound, and
- Vibration Spectrum Analysis.

Such methods and applications can be generalized up to a point and then used across several manufacturing facilities as long as the physical quantity or process in question remains unchanged from application to application, *i.e.* obviously, we could use laser alignment techniques and metrics for most dimension control applications but not for diagnosing an electric motor overload. In addition, given that in a typical automotive manufacturing line every machine or station is fundamentally different and executes a different task from any other one in the same line, unless we can provide diagnostics techniques that are applicable to all machines, then we will not be able to readily scale such R&D investments throughout the entire plant and moreover to the entire corporation.

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Consequently, the type of diagnostics approaches needed to manage the health of large-scale manufacturing systems requires a key characteristic that is missing from the items in the previous list of diagnostics techniques: *horizontal & vertical generalization*. By *horizontal generalization*, we mean, to have the ability to use the same type of data acquisition systems [16], databases [17], metrics [12], and more importantly business processes to perform standardized diagnostics & prognostics operations for each and every one of the machines of the line regardless of their function. By *vertical generalization*, we imply, for example, that real-time diagnostics results from an overload test and from a proximity sensor failure can be aggregated into overall states at the machine, cell, zone, line and ultimately plant level. We do not imply that currently used diagnostics techniques are going to be replaced by the approach presented on this paper; these techniques are in fact complementary. The former, gives us information about critical failures in specific sub-systems or components while the later shows an integrated picture of the system. This combined approach allows plant personnel to focus their efforts on the largest opportunity to improve the overall system performance rather than focus on a number of non-prioritized issues arising on specific machines [18, 19].

The outline of this paper is as follows: In the first section, a description of definitions and objectives of DPHM for large-scale systems is given and in particular, we show how these are translated into the strategic, operational, and tactical environments. This is followed by an analysis of mainstream DPHM approaches and how they relate to metrics and maintenance policies. In the following section, the prediction problem specifics for multivariable system are described. Discussion, examples, and conclusions are presented in the last section.

DPHM FOR LARGE-SCALE SYSTEMS

DPHM systems requirements for discrete manufacturing largely differ from those in the product and service areas. In modern factories, real-time information and data exchange is pervasively available across the entire enterprise [5]. This enables plant operations personnel to have accurate and up to-date records of the system performance, usage, maintenance, and environmental conditions. In the product and service cases, two external agents, end-customers and service personnel, whom which we have no controllability and at times not even observability, dictate the operational load and product perturbations. Even when advanced distributed and autonomous automotive telematics systems such as OnStar™ [20] provide state-of-the-art diagnostics information, these systems are bandwidth limited due to mainly economical factors. This is not the case for factory applications where already existing Ethernet networks provide inexpensive connectivity among all plant floor systems [5]. Alternatively, a combined approach for evaluation of product life cycle management and manufacturing process prediction performance is also possible [4, 21].

Diagnostics

This is the process of detection, identification, and isolation of an *existing* condition and the determination of its nature, circumstances, and probable causes. Usually, this process is more directly related with remediation of the condition rather than to its root-cause or future avoidance. For example, when a patient goes to the doctor due to an excessive cough, the relevant issue is to determine the type of illness that is causing it and what is the correct treatment, not how it was contracted, or how can it be prevented.

In a manufacturing setting, a common practice is to perform *preventive diagnostics*, which in most cases is the detection of an already initiated malfunction that has not, but probably will, reach a critical condition and stop the production process. Such downtime normally occurs when an electrical or mechanical failure degrades one or several Key Performance Indicators (KPI) of the system below an acceptable threshold. This can either occur gradually or catastrophically; in the first case the crossing of a KPI threshold level triggers a fault event, and the second case, which sometimes follows the first one, the entire system cease to operate entirely. Typical KPIs in manufacturing systems include:

- Revenue & profits
- Throughput
    - Good & Bad Parts
    - Jobs/hour & Cycle Time
    - Blocks & Starves
    - Over cycles
- Downtime & Uptime
    - Frequency & Duration
    - Mean Time To Repair (MTTR)
    - Mean Time Between Failures (MTBF)
    - Mean Cycle Between Failures (MCBF)
- Quality
    - First Time
    - Overall
- Maintenance
    - Emergency Maintenance Calls
    - Work Orders Generated
    - Ratios: Reactive/Prevent./ Predict.
    - Stand-alone Availability
    - Overall Equipment Efficiency (OEE)
    - Asset utilization
- Cost
    - Maintenance Labor & Material
    - Assembly Labor & Material

Prognostics

In a general sense, *prognostics* or *predictive diagnostics* is the process of identification of symptoms indicating the future course of the state of a system and the factors contributing to it [22], *e.g.* what is the 5-year survival rate for cancer patients based on historical clinical data and on current symptoms?. In an industrial environment this translates into the use of test, performance, or other related data in the evaluation of a system or equipment for determining the potential of impending faults [23, 24]. Furthermore, prognostics capability is the ability to reliably predict the degradation and therefore the remaining useful life of components, within an actionable time period, with acceptable confidence limits [25].

By dissecting these definitions of prognostics, several key elements can be identified at different time horizons:

- Past
    - Historical system use & performance
    - Identification & detection of abnormal events
    - Isolation of such events once they occur

- Present
    - Current operating conditions (external)
    - Current system performance (internal)
    - Course of action to be taken
    - Current cost of remediation
- Future
    - Target prediction horizon
    - Actionable time period
    - Spacio-temporal uncertainty
    - KPI's aggregation
    - Probability and impact of failures

Health Management

A holistic approach to the diagnostics and prognostics problem is the integration into the business process of a Prognostics & Health Management (PHM) system that provides suitable solutions at the strategic, operational, and tactical levels [14]. Strategic solutions deal with long term and highly aggregated metrics in time, space and function, while operational decisions are shorter term and more granular. Finally, in tactical matters, real-time information and decision-making are crucial for efficient business execution. PHM is in essence, a performance management framework that provides decision support by prioritizing actions used to address the impact of asset degradation and failure [26-29].

Strategic Level. Generally deals with high-level decisions that are taken, executed, and maintained over large periods (months or years). At this level, Product Lifecycle Management (PLM) combined with Reliability Center Maintenance (RCM) approaches can be used from the product conception, design, manufacture, and disposal. Such approaches focus mainly on

- Product and Portfolio Management
- Product Design
- Manufacturing Planning
- Product Data Management
- Identification and establishment of policies for
    - Capital improvement
    - Maintenance operations
    - Equipment risk management

Operational Level. Commonly concentrates on routine process as supply chain control & execution, equipment maintenance and scheduling. Such decisions are taken in order to maintain day-to-day operations in the mid-term (days or weeks). Such approaches include among others

- Preventive maintenance, which is generally estimated to be applied unnecessarily up to 50% of the time
- Predictive maintenance, which minimizes inspections and time-based maintenance
- Scheduled overtime, which is commonly used to compensate for system capability limitations

Tactical Level. In this case, the key for success is to have a Real-time Performance Management (RPM) system in order to provide value through the power of real-time (seconds or hours) information visualization. These activities are mainly composed by

- Reactive maintenance, which are emergency repairs that generally conduce to a loss of production
- Unscheduled overtime, which is used as last resort when the system production targets are missed.
- Real-time monitoring, which is the main source of information for immediate decision making
- Incipient fault detection, which is the pillar of CBM

Integrated View for DPHM

There is an inherent tradeoff between scope & complexity of a DPHM system and its decision support outcome timing. Figure 1 presents a conceptual relationship between the aforementioned aspects. The basic concept is rather simple; use historical and real-time data to provide decision support maintenance activities either after, during, or before the system's KPI's degrade to an unacceptable range.

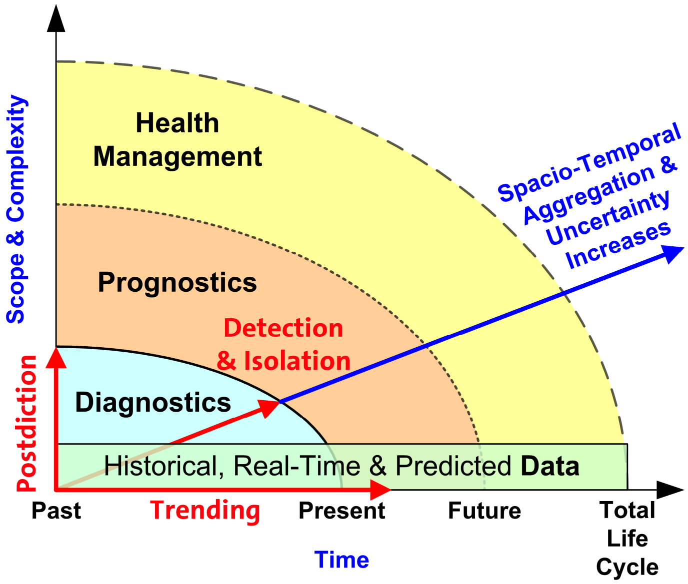

Figure 1. DP&HM

In the diagnostics case, a post mortem analysis can provide clues of why a system failed and what countermeasures can be taken in order to prevent the same issue from occurring again or how to mitigate its effect in the future. This method is sometimes referred as *postdiction*, which is a prediction except that the analysis is done from an unknown past into a known present [30]. If coupled with real-time monitoring this technique can be extended to incipient fault detection and therefore enhanced *detection and isolation* rates [31]. Another approach that can be used independently or complementary to diagnostics is *trending* [32]. In this case, no attempt is done to realize the cause of the failure and the emphasis is focus on the observable effects and the forecasting of KPI's drift or recurrence.

The base of the entire DPHM system is data and as mentioned before it can be either historical or real-time. However, when trying to extend diagnostics capabilities into prognostics and important issue arises

- Should the system predict the future raw data and from there perform its standard diagnostics procedures? or
- Should the system predict directly the future failure and its possible cause and even its solution?

We think the answer is neither. The former is overly low-level; it is impractical to construct models to create predicted data with the granularity, accuracy and time-space resolution needed to be used as you would do with raw data. The later, is too abstract and high-level; the main drawback of this approach is its complexity. Given the number of possible states and failures modes of the system, this renders impractical the generation of bidirectional models that can accurately and consistently produce system performance prediction and at the same time provide attributable causes and feasible solutions for them. The option we are presenting is a hybrid. Past and present data are kept in raw form. Every single event is stored in historical databases such that high-level feature and other KPI extraction and aggregation can be performed and at the same time reversible bijective transformations can be provided. For *"future data"*, our solution entitles intelligent spacio-temporal aggregation of predicted features and KPI's. This means that we do not predict raw data itself, we are a level above that; and we do not attempt to predict directly the occurrence of a specific failure mode but instead the KPI and data features in aggregated and extracted form, which in fact transforms the problem into a variant of the well-known paradigm of incipient fault detection.

The spacio-temporal future data aggregation is determined by the following factors:

- Actionable time available once a condition has been determined. This is related with the business process integration; if there are weekly maintenance meetings to determine overall maintenance priorities for that period neither hourly nor monthly predictions would be adequate to support the maintenance staff in their decision making process.
- Loss of prediction accuracy with increased prediction horizons. In practice, there is always a tradeoff between the accuracy and the time in the future for which we are providing predictions. Therefore, if we are providing for example, 1-step-ahead predictions in 1-day intervals with a reasonable accuracy, making the prediction horizon 1 week will not benefit us at the end, even when the aggregated metric seem to minimize the bias, it will most likely increase the variance to intolerable levels.
- Subsystem criticality and business process hierarchy. Spatial aggregation in manufacturing system is normally done following either a physical, a functional, or a logical hierarchy. Physically, for example, all faults from a component, machine, station, zone, line, or plant can be aggregated by using linear or non-linear transformations. Functionally, events related to a specific business function are aggregated in order to decrease the complexity of the decision making process; for example, a production superintendent may only be interested on body, paint and general assembly end-of-line throughput, which is aggregated or represented with the effective production of the last machine. Logically, faults or events belonging to a specific sub-system can be aggregated by for example:
    - Throughput: blocks, starves
    - Production: production counts & over-cycles
    - Maintenance: fault conditions
    - Quality: Good versus bad parts for first-time and final quality.
- Symbolic/Lexicographic data clusters. In order to reduce complexity and to deal more efficiently with uncertainty, it is possible to qualify either raw or already aggregated KPI's with membership functions or group operators. It generally involves a scaling or thresholding operation and a mapping into a symbolic space; such qualifiers include words such as good/bad, high/medium/low, below/normal/above, etc.

Objectives

For the purpose of this paper, we are focusing on the maintenance side of DPHM for manufacturing systems. PHM main goal is to provide timely and actionable information to support a decision making process. Specifically, we are formulating the following goals given their foremost impact potential.

Maintenance. In automotive manufacturing systems, maintenance costs are in the order of several billion dollars per year. Such expenditures are incurred due mainly to labor costs and to a lower degree to spare parts costs. Even when throughput losses during downtimes may be significant, given the high quality of the production system design and operation, the impact on the overall systems is in the order of only a few percentile points. Conversely, improvements in maintenance efficiency and therefore labor cost reductions are usually in the double-digit range; the challenge here is to find benefits in a fix-cost based maintenance system. For example, minimization of maintenance overtime by being able to efficiently perform most required activities during normal business hours rather than catching up on leftover work with overtime, is a simple way to address this issue. Consequently, some of the most significant maintenance DPHM goals include the following:

- Prioritization of maintenance needs
- Identification of Root-Causes
- Reduction of man-hours, spares, and repair costs
- Avoidance of collateral damage
- Reduction of downtime via opportunistic maintenance
- Minimization of scheduled inspections
- Enhancement of Reliability and Safety

Procurement & Asset Visibility. Generally deals with a system level prospective where it is not as important to assess why the system is failing or will fail but to provide adequate contra-measures with an adequate level of coverage. These types of requirements indirectly establish a tradeoff between cost and functionality of the systems as a whole. In order to do so, the following requirements become of relevance

- Automatically Isolate Faults to 1 Least-Replaceable-Unit (LRU)
- Eliminate Can-Not-Detects (CND) and Re-Test-OKs (RTOK)
- Provide Real Time Notification of about impending failures
- Support operational decision making

DPHM APPROACHES

DPHM is a largely automated extension of Condition Based Maintenance (CBM) as well as of Reliability-Centered Maintenance (RCM) [28]. There are several general categories in which we can group DPHM approaches [26], some of them include the following

Experience Based

In this approach, usually an expert user analyzes the history of the failure of the system on a case-by-case basis and tries to find other instances of previous events that may suggest the appropriate course of action to be taken. This *ad-hoc* approach is labor intensive and is widely variable even among experienced practitioners. Furthermore, its lack of scalability and transferability to other location and applications makes it unreliable. Methodologies as Root Cause Analysis (RCA) have formalized some of the learning of this process; however, it remains highly unsuccessful and expensive in terms of cost and time.

Physics/Model Based

This approach relies on first principle analysis of the system. The assumption is that the designer can develop a synthetic model that approximates the physical process to an acceptable degree of uncertainty. This approach is well suited for simple electrical & mechanical systems. The implementation of this model commonly relies on the numerical or even symbolic approximation to an ordinary differential equation (ODE) solution. Its main weakness is that when modeling hybrid systems, like real plants, or in presence of combined analog and discrete spacio-temporal variables, the solutions of the ODE become highly stiff, making its solution to expensive in computational complexity terms. A typical example of this approach includes forms of Condition Based Maintenance (CBM).

Statistics Based

In this approach, the raw data is analyzed and a type of Probability Density Function (PDF) is estimated [33]. Once the PDF parameters are estimated, probabilities of failure are assigned to detected anomalies. For simplicity, widely used models in category generally ignore any or most correlation information present in the data. Typical techniques that could fit this approach include

- Reliability Centered Maintenance
- Autoregressive Models, *e.g.* ARMA
- Bayesian approaches

Data-Driven

This approach intends to create non-linear dynamic mapping between the inputs and the outputs of the system without making assumptions about the underlying physical principles that drive it. This approach is generally preferred by applied practitioners rather than mathematicians given than in many cases is difficult to provide proof of optimality and convergence of solutions. Typical examples of these techniques are Artificial Neural Networks (ANN) and Genetic Algorithm (GA).

Hybrids

This self-explanatory category includes mixture and fusion of most of the aforementioned techniques. These approaches are generally driven by the need to integrate dissimilar and often incompatible DPHM system requirements into a final product. The mixture is usually done across hierarchical levels, leaving the numerically intensive, hard computing ones on the lower-levels and the soft computing ones on the higher-levels. Other approaches also include combinations of the following

- Temporal Data Mining (TDM)
- Support Vector Machines (SVM)
- Liquid State Machines (LSM)
- Evolutionary Multi-Objective Optimization (EMO)

MAINTENANCE METRICS FOR DPHM

Maintenance Ratios

An important set of metrics on plant operations are the ratios between reactive, preventive, and predictive maintenance [34]. These ratios relate directly with their cost and impact on production and labor utilization. Table 1 presents a qualitative comparison of the typical relative characteristics of the different types of maintenance; we postulate that an increase in predictive maintenance will add more value to the business or will have increased savings when compared with investments on reactive or even preventive activities. In conclusion, the best Return On Investment (ROI) is generally going to be achieved through predictive technologies applications. U.S. Department of Energy and other estimates give a 10:1 ROI to predictive maintenance as well as a 25% to 30% reduction in maintenance costs [35, 36].

Table 1. Maintenance Types Characteristics

Maintenance	Reactive	Preventive	Predictive
Frequency	On Demand	Scheduled, Time- or Cycle-based	Condition Based
Labor Cost	High	High	Low
Labor Utilization	High	Low	Low
Parts Cost	High	Medium	Medium
Throughput Impact	High	Medium	Low
Urgency (Acceptable resolution timeframe)	High (Minutes to Hours)	Low (Days to Weeks)	Very Low (Depends on impact)
ROI	Low	Medium	High
Initial Investment	Low	Medium	High

In Table 2 and Figure 2 we are presenting a benchmark originally based on data from [37] and [34], that we have compensated and expanded based on our knowledge of the automotive industry state, constraints and business practices. The red, blue and green stacked bars represent the ratios between reactive, preventive and predictive maintenance respectively. For *dysfunctional* ratios we can infer that due to the lack of long term planning and investment most manufacturing operations are executed on a run-until-it-breaks mode rather than attempt to prevent unscheduled downtime. This is mainly driven by the uncertainty in the determination and prediction of cost-effective preventive and predictive maintenance schedules.

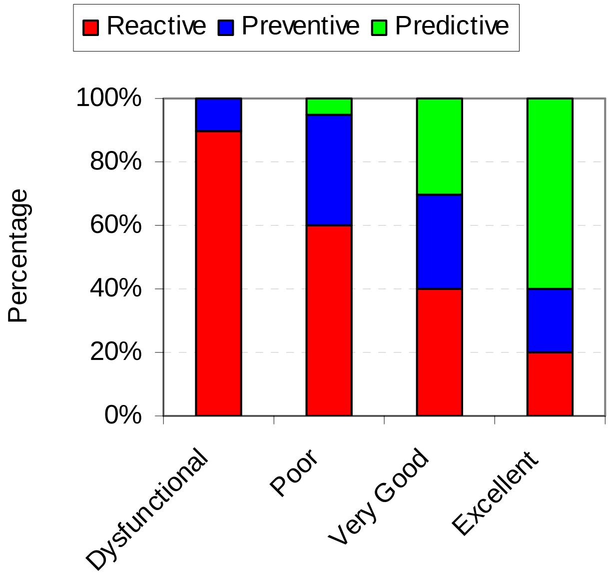

Figure 2. Maintenance Type Ratios Ratings

Table 2. Maintenance Ratios Qualifications

Parameter		Dysfunctional	Poor	Very Good	Excellent
Maintenance	🟥 Reactive	90%	60%	40%	20%
	🟦 Preventive	10%	35%	30%	20%
	🟩 Predictive	0%	5%	30%	60%
Overtime		Above 15%	15%	5%	2%
Data Usage	Quality Control	Below 50%	50%	95%	100%
	Historical Maintenance	**No;** Not reliable at all	**Sometimes;** Not fully reliable	**Often;** Reliable data and info	**Yes;** Reliable data and info

Additionally to the maintenance type ratios ratings data from Figure 2, Table 2 also includes other industry benchmark figures for overtime and data usage [34, 37].

Value of Maintenance Prognostics

We can divide maintenance activities into two main categories: Reactive & Proactive Maintenance. Even when reactive maintenance will never go away, an optimal DPHM system design should aim to minimize it. The proactive maintenance can be further divided into the following

- Scheduled Maintenance: basic & mostly redundant preventive measure.
- Prognostics: advanced preventive measure that if applied correctly can lower the number of incidents, lower the cost per incident resolution, lower the cost per processed job, increase the number of problems correctly solved, increase throughput and provide preemptive incident resolution [38, 39]

Maintenance Policy

When going from simple data visualization, to statistical analysis, and to data- and physics-based models, the higher hierarchical level, a Maintenance Policy, is nothing more than the integration of such underlying models. Figure 3 presents a simple maintenance policy assignment based on the ratio between event frequencies versus their severity. We propose that reactive, preventive, and predictive maintenance areas can be defined based on an *impact curve* or *iso-power limit* concept. The iso-power limit (blue asymptotic line) is a transformation in which fault events with different severity and frequency can be compared with a single metric. For illustration purposes, we are using the Cartesian product between them. The main premise is to assume that effects of large faults that occur rarely are comparable with those of frequent but relatively short ones; therefore, if the faults that lie on the same *impact curve*, they will be given the same relative importance.

Even when the power level may seem arbitrary at first, it is really a cost determined variable, the lower the value (impact curve moves toward the origin), the higher the maintenance cost and vice versa. Fault events falling in the (yellow) reactive maintenance zone are left to run to failure. Events in the (green) predictive area which have low frequency and high impact are monitored via predictive and condition based maintenance techniques. Events in the (gray) preventive area are given optimized periodic maintenance schedules based on usage and not time. Other events (red dots outside bounded areas) are generally either reporting/data acquisition system inconsistencies or in the worst case, systematic issues that need to be designed out of the system. Events are considered *acceptable* (green dots) if their occurrence and remediation does not significantly affects the overall system performance or *unacceptable* (red dots) otherwise. Note that in general preventive maintenance addresses failure modes which have high value on the impact curves and that are not accurately predictable; such events justify the added expense [40] of performing preventive maintenance as a throughput tradeoff.

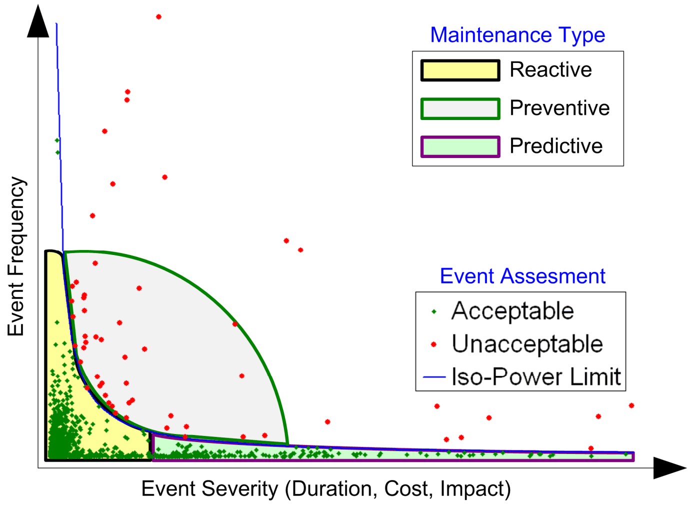

Figure 3. Maintenance Policy

PREDICTION PROBLEM

In order to provide adequate prognostics capabilities to a DPHM system a crucial step is the prediction of KPI's. Normally, this task is accomplished by providing single variable estimates of the future state of the system. In many cases this is the equivalent of providing a marginal PDF estimation of the fault event of interest projected over a single 1-dimensional space. The drawback of this approach is that ignores the high correlation and interaction among variables.

Multivariable Prediction

Figure 4 depicts a two-variable joint prediction for a specific manufacturing system machine while accounting for all failure modes (functional aggregation); in this case, we only care about the machine being up or down and we do not care why. Raw historical data has been binned in weekly intervals (temporal aggregation) and two features, total downtime and counts, have been extracted from it (statistical aggregation).

In order to construct and verify the prediction model the historical data is divided into training, validation, and testing data. This allows us to have a measurement of the quality of the model and therefore the inherent uncertainty associated with the predictions. A common and unnecessary assumption is to make the prediction horizon and the predicted interval of the same length as the bin interval for the historical data; however, that need not be the case. Actually, they can all be different and optimized for different type of prediction performance parameters or business needs.

Given the high correlation existing among KPI’s, is computationally less complex and yields better prediction results to estimate the future *joint* PDF’s rather than the projected *marginal* PDF’s. If single variable predictions are required, the joint PDF’s can be marginalized. This can also apply to linguistic qualifiers (high/medium/low) which may correspond to different degrees of membership of the variable; see Gaussian-like marginal projections in the *y* and *z* axis.

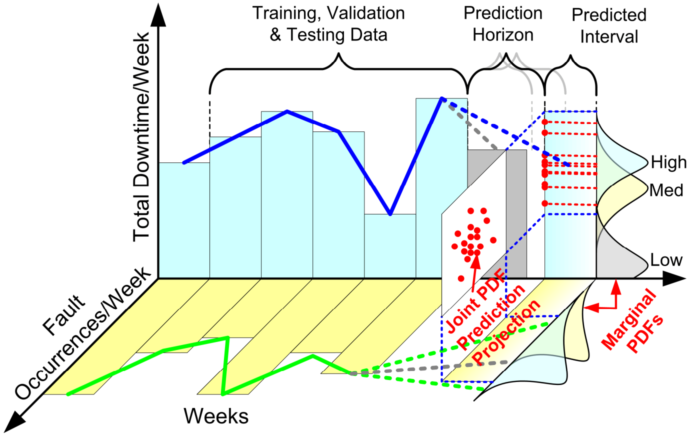

Figure 4. Multivariable Prediction

Multiple Prediction Fusion

The next problem at hand is the integration of prediction from different approaches. Unfortunately, there is no universal predictor that can give accurate estimates for all variables and prediction horizons. In a consistent predictor, as its complexity and execution time increases so should accuracy, precision, and other metrics improve; however in some cases even this necessary condition may not be sufficient [41]. Furthermore it is necessary to validate the prediction power and obtain confidence intervals and/or statistical significances for all predictors [13, 42]. Predictors can range from those that are no better than a coin toss, to predictors that are so overspecialized and difficult to optimize that they surpass the target user or system usability limit. Figure 5 represents this idea. The coverage of a predictor, which is the number of different failure modes that it can predict, determines how *generic* and sensitive the predictor is; this property is also called *recall*.

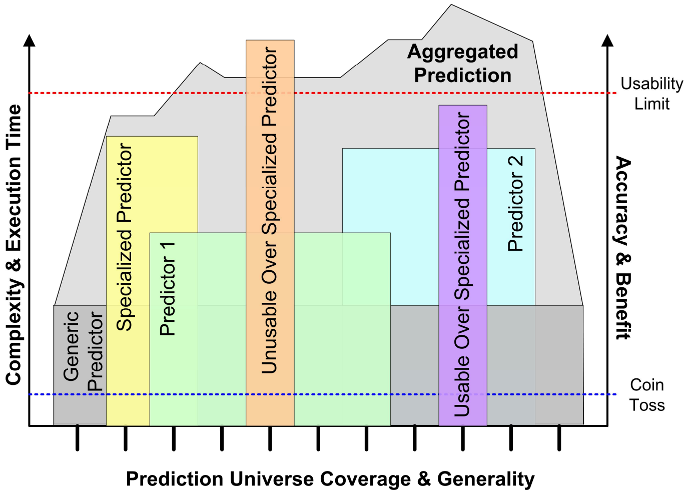

Figure 5. Prediction Ensemble

Data fusion from different predictors is a feasible but complex task. First, some predictors will yield numeric prediction values, while other will use symbolic ones. Second, the measures of confidence, accuracy, false alarms, and significance may not be compatible with each other. Finally, the prediction horizons of each predictor may differ from all others. Therefore re-normalization in time and space may be required in order to be able to operate of these dissimilar sources of information. The final step is to estimate the best *aggregated prediction* via a Kalman filter, a predictor corrector method, or even an Expectation Minimization (EM) Algorithm.

DISCUSSION & CONCLUSIONS

Implementation Gaps

The most difficult obstacles to overcome in order to implement an adequate DPHM strategy for a target application start by the acquisition and transport of consistent, clean, and reliable data. It is common knowledge among practitioners that this step entitles about 90% of the system development effort. Then the next largest barrier is an efficient integration into the company business process; pristine data and perfect predictions are not useful if the people that need to act upon it are not engaged. If the information is difficult to access or visualize and does not provide apparent business value then it will most likely be disregarded.

The use of *predicted* KPI’s is the basis for the success of the DPHM; however, they are also the harder ones to define. Any KPI can be easily misused and abused. Typical examples are Indexes as Stand-Alone Throughput (SAT) and First-Time Quality (FTQ), which can produce pathological cases under low or interrupted production and therefore are not consistent across the entire set of production conditions. The incorporation of the human factor in the DPHM equation is necessary for success. Perform Human-Driven Predictive Diagnostics by providing the right people, with the right information at the right time, nothing more, and nothing less is what is required for DPHM successful deployments.

The final but no less important barrier is to overcome fear of initial investment. Effective DPHM has significant upfront costs [27] that are, however, vastly overshadowed by its benefits [43]. It is better to invest in prediction and prevention now that have to pay a premium cost during full production where it will be too late even if you have the money to invest.

What DPHM can do for you?

From the manufacturing perspective, the bottom line is that DPHM is a key enabler to diminish the loss of revenue mainly due to throughput losses and rising maintenance costs. It can provide maintenance savings by predicting fault event and it can alert about potential impending failures before they occur, or diagnostic tests are available.

DPHM reduces spatial & temporal uncertainties about the future state of a system or process and it contributes to

- Size reduction for fault isolation groups [13, 38, 39],
- Selection of prediction horizon for fault events [44],
- Estimation of faults PDF's and their parameters [33].

What DPHM can NOT do for you?

DPHM cannot increase fault detection coverage. "You cannot predict what you cannot diagnose." It will not provide accurate predictive diagnostic information for every system, component, or failure mode unless designed in from conception, which will tend to be an expensive initial investment.

DPHM may not be able to find the cause of the failure event when correctly predicted. Even when feasible fault diagnostics detection & isolation rates to 1 Least Replaceable Unit can normally be 99% & 95% respectively [45], prediction accuracy rates will NOT be anywhere near such values and it will be highly dependent on the application and evaluation metrics used. In addition, DPHM will not work well if performance metrics are ill defined or inconsistent.

Challenges

DPHM can have significant startup costs associated with staff training & process changes, equipment & IT infrastructure, data cleanliness, and feedback loop for predictions (what were the maintenance personnel's actions). On the other hand, as estimated by the Department of Energy and others, typical prognostics ROI are in the order of 10:1 [27, 35, 36].

Effective DPHM Implementation

Our final contribution on this paper is the proposition of the following business process that can be used to enable and achieve a successful DPHM implementation

- Understand the business process
- Get appropriate and reliable data
- Perform Predictions for "required" prediction horizons
    - Events
    - Systems performance metrics
    - Prediction confidences and statistical significance
- Estimate benefits achieved by acting on such data
- Act on predicted results
- Measure and validate results
    - Prediction: Accuracy, Precision, Type I & II Errors, Significance, ROC(t), …
    - Value of the Prediction
    - Business Impact
    - Financial Benefit
- **Repeat with rigor and discipline**

Automotive Industry Examples

The automotive industry has been long committed to the use of advanced diagnostic techniques given that they are an ever-present enabler to achieve high levels of process and product quality and consequently sustainable revenue. Through several internal programs and external partnerships General Motors has implemented a number of advanced prognostics technologies across its manufacturing facilities. Such complete life cycle management experience related to the research, development and deployment of prognostics tools in industrial environments was used as the knowledge-base for the findings and recommendations presented on this paper. Specifically, as a long standing member of the Intelligent Maintenance Center (IMS) at the University of Michigan, we have initiated and driven industry-wide collaborative efforts in areas ranging from predictive maintenance policy [46] to industrial networks health management [47]. As part of such collaboration we have heavily influenced the research agenda on prognostics technologies by providing funding, in-kind contributions, internships and access to industrial grade test-beds to both academic and industrial researchers.

An integral part of our global collaboration network is lead by HRL Laboratories, where we have conducted collaborative and directed research in prognostics for manufacturing systems for the last few years. Examples of these technologies range from advanced trending techniques [48] to downtime prediction via Markov models [49, 50], evolutionary hybrid temporal data mining [51] and genetic algorithms [52, 53]. These technologies have been developed, tested and deployed at engine and general assembly plants while working in closely with their maintenance staff and upper level management.

This paper presented a view of DPHM from the automotive manufacturing perspective when applied to large-scale manufacturing systems. Specifically, we provided benchmarking and best practices information for the automotive industry. Different approaches and maintenance metrics for DPHM were presented and discussed. Finally, extensive conclusions, examples, and a discussion of our recommendations were provided.

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