Auto-steered Information-Decision Processes for Electric System Asset Management

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Abstract. The total replacement value of the US transmission lines alone (excluding land) is conservatively estimated at over $100 billion dollars [1] and triples when including transformers and circuit breakers. Investment in new transmission equipment has significantly declined over the past 15 years. Some of the equipment is well beyond intended life, yet is operated under increasing stress, as load growth, new generation, and economically motivated transmission flows push equipment beyond nameplate limits. Maintaining acceptable electric transmission system reliability and delivering electric energy at low energy prices requires innovations in sensing, diagnostics, communications, data management, processing, algorithms, risk assessment, decision-making (for operations, maintenance, and planning), and process coordination. This paper overviews a comprehensive approach to develop methods and processes in these areas, driven by the ultimate objective to develop a hardware-software prototype capable of auto-steering the information-decision cycles inherent to managing operations, maintenance, and planning of the high-voltage electric power transmission systems.

1 Introduction

In electric power transmission systems, the assets include transmission lines, support structures, transformers, power plants, and protection equipment. Condition information includes loading or operating histories, inspection data, periodic and as-needed testing and diagnostic results, and continuous diagnostic measurements, the latter of which are typically collected via intelligent electronic devices (IED) and stored within substation servers. A single transmission company, each of which has their own centralized control center, has responsibility for many thousands of each equipment type. A single control area, represented by an Independent System Operator (ISO), oversees and coordinates activities of a number of different transmission companies. The eastern and western US interconnections are each comprised of a number of ISOs; the only other US interconnection, Texas, has only one. Failure of an asset may affect physical and economic performance of the entire interconnection and always increases likelihood of additional failures. Because economic performance (power supply allocation among power plants) affects transmission loading which affects failure likelihood and consequence, operational

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risk-reduction inevitably results in less economic power supply. Frequency and severity of blackout scenarios as observed on August 14, 2003 are affected by policies associated with equipment operation, maintenance, and planning.

The objective in this work is to develop a hardware-software prototype capable of auto-steering the information-decision cycles inherent to managing operations, maintenance, and planning of the high-voltage electric power transmission systems. We focus on the needs of the most critical electric transmission equipment, including power transformers, circuit breakers, and transmission lines. Similar equipment exists at the distribution level, so the work will find direct application there. Figure 1 illustrates the structure of the problem and facilitates description of how we intend to approach its solution. We overview intended implementation of the 5 different layers in what follows.

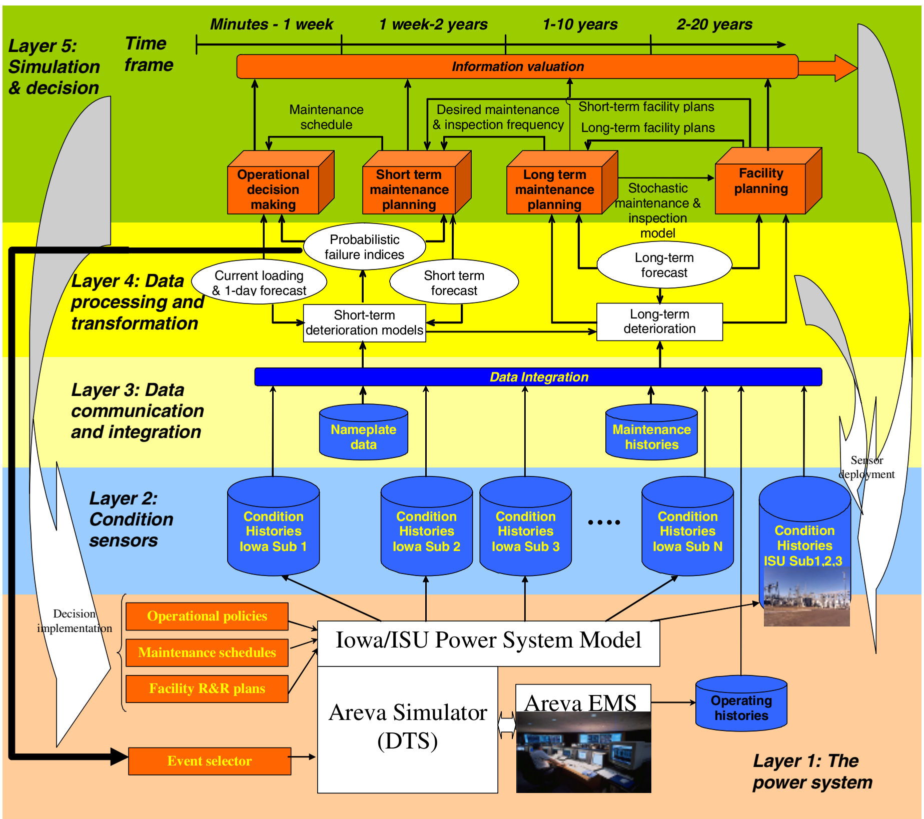


Fig. 1. The structure of the asset management problem

Layer 1, The power system: The prototype will center on a continuously running model of the Iowa power system using network data provided by local utility companies using a commercial-grade (Areva) simulator.

Layer 2, Condition sensors: As indicated by the taller "Condition History" cylinder at the far right of layer, 3 campus substations will be equipped with sensors, communication equipment, and servers to provide a benchmark prototype for hardware implementation. Other substations will be represented virtually, each with its own unique database containing the condition data for that substation provided by the utility company.

Layer 3, Data communication and integration: This will entail intra-substation communication using wireless between IEDs and substation server together with federated data integration to provide efficient, dependable, and secure mechanisms for interfacing Layer 4 data transformation algorithms with the data resources.

Layer 4, Data processing and transformation: This layer will operate on the integrated data from layer 3 to produce, for each component/failure mode/time, an estimate of that particular component/failure mode deterioration level at the given time. This will require deterioration models, and we target such models for the chemical degradation processes in oil and cellulose (both of which provide insulation in power transformers). We will also need stochastic models to predict future degradation, and we further describe these models in Section 2.

Layer 5, Simulation and decision: This layer will utilize the component probabilistic failure indices from layer 4 together with short and long-term system forecasts to drive integrated stochastic simulation and decision models. These models will operate interactively, so that simulation and decision in each time frame utilizes information from simulation and decision within other time frames. Resulting operational policies, maintenance schedules, and facility reinforcement plans will then be implemented on the power system (as represented by the Areva simulator). The decision models will also be used to discover the value of additional information. This valuation will be used to drive the deployment of new sensors and redeployment of existing sensors, impacting Layer 2. This layer is further described in Section 3.

2 Layer 4: Data Processing and Transformation

Component condition, deterioration level, or propensity to fail, is essential information for asset management decision problems. Our objective in this part of the work is to develop methods of computing component (or subsystem) failure probabilities. One unique aspect of this work is that in addition to steady-state failure probabilities that capture average behavior over a large number of components and over an extended period of time, we also require transient failure probabilities to capture instantaneous behavior for each specific component.

Consider a set of condition vectors $c(t)=[c_1(t),c_2(t),\ldots,c_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$, where each vector $c_k(t)$ provides M different measurements $c_{k1}(t)$, $c_{k2}(t),\ldots c_{kM}(t)$, on component k characterizing its condition at time t. The total possible number of measurements is less than K×T×M because there are different frequencies for which different measurements are taken. We will augment c(t) with operational and environmental information in building predictive failure models. For some system components, failure is closely related to a single condition measurement that can be measured over time and modeled in a manner that allows reasonably accurate prediction of failure (e.g., extent of vegetation growth or the amount of chemical degradation). Let c(t,e;β) denote the expected level of degradation for a unit subjected to environmental conditions e, where β is a vector of unknown model parameters to be estimated from available data. The form of the function c may be suggested by physical-chemical theory, (see, for example, [2,3,4]), past experience, or the available data. A failure-time cdf F(t) is induced by a specified model for c(t,e;β), the environment e, and a definition of failure (usually a specified value c_f, beyond which failure is said to have occurred). Stochastic behavior in c(t,e;β) can be captured either by using a stochastic process model (e.g., [5]) or by driving a deterministic model with a stochastic environmental model (e.g., [6]). As new condition information is received for a given unit, it is possible to update the failure probability for that unit. For the special case in which all units are in a common and constant environment, [7] develops a model to describe the effect that nondestructive inspections will have on the failure probability. It is possible to generalize this "degradation analysis" approach to a vector of condition measurements, but statistical modeling of the joint distribution of a vector of condition measurements is more difficult, especially if the dimension exceeds 2. The Markov modeling approaches discussed next provide a useful alternative.

We can often characterize boundary conditions separating J states of deterioration in component k in terms of the measurements $c_k(t)$, via a deterioration function $g[c_k(t)]$. The deterioration function returns a deterioration level j identified by $d_{j-1}<g[c_k(t)]<d_j$, where the last state j=J represents the failed state. State J need not represent the rare "blue smoke" condition where the component has catastrophically failed (and for which little data is typically available). Rather, state J represents a set of measurement values for which engineering judgment indicates the component should be removed from service. This approach to computing failure probabilities is illustrated in Fig. 2, based on multistate Markov models, where each of J states is represented as a deterioration level. The representation of Fig. 2 shows J=4 deterioration levels, and deterioration level j is reached only from deterioration level j-1. Yet, the model is flexible; any number of deterioration levels can be represented, and, if data indicates transitions occur between non-consecutive states (e.g., 1 to 3), the model can accommodate this.

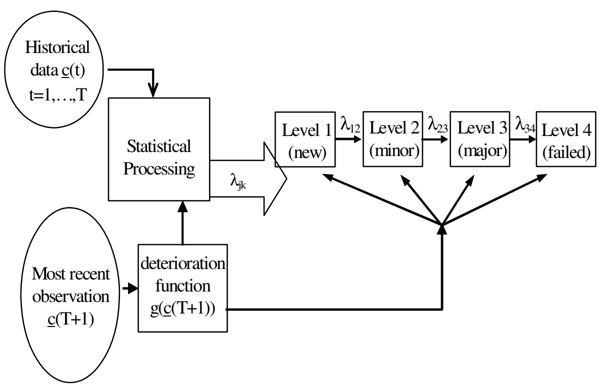


Fig. 2. Computing contingency probability reductions

The model parameters capture the deterioration in equipment state as influenced by past loading and environmental conditions. To capture future effects of variation in such conditions on model parameters, one needs to model the dependency of the transition intensities on these parameters. To account for uncertainty in state identification through observation or indirect measurement, the variance of the conditional probability of observation given the state, referred to as σ_{ki} for component k, state i is used. This parameter can also facilitate the analysis to identify investments to make for obtaining better or more information, described in Section 3.2.

Once transition intensities are determined, state probabilities are obtained from the transition probability matrix and initial state vector. We denote this failure probability for the k^{th} component as $p_k(c)$, a function of the time-dependent physical condition of the equipment c(t). This modeling provides the ability to predict the effect that maintenance will have on failure probability and expected time to failure, metrics that are important for a number of decision problems. The expected time to failure is captured by computing first passage times [8,9].

3 Layer 5: Simulation, Decision and Information Valuation

Asset management decision problems are characterized by: (1) strong interdependencies between physical performance of individual assets, physical performance of the overall system, and economic system performance; (2) limited resources; (3) important uncertainties in individual component performance, system loading conditions, and available resources; (4) multiple objectives. We describe these decision problems in this section, together with our intent to solve them in an integrated fashion.

3.1 Simulation and Decision

Asset management decision problems can be classified into one of 4 types which all involve resource allocation with the objective to minimize cost and risk. These specific asset management decision problems include (a) Operations, (b) Short-term maintenance selection and scheduling, (c) Long-term maintenance planning, and (d) Facility planning.

These problems differ primarily in their time scale but are linked by a common focus on the interactions between the condition of equipment and the decisions taken. The operational decision problem of how to meet demand in the next hour to week treats facilities available and their deterioration levels as given (though the deterioration is not known precisely). The contribution here is to use condition measurements to more accurately estimate short-term failure probabilities along with the deterioration effects of loading each piece of equipment at various levels, and to integrate these improved estimates into the dispatch and unit commitment decisions. The tactical decision problem to allocate resources for maintenance in the next 6-24 months suppresses detail about hourly operations but considers an aggregate description of equipment loading when deciding how to allocate resources to best manage the condition of the equipment. Our approach will use historical data to better judge the combined effects of maintenance and loading on the equipment deterioration and use this information to improve maintenance scheduling. The long-term maintenance problem examines tradeoff between maintenance expense and equipment life to find inspection and maintenance policy to minimize expected long run cost of keeping the equipment in service reliably. The strategic decision problem to both expand capacity and replace equipment over the next 2-20 years takes as input distributions of equipment life lengths resulting from adopted maintenance policies and determines when to replace existing equipment and invest in additional assets. Unlike previous models for equipment replacement and capacity expansion, we consider the cumulative effect of power flow on equipment life and take advantage of better data-driven life length predictions.

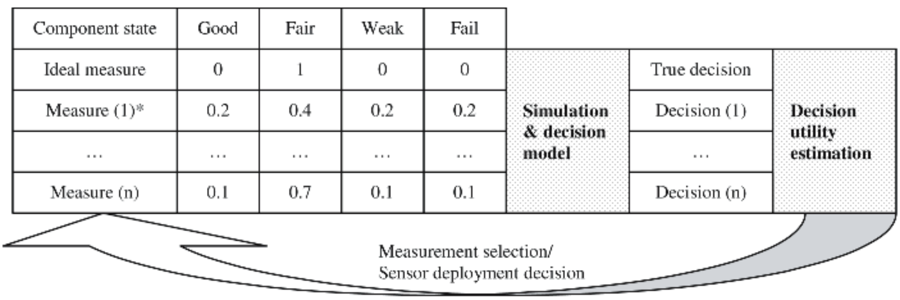
When we integrate these optimization problems having different time-scales together, we will treat the quantities that vary much more slowly as static and model quantities that vary much faster in a way that ignores the details of their variations, such as by replacing fast-moving quantities by their averages. A similar strategy is used in hierarchical planning of manufacturing systems [10].

3.2 Information Valuation and Sensor Deployment

A last but critical decision problem to be addressed is how to extract from data transformation (Layer 4) and decision (Layer 5) algorithms identification of economically sound opportunities for obtaining better information, thereby reducing uncertainty and improving decision-making capability. A simple case is when an abrupt measurement change causes immediate suspicion that a failure is imminent. The response is to inspect the equipment. Additional more specialized measurements may be done, and if those measurements confirm a problem, the equipment is removed. Such situations are addressed via alarms. A decision to obtain information is clear in this case, because imminent failure poses high capital loss and physical harm to humans.

Decision to gather information is more difficult for maintenance and planning problems because the payoff (or avoided loss) is not so pronounced. We address this problem via a two-stage information valuation approach [11,12,13,14]. In the first stage, we determine candidate components for which additional information may be of interest. Denoting the value of the objective function at the solution as Γ, we compute an index giving sensitivity in Γ due to component k, as $\sigma_{ki}(\partial\Gamma/\partial p_k)$ where p_k is the failure probability of component k and σ_{ki} (see end of Section 2) is the deviation in the observation for component k given that it is in state i. Components having high index are candidates to consider in the information valuation stage. Other selection criteria can be considered, e.g., we could identify components that are almost or barely selected by the decision algorithm. We denote additional information associated with candidate component k as r_{km}, which indicates component k is in state m. Such information may be obtained by installing more or better sensors at a cost. For example, a 50 year-old transformer that is a clear candidate for replacement may be operating with no monitoring equipment, yet installation of such equipment, providing information r_{km}, may result in decision to operate the unit for more years.

Following [13], states in which component k may reside are identified by $i=\{1,\ldots,S\}$, with each state having probability π_i obtained from procedures described in Section 2. Simulation and decision algorithms are then repeated once for each possible state of component k, generating solutions with corresponding objective values. Denote identified solutions (alternatives) by a={1,…,A}. Thus, for each combination of state and alternative we have a consequence c(a,i). Denoting the utility of an alternative as u(a) and of a consequence as v(c), we desire to choose the alternative to maximize expected utility $u(a,\pi)=\sum_{i=1,S}[\pi_i v(c(a,i))]$. The decision to obtain additional information is based on expected utility gains from shifting to better choices among the set of actions. Denote a_0 as the optimal alternative with no additional information, identified using prior probabilities π_i, and a_m as the optimal alternative with the additional information r_{km}. Then the value of information r_{km} is given by $\Delta(r_{km})=u(a_m, \pi_{i,m})-u(a_0, \pi_{i,m})=\sum_{i=1,S}[\pi_{i,m}v(c(a_0,i))]-\sum_{i=1,S}[\pi_{i,m}v(c(a_m,i))]$, where the posterior probabilities $\pi_{i,m}$ are given by $\pi_{i,m}=\Pr\{r_{km}|i\}\pi_i/\Pr\{r_{km}\}$. However, the decision to seek the additional information must be done ex-ante to be useful, and so



* Current measurement.

Fig. 3. Illustration of information valuation and sensor deployment

we cannot know that we will obtain r_{km}, i.e., that we will learn that component k is in state m. But we can assess (subjectively, or from historical data) the probability of learning from the new information that the component is in state m, which is $\Pr\{r_{km}\}$. Then we may compute the expectation of the value associated with the new information as $E\{\Delta(r_{km})\}=\sum_{m=1,S}\Pr\{r_{km}\}[u(a_m,\pi_{i,m})-u(a_0,\pi_{i,m})]$. We will use this approach to interface with Layers 4 and 5 procedures for assessing where and when to obtain additional information.

4 Conclusions

This paper gives a framework of a hardware-software prototype capable of auto-steering the information-decision cycles inherent to managing operations, maintenance, and planning of the high-voltage electric power transmission systems. The framework is divided into 5 layers and described in this paper accordingly. Although each layer represents an essential and substantive part of the framework, the paper focuses on the data transformation (in layer 4) and decision (in layer 5) elements.

Acknowledgments

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