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Big Data Opportunities: System Health Monitoring and Management

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ABSTRACT The concept of a system, generally defined as an organized set of detailed methods, procedures, and routines that are created to carry out a specific activity or solve a specific problem, has been successfully applied to many domains, ranging from mechanical systems to public health. System health monitoring and management (SHMM) refers to the framework of continuous surveillance, analysis, and interpretation of relevant data for system maintenance, management, and strategic planning. This framework is essential to ensure that an entire system is stable and under control. A fundamental problem in SHMM is the optimal use of correlated active and passive data in tasks including prediction and forecasting, monitoring and surveillance, fault detection and diagnostics, engineering management, and supply chain management. In this paper, we provide a new perspective on SHMM in a big data environment, discuss its relationship with other disciplines, and present several of its applications to complex systems.

INDEX TERMS Active and passive data, big data, complex systems, system health monitoring and management.

I. INTRODUCTION

With the rapid development of information technology, social media, data collection capacity, and data storage, the field of big data analytics is now rapidly expanding into all science and engineering domains. Real-world applications such as telecommunications, health care, pharmaceuticals, and finance generate massive amounts of data round the clock [1]. Taking online social media alone, for instance, today's customer base is estimated to generate 2.5 quintillion bytes of data per day in the form of tweets, likes, comments, blogs, videos, and images [2]. These big data streams contain abundant information stored in the form of hidden patterns and unknown correlations. Analyzing big data streams that were previously untapped or inaccessible will enable new insights resulting in better and faster decisions.

The process of examining big data to uncover hidden patterns, unknown correlations, and other insights is referred to as big data analytics [3]. Its primary goal is to help make intelligent decisions through analyzing large data streams from multiple sources. Big data analytics has benefited many industries in various aspects, and created many opportunities for research [4]–[6]. At the same time, many challenges have been raised along with these opportunities, such as increased noise in large data, and under-developed policies for protecting individual privacy and security [7].

Systems health monitoring and management (SHMM) presents a new opportunity for big data-related research. SHMM refers to the framework of continuous surveillance, analysis, and interpretation of relevant data for system maintenance, management, and strategic planning. This framework is essential to ensuring that an entire system is stable and under control. The concept of the ''system'', generally defined as ''an organized set of detailed methods, procedures, and routines created to carry out a specific activity or solve a specific problem'', has been successfully applied to many domains, ranging from mechanical systems to public health [8]–[10]. A fundamental problem in SHMM is the optimal use of correlated active and passive data in tasks including prediction and forecasting, monitoring and surveillance,

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fault detection and diagnostics, engineering management, supply chain management, and many more. A promising aspect of research into SHMM is a focus on complex systems, which can be either machine or human. In complex human and engineering systems, challenging research problems may arise in various domains driven by big data analytics, such as syndromic surveillance [11], [12], electronics-rich system management [13], simulation and optimization of emergency departments in medical systems, [14] and mass transit planning [15].

This paper reviews the issues facing big data analytics associated with SHMM in a general sense, by discussing the evolution of big data analytics, categorizing data types based on data sources and collection processes, and providing specific insights into the research opportunities and challenges brought about by big data. Specifically, we propose a general framework of SHMM, discuss its relationship with other disciplines, and provide several application examples of SHMM for complex systems and critical components in a big data environment. The rest of this paper is organized as follows. In Section II, the evolution of big data analytics is reviewed. In Section III, the various sources and types of big data are introduced. In Section IV, the formulation and general framework of SHMM are presented. The relationship between SHMM and other disciplines is clarified in Section V. In Section VI and VII, SHMM for complex systems in a big data environment is introduced. Further discussions of SHMM are presented in Section VIII. Finally, Section IX concludes the paper.

II. EVOLUTION OF BIG DATA ANALYTICS

The origin of big data analytics can be traced back to the 1970s or before, when research communities in computer science (CS) and statistics, working in fields such as machine learning and statistical computing, began to play a major role in data mining. In the following decade, the scale and volume of data grew dramatically due to the increasing capability of computing power and automation. To distinguish these large datasets from conventional data, they were referred to as ''very large databases'' (VLDBs) or ''massive data'' (MD) sets among the CS and statistics communities. The 1990s witnessed an unprecedentedly fast development and maturation of the methodology and theoretical foundations of data analytics across various disciplines from data mining, statistical learning, to knowledge discovery in databases (KDD), and we will label this as the first wave of big data analytics. In this period, the development of data analytics fell primarily in the realm of academia.

Humanity has never stopped pushing the boundary of knowledge. After the first wave, the huge success in methodological and theoretical development of data analytics quickly spread to every corner of the research world, and even industry. The value of big data was increasingly recognized as its potential to change and improve society and human lives became apparent. Since 2000, big data analytics has been successfully adopted in many more disciplines, such as

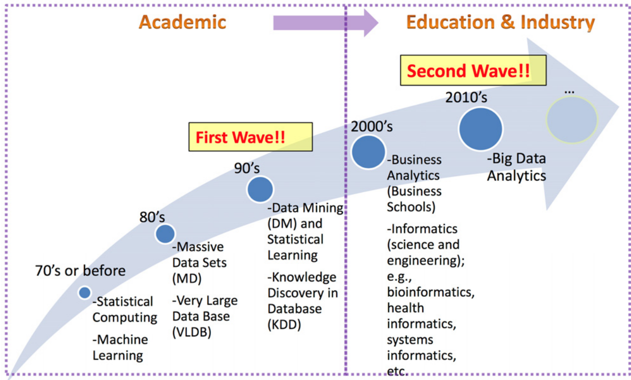

FIGURE 1. A brief history of big data analytics.

business analytics in business and management schools, and informatics in the fields of science and engineering, including bioinformatics, health informatics, systems informatics, etc. We label this period as the second wave, which was accompanied by a parallel development in the fundamentals of big data analytics in academia, education, and industry. Fig. 1 briefly depicts the history we have outlined above, to provide a clear picture of the evolution of big data analytics.

III. BIG DATA SOURCES AND TYPES

A. QUALITY DATA AND USEFUL DATA

Data quality is a prerequisite for effective big data analytics. Although practitioners and researchers may boast of having good data or improving data quality, defining what these qualities represent is a real challenge. Traditionally, data quality refers to the overall utility of a dataset as a function of its ability to be easily processed and analyzed for other uses, usually by systems for databasing, data warehousing, or data analytics. To be of high quality, data must be consistent and unambiguous. Quality data are characterized by various attributes, such as accuracy, timeliness, objectivity, completeness, reliability, etc. The appropriate set of attributes and their acceptable levels may differ depending on research purpose and setting. Judging a dataset's quality requires an examination of its attributes and then weighing those attributes according to their importance for the task at hand.

In reality, quality data of key performance indicators are often expensive, unavailable, or time-consuming to collect. Data that arrive too late, e.g. cases of clinically confirmed infectious disease, or take too long to gather, e.g. failures of systems or key components, will no longer be effective for intelligent decision-making and operations. However, correlated data are often available and can be highly useful for problem-solving. Such data are referred to as ''useful data'' in this context. Useful data can be correlated with specific research purposes or work tasks and are often available from multivariate sources. For example, data on internet-based search queries can be correlated with infectious disease patterns, and thus utilized for outbreak forecasting. For another example, meteorological data collected at observatories can be correlated with wind power outputs, and thus used as covariates for wind power prediction.

Quality data can be easily processed and analyzed, while useful data that are also high-quality can further lead to insights that facilitate better decision-making. Such data are essential to SHMM intelligence efforts and other types of data analytics, as well as better operational efficiency.

B. ACTIVE DATA AND PASSIVE DATA

Reliable data sources are crucial to the effectiveness of data analytics. Depending on the data source and collection manner, we divide useful data into two main categories: active and passive.

Active (or primary) data are collected to study scientific, health, engineering, or business problems, through data generation or collection mechanisms that are specifically designed or planned for the purpose of research. This is analogous to design of experiment (DOE) studies in manufacturing applications. Examples of active data can be found in many applications, such as digital surveying of the sky in astronomy, monitoring and surveillance in risk management in finance and banking, sensor data for prognostics and systems health management (PHM), transportation management, computer and communications management, etc.

In contrast, passive (or secondary) data are readily available or have been previously collected for other, unrelated, purposes, but may still be useful for addressing the current questions of interest. This is analogous to production data in manufacturing applications. Examples of passive data include customer transactions, electronic medical records, web searches, social media data, etc.

In real applications, active and passive data are complementary to each other. The most effective approach is therefore to make use of both in applications of real-world data analytics. In the next section, we will present some examples of data analytics that follow this approach.

C. GRAY AREAS BETWEEN ACTIVE DATA AND PASSIVE DATA

Note that there is no clear distinction between active and passive data in certain scenarios, or ''gray areas''. This ambiguity is especially likely when the study designs and objectives are uncertain. Complex systems usually involve numerous components that interact among themselves, which complicates the definition of health indicators for system monitoring. To determine effective health indicators, it is necessary to collect relevant data and examine their correlations with system health at an early stage. For example, tracking experiments have been widely conducted to collect relevant data for monitoring high-speed train systems in China [16]. In these experiments, thousands of sensors were deployed to collect real-time data. However, how to most effectively correlate these collected data with component/system health is still a topic of debate.

Besides categorizing data sources into active and passive data, other types of data classification may also be useful. For example, depending on whether data are generated by DOE analysis or collected from manufacturing processes and other applications, they can be categorized into lab and field data. Alternatively, data sources can be categorized into observational vs. survey data, sensor-based vs. non-sensor-based data, etc.

D. SOME PRACTICAL EXAMPLES

The availability of useful active and passive data in many new areas introduces new research opportunities in statistical modeling. In particular, enormous and detailed data at various locations and spatiotemporal domains have the potential to be used for model development at both population and individual levels. For example, [17] provides a thorough discussion on the feasibility and challenges of data analytics in personalized medicine. A possible global approach to data-driven personalized medicine would be to model population heterogeneity in real time, as well as to integrate and manage various data sources and types to improve patient treatment. An example from another field is to develop in-situ automotive prognostics by tracking and analyzing user-specific driving records over the lifetime of an automobile [18].

The integration of active and passive big data leads to a new challenge in big data analytics. Instead of solely relying on active data, researchers are now trying to incorporate existing passive data to enhance models for data analytics, prediction, and decision-making. For example, in wind turbine applications, engineers have attempted to improve wind power prediction by integrating wind speed (active data) with environmental factors (passive data), such as wind direction, air density, humidity, turbulence intensity, etc. [19]. In public health applications, one would like to improve the predictive accuracy of cases of influenza-like illness (ILI) by integrating ILI activity reports (active data) from the Centers for Disease Control and Prevention (CDC) with data on internet searches (passive data) [20].

Among the many other research opportunities to recently appear are the optimization of sensor locations, development of new modeling methods for incorporating web data into predictor variables and scaling datasets with large size and dimensionality, and improvement of forecasting with process parameters, etc.

IV. FORMULATION AND GENERAL FRAMEWORK OF SHMM

A. FORMULATION OF SHMM

SHMM is a potentially broad topic, covering everything from experimental design and data collection phases, all the way to data analysis and the inevitable decision-making phase at the very end of the process. As a growing number of systems become data-rich, the theoretical foundation of SHMM is likely to fit into the ''data to knowledge to action'' paradigm, and therefore to benefit from future developments in data science. Data science shows all the signs of growing into a discipline in its own right, with a strong theoretical foundation at its heart, such foundations being paramount in the development of any new scientific field. It is anticipated that theoretical research relevant to SHMM will also boom in the near future.

Theoretical research on the foundation of SHMM will therefore build on theoretical foundational research in data science, which is intrinsically inter-disciplinary (in the sense that many different scientific domains will need to work together and develop novel theories that transcend disciplinary boundaries). In particular, establishing the theoretical basis of SHMM is likely to involve interdisciplinary collaborations between computer scientists, mathematicians, and statisticians, as these three disciplines are at the heart of the theoretical foundation of SHMM's closest relative, data science.

The importance of SHMM in a range of real-world application domains is undoubted. Domain experts must keep a keen eye on developments in SHMM with potential implications for their own field. This will require strong communication mechanisms between SHMM researchers and practitioners. Algorithms developed "in a vacuum" for theoretical purposes only will likely fail to take into account the peculiarities and incompleteness of real data in real problems. The success of SHMM will strongly depend on the trade-offs between statistical accuracy and quality-of-approximation necessitated by the various computational constraints imposed by modern computing infrastructure.

We believe that much of the theoretical foundation of SHMM lies at the intersection between computer science, statistics, and mathematics. Each of those disciplines, however, has been built around particular ideas and in response to particular problems that existed several generations ago. Thus, building a foundation for SHMM requires rethinking not only how those three foundational areas interact with problems in SHMM and with each other, but also how each interacts with implementations and applications. For example, historically, computer science and scientific computing have each carved out different realms of application, leading to differences in the formalization of models, questions to consider, and computational environments (such as single machines versus distributed data centers versus supercomputers). In the contemporary framework of SHMM, the design requirements of business, internet, and social media applications lead to questions that tend to be very different from those in scientific and medical applications. Both the similarities and differences between these areas are striking. Designing the theoretical foundations of SHMM requires paying appropriate attention both to the problems of researchers implementing SHMM in specific fields and to the environments and platforms where computations are to be done.

B. GENERAL FRAMEWORK OF SHMM

A general framework of SHMM is summarized in Fig. 2, introducing a division into six main steps. In the first step, the specific problems and objectives of concern are defined, which can be either human or engineering systems. The second step involves selecting appropriate sensors for collection of the specific data to be further investigated and analyzed. For example, for engineering systems and critical components, the relevant sensor types may include thermal, electrical, mechanical, humidity, chemical, optical, and magnetic sensors, etc. The third step, corresponding to studies in phases from I-1 to I-3, is the monitoring of conditions and fault detection. Specifically, given the availability of historical data, a Phase I-1 study conducts exploratory data analysis to summarize the main characteristics of the system's data under normal health conditions. In a Phase I-2 study, data preprocessing, feature extraction, feature selection, dimensionality reduction, and associated models with their parameter-estimation procedures are selected to improve the data mining of normal health characteristics. In a Phase I-3 study, the rules and acceptable limits for monitoring data are determined so that the criteria for any abnormal health condition can be defined in advance. Following this, in the fourth step, a Phase II study is conducted to ensure the timely monitoring of any abnormal health condition and address any specific concerns. In the fourth step, assuming no sudden and unexpected failures, fault diagnostics are utilized to find the causes of abnormal conditions. Here, the available approaches include model-based, signal processing-based, and physical-based fault diagnosis, etc. In the fifth step, to minimize economic losses and maximize the lifetime of specific engineering system and critical components, the remaining useful life (RUL) is predicted before any maintenance decision-making is made. RUL prediction is highly relevant to prognostic modeling and requirements, uncertainty quantification, predictive performance evaluation, etc. Finally, based on both the fault diagnostic and prognostic results, a maintenance model can be built to realize optimal decision-making with minimized economic loss and unexpected risks.

C. POTENTIAL RESEARCH TOPICS ON THE THEORETICAL FOUNDATION OF SHMM

Statistics are expected to play a major role in the theoretical foundation of SHMM. Recent work on the trade-off between computation and statistics may have immediate applications in SHMM. Statistics uses data (also known as information) as a resource, with the goal of developing inferential procedures to minimize population risk (or maximize population entropy). In contrast, in computational science, time is considered as the resource and the goal is to develop efficient algorithms to solve computational tasks with minimal CPU time and memory space. Traditionally, the statistics community focuses mainly on inferential aspects, while the theoretical computer science (TCS) and mathematics communities focus more on computation. A recent impactful area of research is to integrate statistics with computation in a united theoretical framework. This in some cases requires a rigorous characterization of the computation process using formal computational models. Alternatively, one may require methods to characterize the statistical properties implicit in worst-case algorithms. Important themes will include treating data as a resource, performing TCS-style analysis, and

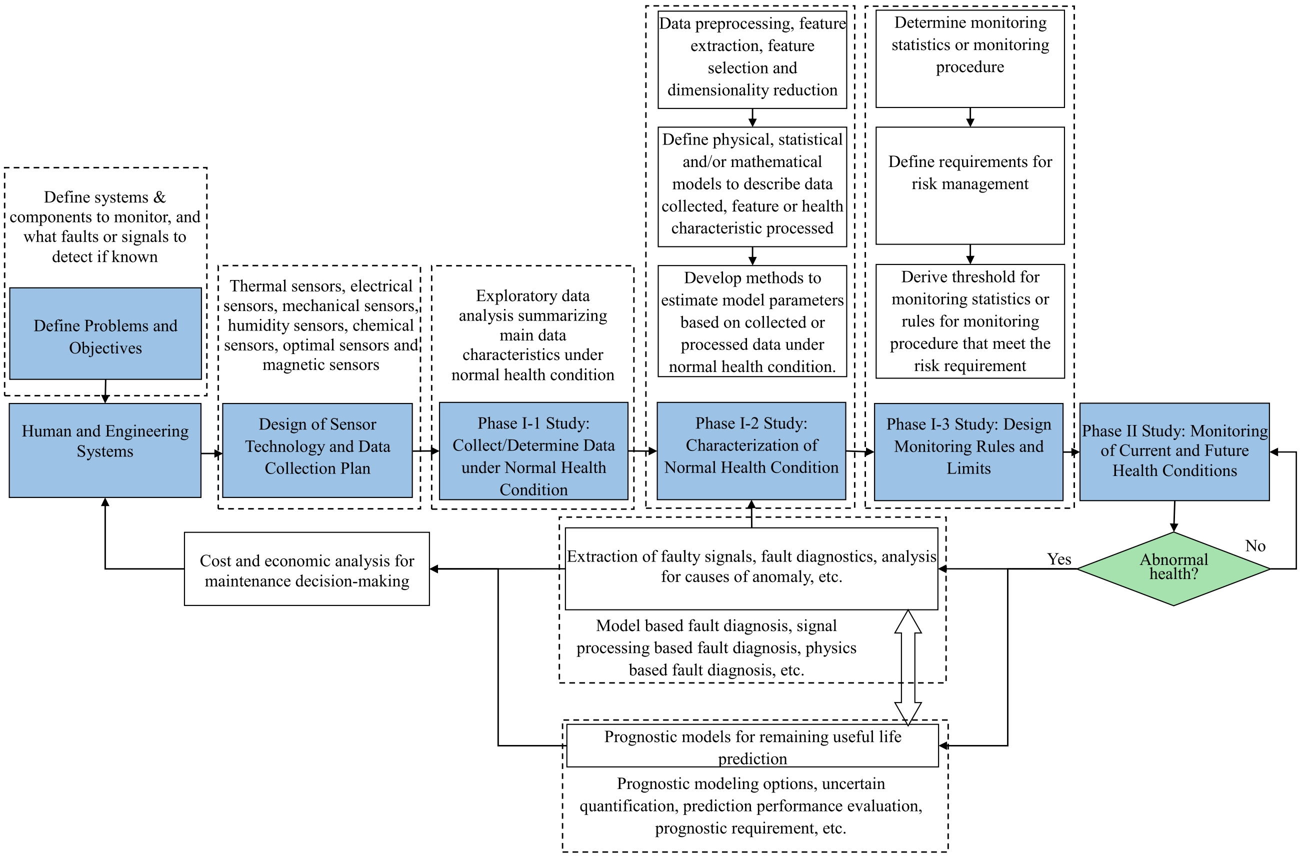

FIGURE 2. General framework of SHMM.

understanding at a much finer level the effect of relaxation of statistical methodological rigor for the sake of tractability. Exciting computational models in this domain include Turing machines, the convex relaxation hierarchy, and statistical query models. Further collaborations between statistics, computer science, and mathematics are expected to create very fruitful results with direct applicability in solving SHMM problems.

Another contemporary line of statistical research is non-convex statistical optimization [22], [23], which is also likely to influence the theoretical foundation of SHMM. Both statistics and optimization are corner stones of modern data analysis. Despite the considerable degree of overlap between the two, most of the overlapping topics are related to convex optimization. However, a salient feature of modern data science is non-convexity, with examples including neural networks and deep learning [24], [25], reinforcement learning [26], spectral methods [27], and many more. Developing the theoretical foundations of non-convex statistical optimization is a critical challenge. This new field lies at the intersection of modern statistics and large-scale optimization. In particular, model-based thinking from modern statistics can be applied to solve large and complex optimization problems. Such applications will depend on a rigorous theoretical framework to sharply characterize the interaction between informational and computational complexity. Non-convexity arises in various forms. For example, while spectral methods are not convex in their most popular presentation, i.e., as vector optimization problems, they are convex when viewed as semidefinite programs. Alternatively, the interaction structure of DNA, while not self-evidently convex, seems to exhibit some sort of soft convexity. In many scientific data applications, this property can be exploited by using a temperature parameter or an annealing schedule, as in simulated annealing [28]. In machine learning applications, low-precision stochastic gradient descent methods [29] perform a similar function. Formally proving the theorems of theoretical computer science and mathematical statistics in this field is difficult, but particularly important. That these methods perform so well for certain applications, while their theoretical basis is so weak, suggests that this is a ripe area for methodological work.

In the theoretical foundation of SHMM, another likely frontier is combined physical and statistical models. These two "cultures" for modeling complex systems are fundamentally different. For example, physical models simulate dynamics by expressing them in terms of partial differential equations or stochastic processes that obey physical laws (like conservation of energy). In contrast, statistical models exploit powerful probability tools, such as probabilistic graphical models, to provide an exploratory model to fit the data. In contrast to the former, the latter do not require that the true dynamics actually satisfy the statistical models. Instead, they use a highly regularized ''substitute model'' to discover a hidden structure in the data and make predictions. We believe that hybrid models of these two approaches are most likely to prevail in the setting of SHMM due to the intrinsic complexity of the problems.

In SHMM, one frequently encounters mixed-type and multi-modality data. For example, a typical dataset may be aggregated from many data sources, including imaging, numerical, graph, and text data, etc. Although each specific data type has been researched intensively in isolation, developing a unified framework will be a more desirable approach to study mixed data systematically. This field has both theoretical and applied implications, and would benefit from a collaboration between statistics, theoretical computer science, mathematics, and practitioners of SHMM. Further research promises to lead to breakthroughs and important progress in science and engineering.

V. RELATIONSHIP OF SHMM WITH OTHER DISCIPLINES

A. PROGNOSTICS AND SYSTEMS HEALTH MANAGEMENT (PHM)

PHM for complex systems is of particular interest in the contemporary world and has attracted much attention from mechanical engineering [30], [31], electrical and electronic engineering [32], [33], manufacturing [34]–[36], aerospace [37], [38], and industrial engineering [10], [39], etc. Taking advantage of progress in sensor technology, computation power, and data analytics algorithms/methods, engineers are seeking paradigm-shifting approaches to extend the current methodology in several aspects. (1) Corrective [40], preventive [41], and condition-based maintenance are competing approaches to predictive maintenance for machines and plant equipment. In the corrective paradigm, maintenance is performed only when failure happens, in which case the failed equipment or machine is restored to operational condition. In many practical situations, however, failure is unacceptable, and preventive maintenance is adopted instead. In preventive (or scheduled) maintenance, care and servicing to maintain equipment are performed regularly on a periodic schedule through systematic inspection, tests and measurements, adjustments, and parts replacement. However, it is possible for failure to occur shortly before a scheduled inspection, or conversely, for an inspection be scheduled when no faults and failures are present. In condition-based maintenance, the current health conditions are monitored to inform maintenance decisions. This contrasts with predictive maintenance, where decisions are based on prediction of future health conditions. (2) The concept of machine maintenance may be extended to health management of complex systems. Both condition-based and predictive approaches can avoid any unnecessary maintenance while reducing the risk of failure. (3) Monitoring may be extended from populations (homogeneous groups) to individuals. PHM, with its two components of prognostics and health management, transcends traditional diagnostics and fault detection [42]. Prognostics is the process of predicting the future effective reliability of a product, component, or system by assessing the extent of deviation from its expected normal operating condition. Health management, meanwhile, is the real-time measuring, recording, and monitoring of such deviation [32]. SHMM differs from PHM by its distinct emphasis and its definitions of monitoring, prognostics, and management (prognostics is included as part of monitoring), and can be considered an extended version of PHM. More specifically, system health monitoring includes detection, forecasting, diagnostics, and prognostics, while system health management includes decision, financial, and risk management.

B. STATISTICAL PROCESS CONTROL AND MONITORING

Statistical process control and monitoring (SPCM) [43] is the use of statistical methods to monitor and control processes. The main advantage of SPCM is its emphasis on early detection and prevention of problems of particular concern. SPCM generally includes two phases. In Phase I, a common-cause variation in an underlying process is identified. In Phase II, a characteristic of interest is monitored. The philosophy behind SPCM is to distinguish between a common-cause variation that is attributable to a relatively stable underlying process, and a special-cause variation that is unusual for the underlying process. From the definition of SHMM, it naturally follows that SHMM is an extension of SPCM containing additional focuses on fault diagnostics, prognostics, and health management of problems of particular concern, besides their early detection and prevention.

C. RELIABILITY ANALYSIS AND SYSTEM RELIABILITY

Reliability analysis and system reliability [44] describe the ability of systems engineering applications and critical components to function under given operating conditions for a pre-determined period. These processes involve predicting the reliability of systems engineering applications and critical components prior to their use in practice based on a population of historical data. In contrast, reliability prediction in SHMM does not solely depend on historical data but also makes use of online observations for timely updating to boost the performance of SHMM. Simply speaking, SHMM provides more accurate reliability prediction for systems engineering applications and critical components.

D. DESIGN OF EXPERIMENT (DOE)

DOE is a statistical method of establishing which variables are important in a process and the best settings for these variables to optimize the process [45]. DOE methodology is long established in industry for quality optimization, and plays an important role in the pre-stage of SHMM during data collection for subsequent analysis. The power of DOE is in systematically describing the variation of measured information under conditions that are hypothesized to reflect the real-world variation. Taking sensors in engineering systems, for example, the carefully chosen placement of sensor locations is a prerequisite for obtaining quality data to enable reliable health monitoring of key components in a complex system.

E. DATA MINING AND KDD

Data mining is the process of turning raw data into useful information, including discovery of hidden patterns and connections and prediction of future trends, etc. [46]. Data mining is sometimes referred to as knowledge discovery in databases (KDD). Various data mining algorithms [47], such as logistic regression, support vector machines, convolutional neural networks, decision trees, and combinations of these, have been widely adopted in SHMM applications [48]. Some application examples include health assessment, fault diagnosis, and RUL prediction. Data mining algorithms serve as solutions to these tasks. However, one major challenge is the efficient selection of appropriate methods for problems in SHMM.

VI. SHMM APPLICATIONS IN PUBLIC HEALTH AND HEALTHCARE SURVEILLANCE

A. SURVEILLANCE OF PUBLIC HEALTH SYSTEMS

The objective of public health surveillance is to examine health trends, detect changes in disease incidence and death rates, and to plan, implement, and evaluate public health practice by systematically collecting, analyzing, and interpreting public health data (chronic or infectious diseases).

Understanding challenges to nations' public health systems and how those challenges shift over time is of crucial importance for policymakers to establish effective strategies. In general, databases containing rich and detailed information about mobility and mortality across regions, time, age, and gender are a prerequisite for informed analytics. Many public health organizations have made great efforts to maintain such databases, such as the Global Burden of Disease (GBD) project by the World Health Organization (WHO) for quantifying the health-related losses from hundreds of diseases, injuries, and risk factors [49], and a wide array of disease databases maintained by the CDC (http://www.cdc.gov/DataStatistics/).

In public health surveillance, the volume and velocity of data streams have dramatically grown in recent decades. Taking the sample-based mortality surveillance system in China as an example, the surveillance population increased from 6% to 24% of the Chinese populace from 1978 to 2013 [50]. In spite of the growing data volume, advances in information technology have enabled collection of cause-of-death data in a more timely manner. Since 2008, information on individual deaths in all population catchment areas in China has been reported in real time via an internet-based reporting system [51].

The availability of public health big data provides a comprehensive picture of health system status in terms of the causes of significant population-wide changes, the underlying risks, the changes in the pattern of health-related losses, etc. Numerous efforts have been made to monitor and evaluate the health of populations by taking advantage of public health big data. For example, the GBD 2013 Mortality and Causes of Death Collaborators [52] systematically analyzed the levels and trends for age-sex-specific all-cause and cause-specific mortality for 240 causes of death; [53] studied the effect of ambient air pollution on adult respiratory mortality in China at city level; and [54] investigated the impact of armed conflict on gender structure in life expectancy.

B. SENSOR-BASED MONITORING OF PERSONAL HEALTH

The objective of personal health surveillance is to monitor personal health performance indicators, such as medical history, real-time health information, and vital signs, for the sake of understanding individual health conditions, early detection of health risks, and providing effective individualized medical care.

In this field, the big data approach promises to facilitate the development of an effective medical care system and enable more personalized management of individuals to improve the health of entire populations. Researchers have actively sought innovative solutions to improve the quality of patient care via big data analytics.

One example is the use of unobtrusive sensing and wearable devices for personal health monitoring. For patients, devices can provide real-time information and facilitate timely remote intervention in case of acute events such as stroke and heart attack. This type of implementation would be particularly effective in rural areas where expert treatment may be unavailable [55]. Additionally, for healthy populations, unobtrusive and wearable monitors provide close tracking of health and fitness, enabling detection of health risks and facilitating the implementation of preventive measures at an earlier stage. For example, a continuous health monitoring system has been developed for elderly citizens and patients with chronic diseases [55]–[60]. Successful continuous monitoring of heart rates and delineating their temporal variation with various types of wearable devices is another significant milestone in health management [61], [62]. In recent years, research trends have shifted from hardware development and measurement validity [14] to the application level. However, a wider acceptance of existing systems for continuous monitoring is still limited for several reasons. Traditionally, personal medical monitoring systems, such as Holter monitors, have been used only to collect data. Data processing and analysis are performed offline, making such devices impractical for continuous monitoring and early detection of negative health conditions [63]. Besides, most current systems focus on the use of an individual smart device and offer mainly instantaneous single-parameter measurements, which provide only a one-sided understanding of health conditions.

Personalized health monitoring systems take advantage of data mining, a decision support system, and a context-aware system to facilitate diagnosis, treatment, and care based

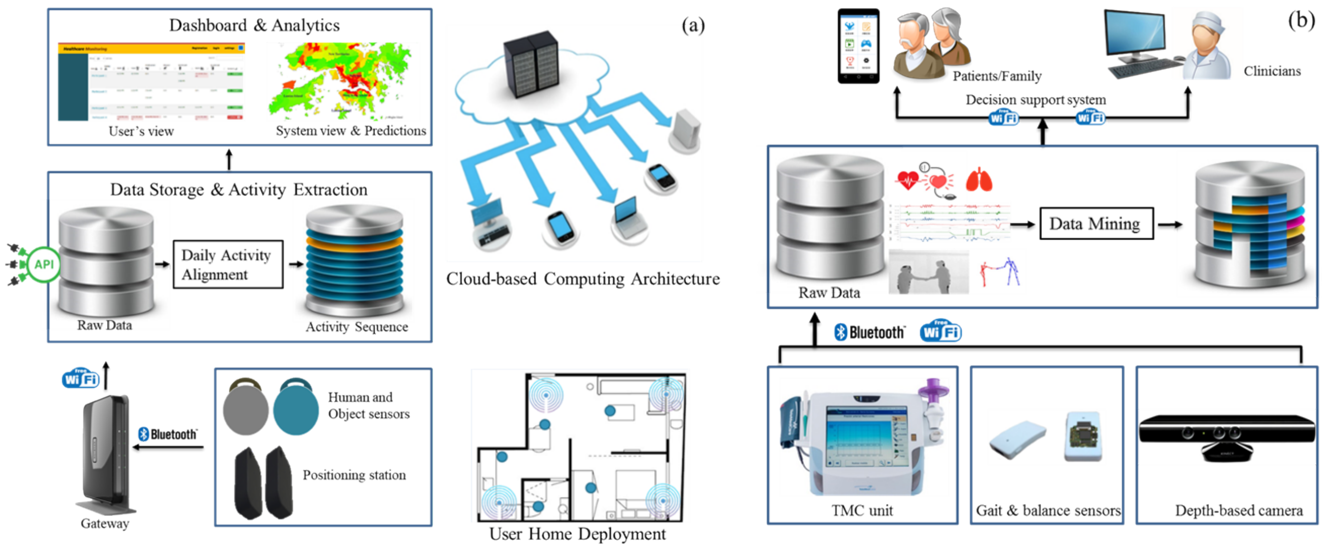

FIGURE 3. Design of (a) lifestyle habit monitoring system; (b) tele-monitoring system.

on an individual's genetics and lifestyle. Fig. 3 illustrates a standard design of a tele-monitoring system for lifestyle habits and health. In several studies, an Australian research team has evaluated the potential benefits of home tele-health monitoring for the elderly with the use of an all-in-one station-based health monitoring system [64]–[69]. The study found promising results for personalized elderly care, where forecasting models for common geriatric health conditions were built based on daily monitoring of vital health signs of the participants. This implies that the implementation of a health monitoring system at the community level, with the use of appropriate statistical analysis and data mining tools, can be an effective solution for healthcare services. It has been reported that remote monitoring of personal wellbeing, through vital signs together with existing data, could significantly improve disease prevention, management, and rehabilitation [70], [71]. Ruiz-Zafra *et al.* [72] investigated the effectiveness of a centralized (cloud-based) health platform for integrating advice from different health experts on collaborative management and monitoring of different types of patients.

At the population level, data collected from individuals can be aggregated to evaluate the medical care effectiveness of an entire cohort. Various analytic methods have been proposed to monitor patient disease conditions, such as sets-based [73] and risk adjustment methods [74]. Reference [75] provides detailed discussions of these methods for healthcare applications.

VII. SHMM APPLICATIONS IN SYSTEMS ENGINEERING AND CRITICAL COMPONENTS

SHMM of systems engineering applications and critical components includes four main aspects: construction of health indicators for condition monitoring and fault detection, fault diagnostics, RUL prediction, and system health management. Health indicators can be used to provide statistical parameters with specific upper and lower bounds for evaluating and quantifying the current health condition of a system or component. In some cases, it is difficult or impossible to directly use health indicators measured from sensors, so the indicators must be indirectly and artificially constructed from the sensor measurements [42]. For example, rolling element bearings are one of the most commonly used mechanical components in industrial machines [76], [77], such as electric motors, generators, pumps, gearboxes, railway axles, turbines, and helicopter transmissions. Once a defect is found on the surface of an outer or an inner race, bearing failures are inevitable and will accelerate the failures of adjacent components, finally resulting in machine breakdown and unexpected accidents. In practice, although temperature can be used as a health indicator to directly assess severe bearing failures, it is difficult to assess bearing fault propagation at an early fault stage in this way. Consequently, for monitoring, diagnostics, and prognostics of bearing condition, other measurements are preferable, such as vibration signals collected by accelerometers and acoustic signals collected by acoustic emission sensors and microphones. Thus, construction of health indicators from vibration or acoustic signals is a prerequisite for predicting the RUL of bearings. Wang *et al.* [78] provided a thorough review of vibration-based bearing and gear health indicators constructed from mechanical signal processing, modeling, and machine learning, and forecast several future directions in the construction of bearing and gear health indicators, which were further supplemented by Lei *et al.* [79]. Once health indicators are established for the abnormal health conditions of bearing faults, SHMM enters the next phase, diagnostics, which aims to identify each specific bearing fault type [80], such as those affecting the outer race, inner race, roller, or cage. If there is no sudden failure, the bearing RUL is then predicted in the third phase [81]–[83]. Here, RUL can be defined as the period from the present to the time at which the bearing will no longer satisfy its functionality. The methodologies of RUL prediction have been widely investigated. Si *et al.* [84], in a thorough review of data-driven statistical models, categorized them into two types: those based directly on condition monitoring data, such as regression-based models, Brownian motion with drift, Gamma processes, and Markovian models; and those based indirectly on condition monitoring data, such as stochastic filtering-based, covariate-based hazard, hidden Markov, and hidden semi-Markov models. Heng *et al.* [85] summarized prognostic techniques for failure prediction of rotating machinery and classified them as conventional reliability models, condition-based prognostic models, and hybrids. Ye and Xie [86] reviewed degradation models and classified them as stochastic process models, general path models, and others beyond these types. Later, the same two authors [86] made a comprehensive comparison between stochastic process and general path models. Lee *et al.* [87] systematically classified the methods to develop prognostic systems, and the visualization tools for displaying prognostic information. Further, Zhang and Lee [88] thoroughly reviewed RUL prediction technologies for rechargeable batteries, noting that these are potentially applicable to many other components, such as bearings and gears used in machines. Here, the main differences between machine prognostics and battery prognostics were summarized as follows. Firstly, the health condition of a battery can be easily quantified from its capacity, which is directly calculated from output measurements. However, in machine prognostics, health indicators must be artificially constructed so that they can be correlated with the machine's physical health. Secondly, establishing a predetermined failure threshold is straightforward in battery prognostics, while in machine prognostics the failure threshold is highly dependent on constructed health indicators, historical data, and expertise. Recently, Zhang *et al.* [89] provided a thorough review of Wiener process-based degradation models and their applications to RUL prediction. Meanwhile, PHM and its applications to advanced manufacturing were reviewed in depth by Xia et al. [90]. Other recent works have shown how, based on the first three phases of SHMM, system health management can be conducted to determine an optimal replacement policy for a system or component [91]–[93]. Finally, thanks to the development of advanced sensor and communication technologies, an increasing diversity of mechanical degradation data has become available, which indicates that SHMM is entering the big data era [94]. For example, massive data are now collected from many different types of sensors for timely and accurate monitoring of the health condition of turbofan engines [95], [96]. With the dawning ubiquity of big data, SHMM will need more efficient and effective methods and models to construct suitable health indicators for real-time system and component monitoring and improved RUL prediction. The payoff to industry will be optimal replacement policies and the prevention of unexpected accidents.

A. SHMM OF ROLLING ELEMENT BEARINGS

In this section, SHMM of rolling element bearings is taken as an example to specifically illustrate the principles of SHMM in mechanical and industrial engineering. As shown in Fig. 4, a vibration signal is collected by an accelerometer in a laboratory at a constant operating condition, then processed by squared envelope spectrum analysis with band-pass filtering to remove unwanted strong vibration components and identify bearing defect frequencies for health monitoring and fault diagnosis of rolling element bearings. The purpose of band-pass filtering is to retain a resonant frequency band for further demodulation by envelope analysis, exploiting the fact that impacts generated by rollers striking a defect surface excite the resonant frequencies of a structure, such that modulation phenomena occur in the presence of a bearing defect [97]. The selection of an appropriate band-pass filter is a major theme in bearing fault diagnostics [98]. Two classic techniques for bearing monitoring and diagnostics are spectral kurtosis [99] and spectral correlation [100]. In the former, the statistical parameter of kurtosis is calculated to characterize a signal filtered by various band-pass filters. The filter with the largest kurtosis is then selected for bearing fault diagnosis. A new methodology for extending various spectral kurtosis algorithms to optimal filtering was presented by Wang and Tsui [101] in the framework of wavelet transformation and dynamic Bayesian inference. Spectral correlation, meanwhile, involves simultaneously displaying resonant frequency bands and bearing defect frequencies in a spectral frequency-to-cyclic frequency plane. Integrating the spectral correlation over a specific resonant frequency band generates a squared envelope spectrum identical to that obtained by squared envelope spectrum analysis with band-pass filtering, and in the final frequency domain, only the bearing defect frequencies are displayed [102]. Then, different bearing health indicators, such as the sum of a bearing defect frequency and its several harmonics (Fig. 4), are used to characterize these identified defect frequencies in a time or frequency domain to track defect propagation over time. Besides the bearing health indicator exhibited in Fig. 4, in our previous work [103], a generalized dimensionless indicator with specific upper and lower bounds was proposed to quantify bearing defect propagation. The proposed indicator proved insensitive to varying operating conditions. From inspection of Fig. 4, it is clear that bearing degradation, as tracked by the chosen health indicator, has two distinct phases. In Phase I, the bearing is in a normal health condition and its health indicator is stable. After a bearing defect frequency and its several harmonics are detected, the bearing health indicator deviates greatly from the previous stable level. Following this, the bearing enters Phase II and the health indicator degrades exponentially. Moreover, in Phase II the health indicator is not monotonic and shows large fluctuations over time. For bearing prognostics, especially RUL prediction, one

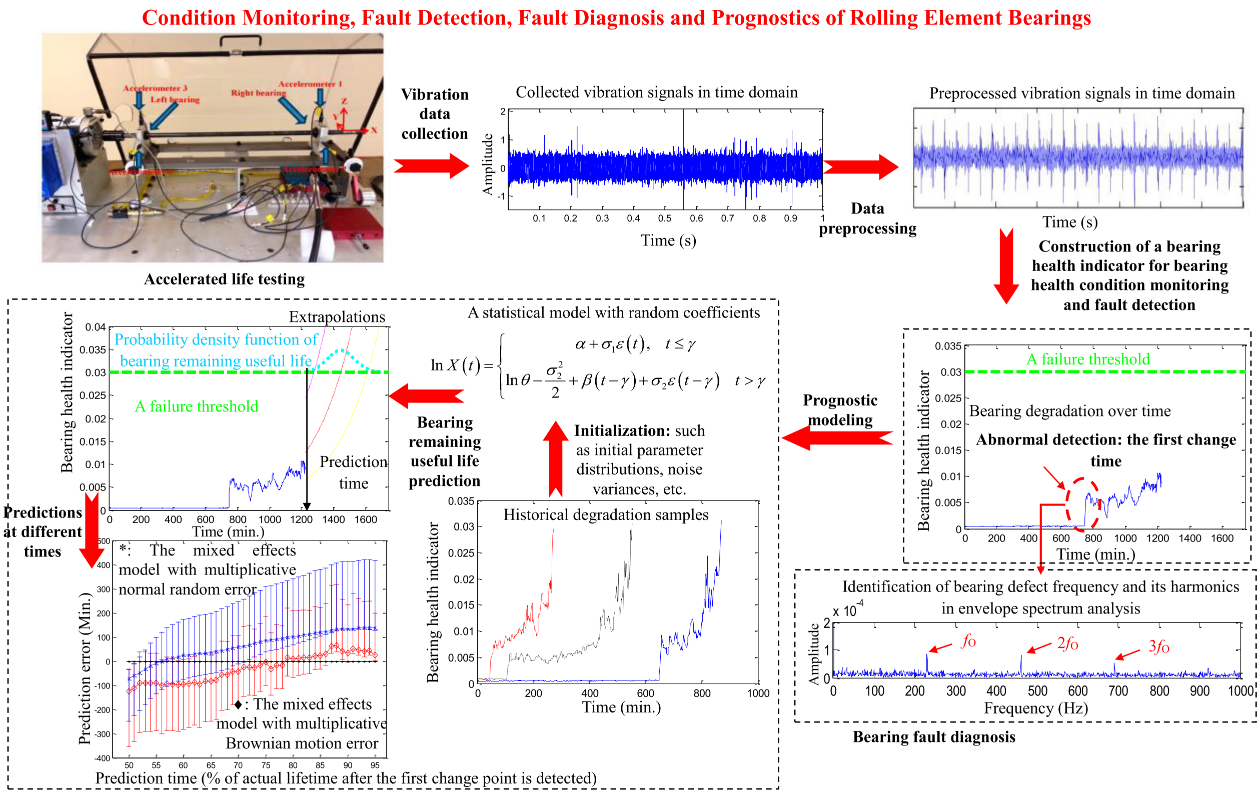

FIGURE 4. SHMM of rolling element bearings.

strategy is to build a statistical model containing random coefficients. Based on the work of Lu and Meeker [104], Gebraeel *et al.* [105] used the Bayesian theorem to derive analytical expressions for the posterior parameters of two statistical models to update the prior distributions of the parameters of two models obtained from a population of bearing degradation data. Once the posterior parameters are updated by online observations of the bearing health indicator, the bearing RUL can be inferred by extrapolating the updated statistical model to a predetermined failure threshold. Further, Chen and Tsui [106] proposed a piecewise statistical model with random coefficients and heterogeneous noise variances to extend the work of Gebraeel to a more general prognostic method. The application of Chen and Tsui's prognostic model is schematized in Fig. 4, where the model with multiplicative Brownian motion error results in more accurate RUL prediction than the model with multiplicative normal random error. Moreover, the Brownian motion-based statistical model [107], [108] can be reformulated as a state space model so that only the latest bearing health indicator, rather than the entire time history of the indicator from the very beginning to the present, can be used to iteratively update the model parameters for RUL prediction.

B. SHMM OF RECHARGEABLE BATTERIES

In this section, rechargeable batteries are taken as another example to illustrate the principles of SHMM. For rechargeable batteries, the SHMM process is similar to that of PHM inasmuch as both include two main aspects, state of charge estimation and state of health prediction. State of charge estimation is inferring the remaining charge at a specific charge-discharge cycle, while state of health prediction is inferring how many charge-discharge cycles are left until the battery fails to provide sufficient power for the corresponding electrical product, such as a cell phone, hybrid electric vehicle, unmanned aerial vehicle, etc. Conceptually, state of health prediction is closely analogous to battery RUL prediction. In contrast to bearing condition monitoring, fault diagnostics, and prognostics, in the case of state of health prediction of rechargeable batteries, the battery capacity (calculated from integration of current over time in a discharge process) can be directly used as a health indicator to indicate the current health of the battery. For state of charge estimation, equivalent circuit models [109], [110] are popularly used to connect the state of charge to measurable outputs, such as current and voltage. Based on these equivalent circuit models, state space models are then built to dynamically and posteriorly infer the state of charge from online output measurements. A battery equivalent circuit model and its associated state space model [111] are shown in Fig. 5, where the state of charge can be accurately tracked and posteriorly estimated even though the initial state of charge (0.75) is incorrectly set to 0.3 in the state space modeling. Alternatively, Fig. 5 depicts an empirical battery degradation

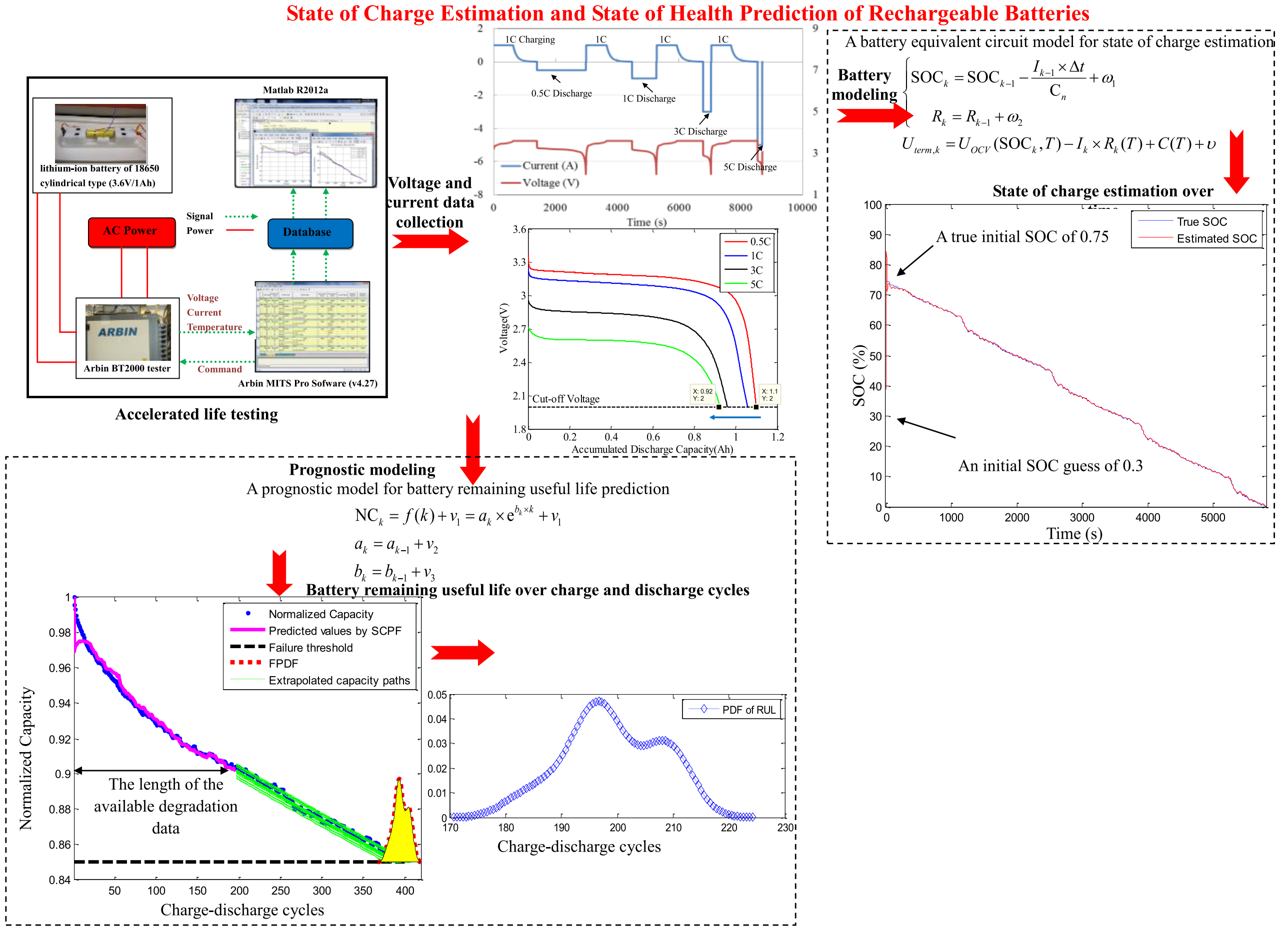

FIGURE 5. SHMM of rechargeable batteries.

model with an exponential trend [112] that can be used to construct a non-linear state space model for tracking and updating the amplitude and slope of the battery degradation. The non-linear state space model can be iteratively solved in the framework of particle filtering or its variants [113]–[117]. Extrapolations of the posteriorly updated state space model to a failure threshold are used to infer the battery RUL. Here, the failure threshold can be defined by the user within a range from 1 to 0, corresponding to the constraint range of the present capacity normalized by the initial capacity.

VIII. DISCUSSION

A. TRAPS OF BIG DATA

While big data create myriad opportunities for traditional system health monitoring, we should be aware of potential risks as well. Below we illustrate both the opportunities and risks of big data analytics through the example of the well-known Google flu trend (GFT). GFT is a data analytics model developed by Google for predicting weekly reported ILI rates using instant query data [11], [118]. ILI is defined as an influenza-like clinical syndrome, such as fever or cough, without a known cause, and is regarded as an indicator of influenza activity levels in a region. The CDC reports weekly ILI rates in the US with state-level detail, but always with a one-to-three week delay in reporting. Timely detection of an acute disease outbreak is recognized to translate into more days gained, and in turn more lives and resources saved. Therefore, an accurate prediction of ILI rates before the release of a CDC report would be helpful for developing intervention strategies and remedies. In 2008, researchers from Google developed the web service-based GFT, claiming to accurately predict (“nowcast”) ILI rates by modeling search queries in real time. However, as reported in [118], [119], GFT failed to provide accurate predictions, and predicted more than double the actual rate of doctor visits for ILI reported by the CDC during the 2012-2013 season. Fig. 6 depicts the ILI trend predicted by GFT and the actual CDC data over those dates [118]. As shown, GFT reported an overly high flu prevalence from August 21, 2011 to September 1, 2013.

The failure of GFT highlights a number of potential risks in prediction and forecasting models based on big data analytics. For example, the number of predictive variables may change over time, and the impact of individual variables may change as well, making it important to periodically update a prediction model. In fact, the GFT prediction model has run continuously since 2009, with a few changes announced

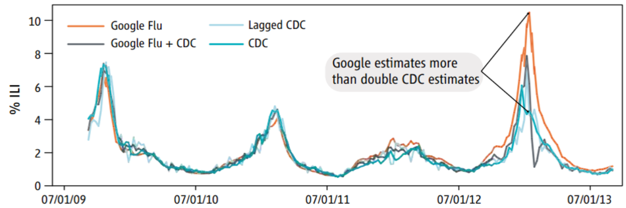

FIGURE 6. Overestimation of flu rates by GFT in the 2012-2013 season. [118].

in October 2013 [11]. The model's failure has led to a large number of research papers aiming to improve its predictive accuracy [20], [120], [121]. One representative method was ARGO, proposed in [20], which not only incorporated seasonality in historical ILI rates, but also captured changes in the public's online searching behaviors over time. Comparing the failure of GFT and the fate of all of the subsequent variants, including ARGO, in ILI prediction, several lessons can be learned. First, it is important to understand precisely why any given search term has predictive utility. Second, relying solely on big data sources for inference may yield misleading conclusions. Interrogating big data as a source of information must be done in tandem with traditional knowledge.

GFT is only one of many examples that illustrate the potential risks of big data analytics. In medical research, it has been reported that 40% of experiments described in research journals cannot be reproduced. Elsewhere, in financial hedge fund companies, many consultants have claimed to have outperformed the market by applying their investment models to historical data. In truth, however, most of their claimed successes could have been caused by noise rather than informative signals.

B. THEORETICAL FOUNDATIONS OF SHMM

Every scientific field needs firm theoretical foundations, and the development of SHMM is no exception. While asking the right foundational questions is a slow process and will take time to develop, many important theoretical issues can already be clearly recognized. We believe that the maturation of SHMM will benefit from relevant foundational research. The emergence of massive computational power via cloud computing and supercomputing infrastructure presents an unprecedented opportunity to enlarge the impact of SHMM.

Practitioners of SHMM will face many challenges. For example, it is well known that a large fraction of the total data analysis time is spent in data preparation and preprocessing. These tasks pose many intellectually challenging problems related to deep mathematical issues that cannot easily be formalized. This is not "just engineering", but rather a critical aspect of a model's successful deployment in industry or academia. Indeed, these tasks can be seen as the "before and after" of many high-profile machine learning problems. Data in SHMM applications are likely to have their own unique features. Developing standards and preprocessing guidelines may prove to be both crucial and extremely interesting. Quantitatively-inclined disciplines, such as genetics and computational biology, theoretical chemistry and physics, computational social science, etc., tend to ignore the data collecting and preprocessing steps. We would like to present two examples in which computations on data are typically viewed from a computational perspective: (a) in databases, where one does not typically want to make inferential claims but instead to perform computations on the data in the database, regardless of how they were generated, which leads to a focus on data manipulation; and (b) in theoretical computer science, where it is common to formulate computation per se as a function transforming inputs to outputs, while ignoring noise characteristics etc. in the data. Developing an improved foundational understanding of how computation interacts with noise properties in input data, as well as how the output of computation interacts with inference and other downstream goals, will be of central importance. Any progress in this regard is likely to enhance the foundations of SHMM.

IX. CONCLUSION

Nowadays, the concept of big data prevails in numerous applications and research domains. In this paper, we reviewed the issues facing the use of big data analytics in SHMM in a general sense, by discussing the evolution of big data analytics, categorizing data types based on data sources and collection processes, and providing some insights on the research opportunities and challenges brought by big data. Specifically, we proposed a general framework of SHMM, and discussed its relationship with other disciplines. For illustration, we provided several application examples of SHMM for complex systems and critical components.

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