1

Introduction to Importance Measures

Importance measures are used in various fields to evaluate the relative importance of various objects such as components in a system. The absolute values of importance measures may not be as important as their relative rankings. In general, a system is a collection of components performing a specific function. For example, a computer system performs a range of functions, such as computing, data processing, data input and output, playing music and movies, and others. It consists of the following major components: a computer unit, a monitor, a keyboard, a mouse, a printer, and a pair of speakers. The computer unit as a key component of the computer system can also be treated as a system by itself. It consists of one or more central processing units, a motherboard, a display card, disk controller cards, hard and floppy disk drives, CD-ROM drives, a sound card, and possibly other components. This chapter provides a wide range of modern problems that can be dealt with by the various types of importance measures. Some of them are further addressed in the rest of this book.

Example 1.0.1 (Fukushima nuclear accidents) The recent nuclear accidents in Japan have resulted in the release of heavy doses of radioactive materials from the Fukushima I Nuclear Power Plant following the Tohoku 9-magnitude earthquake and the subsequent 46-foot-high tsunami on March 11, 2011. The plant comprises six boiling water reactors as sketched in Figure 1.1. Three had been shut down prior to the earthquake for maintenance, and the other three shut down automatically after the earthquake. Although the emergency generators were functional to cool down the reactors right after the shutdown of the nuclear reactors, they very quickly were knocked out by the flood, so the reactors and even the spent fuel pools started to overheat. As a consequence, partial core meltdown in the nuclear fuels caused hydrogen explosions that destroyed the upper cladding of some buildings housing reactors and the containment inside one reactor. In addition, fuel rods stored in the spent fuel pools began to overheat as water levels in the pools dropped. All these led to the leaking of radiation of Iodine 131 and Cesium 137 to the surrounding cities, including the greater Tokyo area.

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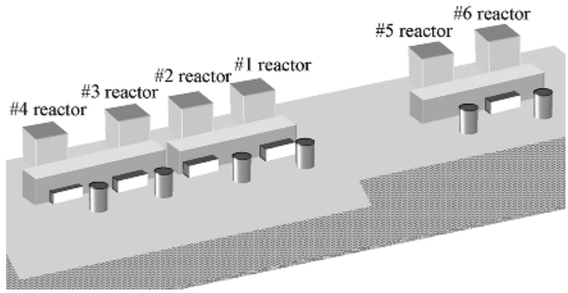

Figure 1.1 Sketch of Fukushima I nuclear power plant

The bottleneck resulting in these accidents was the flooded cable of the emergency generators that supply power to cool down the heated fuel rods in the reactors and the spent fuel pools. Because of the tsunami, the floodwaters prevented assistance from being obtained elsewhere, and apparently no spare parts were put in place for several days. This disaster has highlighted the necessity to know how crucial the emergency generators play in terms of system failure under flooding. The importance measures addressed in this book would provide the most efficient way to identify the bottleneck in the system failure by providing a methodology to follow. In particular, Chapters 3–7 and 19 give an idea and guideline by identifying maintenance methods for practitioners to follow. Smith and Borgonovo (2007) have noticed that importance measures are useful in probabilistic risk analysis (PRA) and probabilistic safety assessment (PSA), which firm a core step in precursor analysis for decision-making during nuclear power plant incidents.

Example 1.0.2 (Random forest variables in bioinformatics) The notion of importance measures as in Chapter 3 is widely used in multivariate data analysis and ensemble learning methods (e.g., a recently developed method – random forests) that generate many classifiers and aggregate their results. Random forests yield variable importance measures for each candidate predictor in identifying the true predictor(s) among a large number of candidate predictors (Archer and Kimes 2008). The importance of a variable is estimated by the extent of prediction error increase when data for that variable is permuted, while all others are unchanged (Liaw and Wiener 2002). The necessary calculations are carried out tree by tree as the random forest is constructed. The importance measures of random forest variables have been used in bioinformatics for investigating factors to the disease risk (Schwender et al. 2011; Strobl et al. 2007) and microarray studies (Archer and Kimes 2008).

Example 1.0.3 (Transportation and rail industry) Importance measures have been used to prioritize rail sections in order to effectively decrease delay in the railway industry (Zio et al. 2007). For example, in the winter season, large areas of rail are often blocked by snow, and some trains have to make detours to the limited open rails outside the snowy areas. The priorities for rescheduling trains could be assigned according to the appropriate importance measures of train lines so that the overall quantity to be conveyed is maximized or the overall

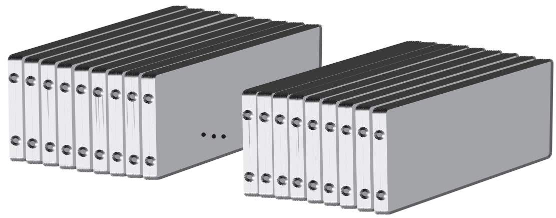

Figure 1.2 Lithium-ion polymer electric battery

delay is minimized, as discussed in Chapters 7 and 15. On the other hand, importance measures could also be used to prioritize the rail sections in the snowy areas for clearing snow with the limited labor and equipment so that the increase of the quantity to be conveyed could be maximized.

In addition to the rail industry, importance measures can find great use in identifying and releasing ground traffic congestion in big cities, dispatching the traffic flow after major sport events, planning highway construction in developing countries, and dealing with other transportation-related issues.

The high-speed train crashed in Wenzhou, China, on July 23, 2011, killed at least 40 persons. During the accident, a train ran into the back of another that had stalled on a viaduct after lightning cut its power supply. This accident has highlighted the crucial role of reliability, safety, and scheduling in constructing and operating a complex high-tech transportation network, no matter if the accident was due to a mechanical fault, a management problem, or a manufacturing problem. If a better planning were studied using the concept of importance measures, such an accident would have been greatly minimized.

Example 1.0.4 (Lithium-ion polymer electric battery) It is expected that more electric buses will, over time, come into operation to make society more environment-friendly. The city of Chattanooga, Tennessee, USA, has operated nine electric buses since 1992; they have carried 11.3 million passengers and covered a distance of 1, 930, 000 miles over 9 years. Two of the Chattanooga buses were used for the 1996 Atlanta Olympics. Beginning in the summer of 2000, the Hong Kong Airport Authority also began operating a 16-passenger Mitsubishi Rosa electric shuttle bus. Electric vehicles are dependent on powerful lithium-ion batteries that must last a long time and are replaced only with fully charged ones at the recharging station to allow failure-free and continuous operation of the buses. Normally, a box of battery cell consists of more than 100 battery units in series, as depicted in Figure 1.2, and typically each unit has an expected life of 5–7 years. In such a system, the power of the battery cell is significantly reduced if more than 4 or 5 units fail. The importance measures of each unit are clearly different depending on the locations and conditions of the units within the cell. This can be typically modeled as a consecutive-k-out-of-n system, as indicated in Chapters 8 and 12. A similar description and illustration can be applied to a recently developed wireless charging system (Naoki and Hiroshi 2004).

Example 1.0.5 (Reliability design) When limited resources are available for upgrading a system (e.g., replacing one or more old components with new ones or adding redundancy),

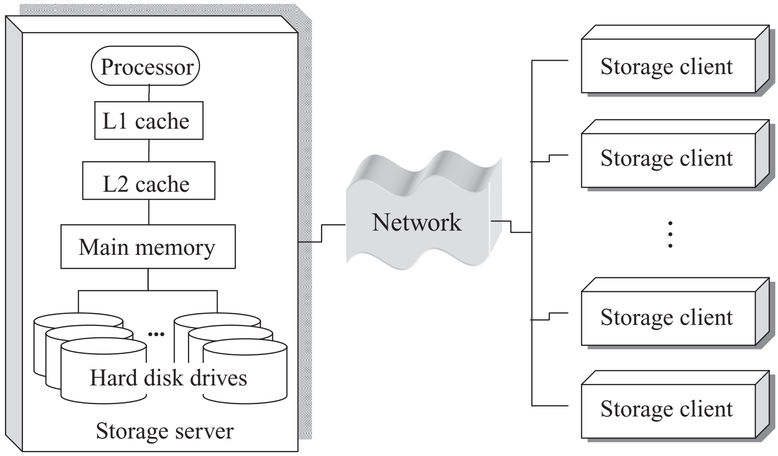

Figure 1.3 Storage system architecture

it is best to put the resources into the components whose upgrade could bring the greatest improvement in system performance (e.g., reliability). The relative importance of components in such a case could be ranked according to the importance measure that is designed to determine which component(s) merits the most additional research and development to improve overall systems reliability at minimum cost or effort as detailed in Chapters 9 and 10. Details on reliability optimization and redundancy allocation and the corresponding mathematical programming techniques can be found in Kuo et al. (2006).

A system may need multiple units that perform the same function, for example, the pump stations in an oil pumping system along a pipeline. Because of a limited budget or different extents of wear, the same functional units that are to be used in distinct positions in the system may have different brands, quality, ages, and/or conditions. Generally, the newer and more expensive ones have higher quality and are more reliable. Allocating these functionally interchangeable units of different reliability into the system is critical. The component assignment problems (CAP*) can maximize the systems reliability by optimally allocating these units into the system with the aid of importance measures, as discussed in Chapters 11–13. Essentially, the CAP is combinatorial optimization.

Example 1.0.6 (Data cache management in cloud computing) A modern distributed data cache consists of multiple layers, which may correspond to different types of storage media with varying prices and performance characteristics. The distributed data cache helps make data more accessible, rendering cloud computing a more appealing option for computation and analysis. As illustrated in Figure 1.3, a typical computer storage system contains L1 and L2 CPU caches implemented in static random access memory, main memory based on dynamic random access memory, and hard disk drives recording data on rotating platters with magnetic surfaces. Generally speaking, the closer to the CPU, the higher price/capacity ratio but the lower access latency a storage component has. Therefore, it is beneficial to place certain

* The singular and plural of an acronym are always spelled the same.

data blocks in fast and expensive storage devices based on predictions of future accesses. In computer science this method is called caching, and the corresponding storage component is a so-called cache. Caches are widely used in computer systems. A data request goes to permanent storage devices such as hard disks only if the data is absent in all caches.

While enhancing the cost-effectiveness of computer systems, this multi-level storage hierarchy also creates opportunities and challenges in data management, including data placement and transfer. Due to the spatial locality of real applications, prefetching is widely used where certain blocks are fetched into a cache from lower levels before they are requested by the applications. The main objective is to minimize the data access latency of the applications.

Given limited cache sizes, two issues that need to be addressed (Zhang et al. 2009) include (i) how to handle the prefetching resource allocation between concurrent sequential access streams with different request rates and (ii) how to coordinate prefetching at multiple levels in the data access path. For sequential prefetching, "what to prefetch" is given and the key problem is to decide "how much to prefetch" and "when to prefetch," two metrics related to prefetching aggressiveness. In many current systems, this is determined at runtime through two prefetching parameters: prefetch degree, which controls how much data to prefetch for each prefetching request, and trigger distance, which controls how early to issue the next prefetch request. Different from a permanent storage device that keeps and deletes data following commands from its users, a cache needs its management mechanism to make the above decisions. In many scenarios, one storage server needs to support many storage clients through local or wide-area networks. This further increases the depth of storage stacks and the complexity of data cache management.

Optimization models and methods are in high demand for data cache management. In a novel view, the problem can be dealt with using supply chain inventory management models and methods, treating data storage system as multiple-echelon, multiple-product, supply chain and each client as a unique product.

However, for such a complex problem, the "optimal" management policy cannot be too complicated due to consideration regarding the practical implementation in the operating system (e.g., the Linux kernel) as well as the issue of consuming and occupying the system memory, which is shared by the operating system, applications, and the memory cache. Over-occupying system resources by calculating and implementing a data management policy will seriously degrade the performance of the whole system and increase the time of operating and data access. It is desirable to use importance-measure-based models and policies so that the decisions could be dynamically made on the basis of a set of index values rather than on other complicated mathematical tools, as shown in Chapter 13. Importance-measure-based methods may potentially become powerful tools in computer science research.

Example 1.0.7 (Survivability in an airline network) Suppose that a flight leg from Houston to New York is down for some reason such as the lateness or breakdown of the airplane or the absence of the crew. If this flight leg is canceled, the entire airplane network will be badly affected. The analysis based on importance measures could enhance the survivability of the entire airline network, for example, by identifying a flight leg that has less effect on the entire airplane network than the flight leg from Houston to New York and reassigning an airplane or crew that was originally assigned to this "less important" flight leg to the one that is down. Therefore, it is logical to enhance the reliability of the link that would add more survivability to the entire network. This is of particular usefulness when the available resources are limited.

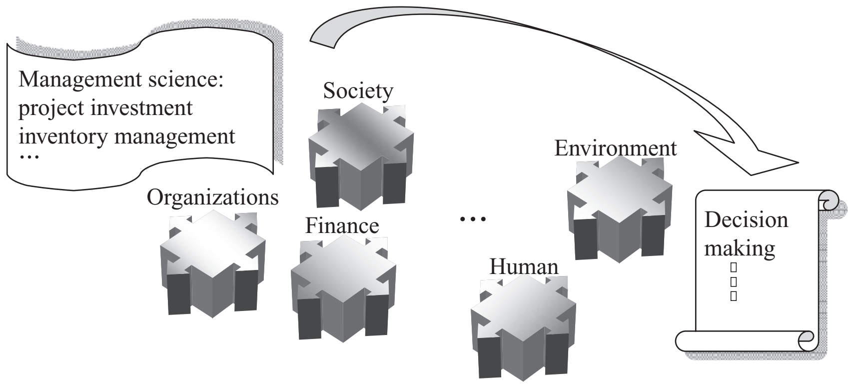

Figure 1.4 Management decision-making

Proper arrangement of resources to each link in the network as a result of careful analysis can enhance the safety and survivability, as addressed in Chapters 16 and 17. In fact, this is a typical mathematical programming problem in operations research. Including the survivability in problem modeling and the importance measures of links can improve the effectiveness of the mathematical programming.

Example 1.0.8 (Software development) Software development is costly, very labor-intensive, and depending on the applications that are also very knowledge dependent. Unfortunately, software is rarely assured for failure-free operation because of the complexity and special requirements of the different users' profiles that may be involved. It is a common practice that for software that requires high reliability, the same specification set may be given to different developers so that redundant software may be adopted. In all of these processes, one needs to identify a critical module or subprogram in the software that requires more resources in the development phase. Therefore, as pointed out by Simmons et al. (1998), it would be very beneficial to find a formal way to identify the important modules of the software and invest in their development in order to achieve the high software reliability and meanwhile minimize the software development cost. Subsection 18.3.1 presents an example to illustrate the concept. Another case study on optimal design for software reliability can be found in Kuo et al. (2006).

Example 1.0.9 (Management science) The importance measures are diversely used in management science and making financial decisions (Soofi et al. 2000), which is a complicated process as in Figure 1.4. For example, Borgonovo and Peccati (2004) applied the differential importance measure (DIM) based on local sensitivity analysis for investment project decisions (see Chapter 18). Borgonovo (2008) extended the DIM in combination with comparative statics technique to inventory management, in which the models are implicit, and the problem is to determine the most influential parameter on an inventory policy.

Example 1.0.10 (Risk analysis) Risk can be analyzed through sensitivity analysis that allows to identify the impact of the variation of individual inputs on the overall decision-making.

The goal is to reduce the risk of a change in the input value and analyze steps to minimize any potential adverse consequences. In a typical sensitivity analysis, the process is repeated for all input variables for which risks and the ranking of the risks are identified. Therefore, one can identify the critical inputs in the analysis process. The commonly used procedures are treated uniformly as importance measures in Chapters 18 and 19.

Importance measures can also be used to quantify the contribution of input parameters on uncertainty over the optimal decision as described in Chapter 18. In this regard, Coyle et al. (2003) conducted a case study on a cost utility analysis of adjunct therapy for the treatment of Parkinson’s disease patients.

Similarly, it is strongly recommended that one identifies the critical elements in a simulation process using the concept of importance measures. By incorporating importance measures in determining the input variables, simulation can be conducted with meaning and efficiency as well.

Example 1.0.11 (Fault diagnosis and maintenance) In a system consisting of multiple components, the system may fail to perform its desired functions due to the failure of one or more components. For example, large pipeline networks are widely used to transport different kinds of fluids from production sites to consumption ones. Transmission pipelines are the most essential components of such networks and used to transport fluids over very long distances. The safe handling of such networks is of great importance due to the serious consequences which may result from any faulty operation. In particular, leaks quite frequently occur due to material ageing, pipes bursting, cracking of the welding seam, hole corrosion, and unauthorized actions by third parties. When a system fails, diagnosis must be efficiently conducted, and maintenance must locate the component(s) that caused the failure of the system and bring the system back to function as soon as possible. Then the maintenance needs to check the component that most likely caused the failure first, then the second most likely component, and so on, until the system is fixed. For this purpose, one might propose an importance measure to indicate how important the different components are in terms of system failure. The importance measures in Section 19.6 may suggest the most efficient way to diagnose system failure by generating a repair checklist for an operator to follow, and indeed, importance-measure-based maintenance methods are used by practitioners (ReliaSoft 2003).

Example 1.0.12 (Nuclear power plant) Nuclear power plants are designed so that major external pressures, including bombing, will not compromise the safety concern. Special attention has also been paid to seismic factors in the siting, design, and construction of nuclear plants and in identifying other critical elements in order to enhance the safety margin. However, in analyzing all key factors, people need formal procedures to identify the risk factors and to design for reliability in power plants before they are put in operation.

Fussell (1975) and Vesely (1970) may be the first to apply the concept of importance measures, that is, the Fussell–Vesely importance (see Sections 4.2 and 5.2), to evaluating systems reliability and risk based on complete probabilistic information. Since then, various importance measures have been applied to evaluate and assess nuclear power plants. In an early work, Lambert (1975) explicitly proposed importance measures of events and cuts in fault trees and used them in generating a checklist for fault diagnosis of a low-pressure injection system, which is a standby safety system that forms part of the emergency core cooling system at a nuclear power plant.

For a recent example, with regard to safety assessment for nuclear waste disposal, Saltelli and Tarantola (2002) used global sensitivity measures to judge the effect of model parameter uncertainty reductions on the overall model output uncertainty (see Section 18.2). In this respect, PRA and PSA are methodologies that produce numerical estimates of the basic events, components, and parameters with respect to a number of risk metrics for complex technological systems. Core damage frequency and large early release frequency are the common risk metrics of interest in nuclear power plants. PRA and PSA are generally conducted using certain importance measures as explained in Chapter 19.

The concept of importance measures of components in a reliability system was initially proposed in the 1960s. After that, many types of importance measures were proposed with respect to the diverse considerations of system performance. Performance of a system can be measured using systems reliability, availability, maintainability, safety, utility in Equation (15.1), structural function of system efficiency, which is a set of discrete values from zero to a positive maximum value (Finkelstein 1994), and so on. Part Two presents major existing importance measures in reliability, including their definitions, probabilistic interpretations, properties, computation, and comparability. Part Three thoroughly discusses applications of importance measures in the areas of systems reliability design and introduces more types of importance measures that were proposed to address problems of interest. Although importance measures reflect different probabilistic interpretations and potential applications, they are related to each other in some aspects. Part Four presents the relationships among these types of importance measures and generalizes them to nonetheless important situations. Part Five investigates broad implications of importance measures to risk, mathematical programming, and even broader categories.

References

Archer KJ and Kimes RV. 2008. Empirical characterization of random forest variable importance measures. *Computational Statistics and Data Analysis* **52**, 2249–2260.

Borgonovo E. 2008. Differential importance and comparative statics: An application to inventory management. *International Journal of Production Economics* **111**, 170–179.

Borgonovo E and Peccati L. 2004. Sensitivity analysis in investment project evaluation. *International Journal of Production Economics* **90**, 17–25.

Coyle D, Buxton MJ, and O'Brien BJ. 2003. Measures of importance for economic analysis based on decision modeling. *Journal of Clinical Epidemiology* **56**, 989–997.

Finkelstein MS. 1994. Once more on measures of importance of system components. *Microelectronics and Reliability* **34**, 1431–1439.

Fussell JB. 1975. How to hand-calculate system reliability and safety characteristics. *IEEE Transactions on Reliability* **R-24**, 169–174.

Kuo W, Prasad VR, Tillman FA, and Hwang CL. 2006. *Optimal Reliability Design: Fundamentals and Applications, 2nd edn.* Cambridge University Press, Cambridge, UK.

Lambert HE. 1975. *Fault Trees for Decision Making in System Safety and Availability*. PhD Thesis, University of California, Berkeley.

Liaw A and Wiener M. 2002. Classification and regression by ramdomforest. *Resampling Methods in R: The Boot Package* **2**, 18–22.

Naoki S and Hiroshi M. 2004. Wireless charging system by microwave power transmission for electric motor vehicles. *IEICE Transactions on Electronics* **J87-C**, 433–443.

ReliaSoft. 2003. Using reliability importance measures to guide component improvement efforts. Available at http://www.maintenanceworld.com/Articles/reliasoft/usingreliability.html.

Saltelli A and Tarantola S. 2002. On the relative importance of input factors in mathematical models: Safety assessment for nuclear waste disposal. *Journal of American Statistical Association* **97**, 702–709.

Schwender H, Bowers K, Fallin M, and Ruczinski I. 2011. Importance measures for epistatic interactions in case-parent trios. *Annals of Human Genetics* **75**, 122–132.

Simmons D, Ellis N, Fujihara H, and Kuo W. 1998. *Software Measurement: A Visualization Toolkit for Project Control and Process Improvement*. Prentice Hall, New Jersey. 459 pages and CD software.

Smith CL and Borgonovo E. 2007. Decision making during nuclear power plant incidents – a new approach to the evaluation of precursor events. *Risk Analysis* **27**, 1027–1042.

Soofi ES, Retzer JJ, and Yasai-Ardekani M. 2000. A framework for measuring the importance of variables with applications to management research and decision models. *Decision Sciences* **31**, 595–625.

Strobl C, Boulesteix AL, Zeileis A, and Hothorn T. 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics* **8**, 1–25.

Vesely WE. 1970. A time dependent methodology for fault tree evaluation. *Nuclear Engineering and Design* **13**, 337–360.

Zhang Z, Kulkarni A, Ma X, and Zhou Y. 2009. Memory resource allocation for file system prefetching: From a supply chain management perspective. *Proceedings of the EuroSys Conference*, pp. 75–88.

Zio E, Marella M, and Podofillini L. 2007. Importance measures-based prioritization for improving the performance of multi-state systems: Application to the railway industry. *Reliability Engineering and System Safety* **92**, 1303–1314.