A QUANTITATIVE ECOLOGICAL BASED THEORY FOR TECHNOLOGY EVOLUTION PREDICTION AND MANIPULATION

A Dissertation

by

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ABSTRACT

Technology evolution prediction is critical for designers, R&D managers, and policy makers to make important design and R&D decisions and to develop effective government incentives. Many descriptive models (e.g., logistic S-curve model and Moore's Law) have been developed for technology performance prediction, but these descriptive models do not identify what factors shape future technology performance and how designers, firms, or governments can manipulate them. In this dissertation, a quantitative ecological based theory is created for technology evolution prediction and manipulation. The quantitative ecological based theory consists of a Lotka-Volterra ecosystem model and a generic method for prediction intervals generation. The ecosystem model and the generic method are able to help designers, R&D mangers, and policy makers to predict technology technical performance (e.g., speed, capacity, and energy efficiency), to discern the causality of technology evolution, and to develop effective strategies to improve technology technical performance.

The Lotka-Volterra ecosystem model is extended from Lotka-Volterra equations in community ecology. The ecosystem model considers the interaction between a system technology and its component technologies in the relationships of symbiosis, commensalism, and amensalism. In addition, every parameter in the ecosystem model is associated with its causal factors, such as R&D investment and technical difficulty. The values and interpretations of these parameters are used to identify the key component

technologies in a system technology and to develop effective strategies on improving system technology performance.

The generic method uses bootstrapping to generate prediction intervals for technology evolution. The prediction intervals help practitioners to assess future uncertainty and make contingency plans accordingly. The method can be applied to any prediction model based on mathematical functions or differential equations involving time. Parameter uncertainty and data uncertainty are considered in the method and the empirical probability distributions of these uncertainties are established. The appropriate confidence level α required to generate prediction intervals is determined using a holdout sample analysis rather than setting α=0.05 as is frequently done in previous research.

The quantitative ecological based theory is proven to be effective through four case studies of three representative technologies (i.e., concrete skyscraper, passenger aircraft, and central processing unit) in this dissertation.

DEDICATION

This dissertation is dedicated to Prof. Dilin Xiong, Prof. Kefa Yao, and Dr. Joe Fowler.

I would not pursue Ph.D. study in Texas A&M University and finish this dissertation if I never met them.

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1. INTRODUCTION

Technology is a basic building block of modern civilization and economy. Technology has a broad definition that includes hardware (e.g., aircraft, automobile, cell phone) and software (e.g., know-how, human knowledge, programs) [1]. The performance, function, and architecture of a technology continuously changes over time. The evolution of passenger aircraft illustrates the significant performance changes of technologies over time. The Benoist XIV that achieved the first scheduled commercial airline flight in 1914 carries only one passenger with a maximum speed of 103 kilometers per hour (km/h) and flies within a range of 200 kilometers (km); the Airbus A380 introduced in 2007 carries 853 passengers with a cruise speed of 903 km/h and a maximum range of 14,800 km [2]. The functional change is also apparent during the evolution of a technology. The cell phones of the 1990's could only make phone calls and send and receive text messages. However, current cell phones are equipped with cameras and internet access. The performance and functional changes of a technology are usually accompanied by technology architecture modification or reconstruction. For example, to improve energy efficiency of automobiles, gasoline engines were displaced by electric motors. The automobile architecture has been modified to accommodate the motor and the battery required by an electric power train.

Research in technology evolution not only tracks the historical technical performance and the functional and architectural changes of existing technologies, but also studies how and why these changes occur and searches for patterns behind these evolutions. The research results of technology evolution are valuable for designers, R&D managers, and policy makers to make important design and R&D decisions and to develop effective government incentives.

Prior research in the area of technology evolution, called technological forecasting or diffusion of innovations, is focused solely on business indicators of technologies, such as cost, price, production, sales revenue, and profit [3-11]. This dissertation focuses on technical performance (e.g., speed, capacity, and energy efficiency) evolution of technologies. In this dissertation, a quantitative ecological based theory is created for technology evolution prediction and manipulation. The quantitative ecological based theory consists of a Lotka-Volterra ecosystem model and a generic method for prediction intervals generation. The Lotka-Volterra ecosystem model and the prediction intervals generation method are able to help designers, R&D mangers, and policy makers to discern the causality of technology evolution, to predict future technology technical performance, and to develop effective strategies to improve technology technical performance.

As the first chapter of this dissertation, this chapter begins with the significance of the research in modeling the technical performance changes of technologies. The descriptive models that are commonly used in technological forecasting are reviewed, and the drawbacks of these descriptive models are discussed. Based on the drawbacks of existing descriptive models, the research motivation and objective of this dissertation are introduced. This chapter is concluded with an overview of the following chapters in this dissertation.

1.1. Research Significance

It is important for designers, R&D mangers, and policy makers to understand the technology evolution of interest and to predict future technical performance of the technology. Specifically, the research results in technology technical performance evolution help designers, R&D managers, and policy makers to establish stable product architecture, set reasonable R&D targets, and develop effective incentive policies.

Technology evolution has significant impact on product architecture. If the technical performance of a technology used in a product is changing rapidly, the designer may choose to include that technology into the product in a modular fashion. If the technology is mature, the designer may decide to include that technology into the product in an integral way. For example, central processing unit (CPU) and random-access memory (RAM) are designed as pluggable modules on the computer motherboard because the technical performance of CPU and RAM changes much faster than that of the other technologies. Similarly for product family design, the maturity of a technology impacts its suitability for inclusion in a product family platform. A technology is not appropriate to be shared among the product variants in a family if the technology is evolving rapidly [12].

R&D managers rely on the technical performance prediction results to set reasonable R&D targets. For example, R&D managers in semi-conductor industries use Moore's Law to predict CPU transistor count evolution and set target values for future CPU technical performance (e.g., clock speed) accordingly [13]. Reasonable R&D targets are critical for a company to succeed in the industry. The company cannot compete with industry rivals and will lose market share if the company sets a low target value for technology performance in R&D planning. On the other hand, the company may not be able to achieve expected outcomes and will exhaust limited R&D capital and human resources if the target value is too high.

Policy makers can also benefit from the research of technology technical performance evolution. Knowing the technology interaction and predicting the evolution of a technology of interest, professionals in public policy can fund key research initiatives that may improve the technology technical performance rapidly. Moreover, public policy officials could develop appropriate regulations and incentive structures for future technology development if they can identify the key factors that have significant impact on the evolution of a technology. For example, government policy makers may consider providing economic benefits (e.g., R&D funding support and tax credit) to not only the passenger aircraft manufacturers but also to the key component (e.g., aero-engine) developers and manufacturers in order to maintain the prosperity of the passenger aircraft industry.

The research results in technology technical performance evolution may also useful for entrepreneurs, business managers, investors, and government officials to make various decisions. In this dissertation, “practitioners” is used to represent the people who are interested in technology technical performance evolution and may employ the quantitative ecological based theory.

1.2. Descriptive Models and Their Drawbacks

Researchers often believe that an underlying law governs the technical performance changes of technologies over time [14]. Such an underlying law is described by continuous mathematical functions involving time, which are called descriptive models. The logistic S-curve model [15, 16] and the simple exponential model (Moore's Law) [13] are two commonly used descriptive models in technology technical performance evolution, where the technical performance evolution is modeled as a standard S-curve and a simple exponential function, respectively. The parameters in these models are estimated based on past technical performance data. Future technology technical performance is predicted by mathematical extrapolation.

There are more descriptive models developed for technological forecasting that focuses on the business indicators, such as cost, price, production, sales revenue, and profit, of technologies [5, 17]. Several popular descriptive models are listed in Table 1, where X_t is the technology performance function with time t.

Despite some successful applications, these descriptive models suffer from several drawbacks. Practitioners have to go through tedious procedures to select an appropriate model or a class of possible models for their problem [5, 17]. Moreover, most of parameters in these models lack physical meaning or interpretation. These models often are at best curve fits rather than richer models that indicate some descriptor of causality. In other words, these models don't allow for the fact that technology evolution is affected by external or internal factors. These models do not identify what factors shape future technology performance and how designers, firms, or governments can manipulate it. Importantly, these descriptive models consider a technology in isolation and not as interconnected with other technologies, which may lead to significant prediction error [18-20]. In addition, the prediction results generated by these descriptive models are expressed as single numbers (i.e., point forecasts) rather than prediction intervals. In practice, practitioners often want to supplement point forecasts by computing prediction intervals to assess future uncertainty and make contingency plans accordingly [21].

Table 1.1 Popular Descriptive Models in Technology Evolution

Model	Formula	Parameters
Logistic	$X_t = \frac{a}{1 + c \cdot exp(-bt)}$	a, b, c
Moore's Law	$X_t = c \cdot exp(bt)$	b, c
Gompertz	$X_t = exp(-c \cdot exp(-bt))$	b, c
Weibull	$X_t = 1 - exp(-(\frac{t}{a})^b)$	a, b
Mansfield	$ln\left(\frac{X_t}{1 - X_t}\right) = a + bt$	a, b
Log-Logistic	$X_t = \frac{a}{1 + e^{b - c \ln t}}$	a, b, c
Erto-Lanzotti	$X_t = X_0 + \left(1 - e^{-bt^c}\right)(a - X_o)$	a, b, c
Richards	$X_t = \frac{a}{(1 + e^{b-ct})^{\frac{1}{d}}}$	a, b, c, d

1.3. Motivation and Research Objective

In this dissertation, a product is referred to as a system technology. The system technology is realized through the integration and support of hardware and software [1, 19, 22], which are referred to as component technologies. For example, the smart phone is a system technology that is supported by several component technologies, such as touch screen, CPU, integrated circuit (IC), battery, and operating system. The descriptive models do not take the interaction between a system technology and its component technologies into account as stated earlier. To overcome this shortcoming, this work seeks inspiration in community ecology. The interaction modes between two species in community ecology are used to study the interaction between a system technology and its component technologies. The Lotka-Volterra equations, which are initially developed to describe the population changes of a predator and its prey in mathematical ecology [23], are analyzed and extended to model the technical performance changes of system and component technologies.

The objective of this research is to develop a quantitative ecological based theory that helps practitioners to predict and manipulate future technology evolution. Unlike the descriptive models, shown in Table 1.1, the quantitative ecological based theory indicates the causality and the uncertainty of technology evolution through a Lotka-Volterra ecosystem model and a generic method for prediction intervals generation.

The Lotka-Volterra ecosystem model comprises a set of differential equations that model the technical performance changes of system technology and its component technologies simultaneously. The ecosystem model includes several interaction terms that represent the interactions between a system technology and multiple component technologies. In addition, the parameters in the ecosystem model are associated with causal factors of technical performance variation. Thus, the Lotka-Volterra ecosystem model is able to help practitioners identify the key component technologies that have a significant impact on system technology performance evolution. The identified key component technologies also provide effective strategies to improve system technology performance.

The generic method for prediction intervals generation helps practitioners to assess the uncertainty of future technology evolution and make contingency plans accordingly. The generic method can be applied to any model that predicts technology performance changes (e.g., the logistic S-curve model, Moore’s Law, and the Lotka-Volterra ecosystem model). The method is based on a bootstrapping approach [24-26] and does not rely on any parametric assumptions (e.g., assumptions of normality). In addition, this method provides the probability distribution of each parameter in a prediction model. The probability distribution is valuable for practitioners when parameter values are associated with the impact factors of technology evolution (e.g., performance upper limit in the logistic S-curve model or technology interaction in the Lotka-Volterra ecosystem model).

1.4. Overview of Chapters

This dissertation begins with a short review of interaction modes (between two species in community ecology and their analogies in technology evolution) and the

Lotka-Volterra equations. The Lotka-Volterra ecosystem model is also introduced in Chapter 2. In Chapter 3, the Lotka-Volterra ecosystem model is validated as an advanced technology evolution prediction model through the mathematical analysis. In Chapter 4, technology commensalism and amensalism are discussed. Commensalism and amensalism are two special cases of technology interactions in which system technology development has a negligible influence on component technologies. Analytic solutions of the Lotka-Volterra ecosystem model are derived under these two special cases. The prediction for concrete skyscraper is carried out using the analytic solutions. In Chapter 5, the general case of technology interaction, including the relationships of symbiosis, commensalism, and amensalism, is examined. Three steps are introduced to apply the Lotka-Volterra ecosystem model in technology evolution prediction and manipulation. The application of the Lotka-Volterra ecosystem model is illustrated using a case study of passenger aircraft fuel efficiency. In Chapter 6, a generic method for prediction intervals generation is developed. Four steps to implement the method are summarized. The application of the generic method is illustrated using two case studies of CPU and passenger aircraft overall performance. Conclusions of this dissertation and future research directions are provided in Chapter 7.

2. BACKGROUND AND RELATED WORK*

The descriptive models do not consider the interaction between a system technology and its component technologies as stated in Chapter 1.2. To overcome this shortcoming, the relationships between a system technology and its component technologies should be studies first, a mathematical model then could be established based on the relationships, also called interaction modes, between the technologies.

This chapter seeks inspiration from community ecology to describe the relationships between a system technology and its component technologies. The interaction modes between two species in community ecology are provided, and their analogies in technology evolution are discussed. The background of the Lotka-Volterra equations is then reviewed. These equations are extended as a Lotka-Volterra ecosystem model for technology evolution prediction and manipulation.

2.1. Interaction Modes between Component Technology and System Technology

The interaction between a system technology and its component technologies critically determines the evolution of the system technology. For example, the fast development of the computer relies on the performance improvement of the CPU; the evolution of electric automobile depends on the advancement of battery performance. To

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capture the evolution of technology performance, concepts from community ecology are employed to study the interaction modes between the component technology and the system technology. There are six different interaction modes between two species in an ecosystem [27]. The six interaction modes are shown on Table 2.1.

In Table 2.1, "0" indicates no significant interaction; "+" indicates growth, survival, or other population attribute benefited; and "-" indicates a reduction of species population or other attribute inhibited. Among the six interaction modes, symbiosis, commensalism, and amensalism are appropriate to describe the interaction between a system technology and a component technology [18].

Table 2.1 Interaction Modes between Two Species in an Ecosystem

Mode of interaction	**Species 1**	**Species 2**	**General nature of interaction**
Neutralism	0	0	Neither species affects the other
Predation (and Parasitism)	-	+	Species 2 (predator) is benefited, Species 1 (prey) is inhibited
Competition	-	-	Direct or indirect inhibition of each species by the other
Symbiosis (include Protocooperation and Mutualism)	+	+	Interaction is favorable to both species
Commensalism	0	+	Species 2 is benefited, Species 1 is unaffected
Amensalism	0	-	Species 2 is inhibited, Species 1 is unaffected

Symbiosis describes two species that benefit each other in community ecology. For example, a clownfish and a sea anemone establish a symbiotic relationship. The clownfish feeds on small invertebrates that harm the sea anemone, and the sea anemone protects the clownfish from its predator [28]. Such a symbiotic relationship is also common in technology evolution because a system technology is often supported by one or more component technologies. For example, the areal density of hard disk drives (HDD) has increased from 10^{-3} Gb/in^2 to 10^3 Gb/in^2 over a forty-year period [29]. The improvement in HDD performance supported the boom of the computer. At the same time, the fast development of the computer also demands that the HDD has larger areal density. Thus, the interaction is favorable to both the system technology and its component technology.

Commensalism is a one-way relationship between two species. In Table 2.1, Species 1 has a beneficial effect on Species 2, but Species 1 is not affected by Species 2. A well-known example of commensalism is the relationship between remora and sharks. A remora adheres to the body of a shark and feeds on the leftovers of the shark's meal, but a shark is neither benefited nor harmed by a remora [30]. In technology evolution, commensalism could be observed when one component technology serves a diverse set of system technologies. One system technology has a negligible impact on the evolution of the component technology. For example, steel is an essential component technology of bridges. Improved steel properties lead to better bridge performance, but the evolution of bridges has negligible impact on steel improvement because steel is also used in many other system technologies, such as automobiles and spacecraft.

Similar to commensalism, amensalism is also a one-way relationship between two species in community ecology. Unlike commensalism, Species 1 has a detrimental effect on Species 2 if they have an amensalism relationship. A typical example of amensalism in community ecology is the relationship between a short tree and a tall tree. The short tree lives in the shadow of the tall tree. The short tree suffers adverse effects from the tall tree but has little impact on the tall tree. It is possible for a component technology and a system technology to also exhibit an amensalism relationship. For example, while technological development has resulted in more compact CPUs, the development has also induced more unwanted heat in the CPU. In this way, the thermal dissipation performance of a laptop system is impaired by the fast development of the CPU component. Meanwhile, the evolution of the CPU is not affected by the laptop because the CPU is also utilized in other system technologies (e.g., desktops and workstations). Of note, the relationship between a system technology and its component technologies depends on the performance metric of interest. For instance, the relationship between a laptop system and its CPU component may vary if practitioners focus on a different performance metric.

2.2. Lotka-Volterra Ecosystem Model

The Lotka-Volterra equations were introduced by Vito Volterra in the early 20th century to model the population changes of sharks and fishes in the Adriatic Sea. At the beginning, the model only described the predation relationship between two species (one predator and one prey). Since then, these equations have been expanded to model other relationships (e.g., competition) between two species and have been successfully applied in demography and ecology during the last century [23, 31].

Pistorius and Utterback modified the traditional Lotka-Volterra equations in community ecology to study the interaction between two technologies [32]. Their model has the mathematical form as follows

$$\frac{dN}{dt} = a_n N - b_n N^2 + C_{nm} NM \tag{2.1}$$

$$\frac{dM}{dt} = a_m M - b_m M^2 + C_{mn} MN \,, \tag{2.2}$$

where $N(t)$ and $M(t)$ denote the performances of two technologies. The derivatives dN/dt and dM/dt represent the performance change rates of the two technologies, respectively. Parameters a (a_n and a_m), b (b_n and b_m), and C (C_{nm} and C_{mn}) are constants derived through a data fitting process.

Eqs. (2.1) and (2.2) are extended to model the interaction between one system technology and multiple component technologies in the relationships of symbiosis, commensalism and amensalism. The Lotka-Volterra ecosystem model is developed as

$$\frac{dy_0}{dt} = a_0 y_0 - b_0 {y_0}^2 + \sum_{i=1}^{n} C_{0i} y_0 y_i \tag{2.3}$$

$$\frac{dy_1}{dt} = a_1 y_1 - b_1 {y_1}^2 + C_{10} y_1 y_0 \tag{2.4}$$

... ...

$$\frac{dy_j}{dt} = a_j y_j - b_j {y_j}^2 + C_{j0} y_j y_0 \tag{2.5}$$

... ...

$$\frac{dy_n}{dt} = a_n y_n - b_n {y_n}^2 + C_{n0} y_n y_0 \,. \tag{2.6}$$

Eqs. (2.3) - (2.6) represent (n+1) equations that model the interaction between one system technology and n component technologies, where i, j and n are positive integers with $i \in \{1,\ldots, n\}$, $j \in \{1,\ldots, n\}$; y_0 is system technology performance, y_i and y_j are component technology performances; a_0, a_j, b_0, b_j, C_{0i}, and C_{j0} are constant parameters derived through a data fitting process.

Unlike the descriptive models, the parameters a (i.e., a_0, a_j, a_n), b (i.e., b_0, b_j, b_n), and C (i.e., C_{0i}, C_{j0}) in the Lotka-Volterra ecosystem model are associated with causal factors in both community ecology and technology evolution [19, 33].

Parameter a represents unlimited growth rate in community ecology. The unlimited growth originates from the breeding instinct of species. In technology evolution, the parameter a indicates the system or component technology performance independent growth rate. The independent growth rate depends on R&D investment, government policy encouragement, and other stimulation factors. For example, the parameter a_0 in Eq. (2.3) will have a larger value if R&D managers invest more in the R&D of the system technology. Generally, the parameter a has a positive value because practitioners want to improve the system and the component technology performances. In rare cases, the parameter a may have a negative value (e.g., due to government regulation restrictions).

Parameter b describes the self-crowding effect of a species in an ecological system. The negative effect arises from shortage of resources, such as food or water. In technology evolution, the parameter b represents technical difficulty, which is the hardship that a component technology or a system technology has to overcome for its performance improvement. The value of parameter b sets the upper limit value of system or component technology performance. For example, the system technology performance y_0 will be bounded by a lower upper limit value if the parameter b_0 has a larger value in Eq. (2.3). Because there is a negative sign in front of the b terms (e.g., $b_0y_0^2$ in Eq. (2.3)) in the Lotka-Volterra ecosystem model, the parameter b has a positive value.

Parameter C denotes the beneficial or detrimental effect from other species in community ecology. Similarly, the parameter C describes the interaction between the system technology and its component technologies in technology evolution. The parameter C could be positive or negative based on the relationship between the system technology and the component technology.

The interaction between system technology performance y_0 and component technology performance y_1 is taken as an example. The parameter C_{01} in Eq. (2.3) represents the impact of the component technology on the system technology; the parameter C_{10} in Eq. (2.4) represents the impact of the system technology on the component technology. The values of parameters C_{01} and C_{10} are not equal in a general case. If the system technology and the component technology have a symbiotic relationship, the parameters C_{01} and C_{10} are positive. The positive C_{01} and C_{10} show that the system technology and the component technology have beneficial effects on each other. If the system technology and the component technology have a commensalism relationship, the parameter C_{01} is positive and the parameter C_{10} equals zero. The positive C_{01} and null C_{10} indicate that the component technology has a beneficial effect on the system technology, but the system technology has a negligible effect on the component technology. Similarly, if the system technology and the component technology have an amensalism relationship, the parameter C_{01} is negative and the parameter C_{10} equals zero. The negative C_{01} and null C_{10} indicate that the component technology has a detrimental effect on the system technology, but the system technology has negligible effect on the component technology. The sign of C_{01} and C_{10} under different component technology and system technology interaction modes are shown in Table 2.2.

Table 2.2 The Signs of Parameter C_{01} and C_{10} under Different Interaction Modes

Mode of interaction	Symbiosis	Commensalism	Amensalism
C_{01}	+	+	-
C_{10}	+	0	0

The interaction between component technologies is neglected in Eqs. (2.3) - (2.6). Specifically, the term $C_{12}y_2y_1$ is not included in Eq. (2.4) to consider the impact of the component technology performance y_2 on the component technology performance y_1. This simplification is valid in many real cases. For example, the touch screen and the CPU are two major component technologies of a smartphone system technology. These two component technologies have significant impacts on smartphone system technology performance. However, the interaction between the touch screen and the CPU is negligible because the performance evolutions of these two component technologies are independent. The interaction between the component technologies may be prominent in some cases. In the laptop system technology example, the advancement of the HDD (hardware) may facilitate the improvement of the operating system (software). Such cases are beyond the scope of this dissertation but provide an interesting and likely important avenue for future research.

2.3. Summary

In this chapter, the interaction modes between two species in community ecology are employed to study the relationships between a system technology and its component technologies in technology evolution. Among the six interaction modes between two species in community ecology, symbiosis, commensalism, and amensalism have analogies in technology evolution. The system technology performance and the component technology performance benefit each other when they have a symbiotic relationship. In the relationships of commensalism and amensalism, the component technology performance is unaffected by the system technology performance. However, as the component technology performance improves, the system technology performance is enhanced in commensalism but inhibited in amensalism.

The Lotka-Volterra equations in community ecology are extended as a Lotka-Volterra ecosystem model for technology evolution prediction and manipulation. The mathematical form of the Lotka-Volterra ecosystem model is shown in Eqs. (2.3) - (2.6). The ecosystem model is able to describe the interaction between one system technology and multiple component technologies in the relationships of symbiosis, commensalism and amensalism. In addition, the parameters a, b, and C used in the Lotka-Volterra ecosystem model are associated with causal factors of technology evolution. Specifically, the parameter *a* represents technology performance independent growth rate that depends on R&D investment, government policy encouragement, and other stimulation factors; the parameter *b* describes technical difficulty, which sets the upper limit value of system or component technology performance; the parameter *C* indicates the relationship of symbiosis, commensalism, or amensalism between the system technology and its component technologies. The signs of parameter *C* under different interaction modes are shown in Table 2.2.

3. MATHEMATICAL ANALYSIS OF THE LOTKA-VOLTERRA ECOSYSTEM MODEL AND IMPLICATIONS FOR PRACTITIONERS*

The Lotka-Volterra ecosystem model is introduced as a new mathematical model for technology evolution prediction and manipulation in Chapter 2. It is necessary to test whether the Lotka-Volterra ecosystem model is able to depict the typical technology evolution curves. The relationships between the Lotka-Volterra ecosystem model and the popular descriptive models are also need to be explored.

This chapter presents the functional equivalence and equilibrium point analysis of the Lotka-Volterra ecosystem model. These mathematical analyses demonstrate that the Lotka-Volterra ecosystem model can be used as an advanced model for technology evolution prediction and manipulation. The analysis also provides important implications for practitioners, such as designers, R&D managers, and policy makers.

3.1. Simplification of the Lotka-Volterra Ecosystem Model

The Lotka-Volterra ecosystem model, shown in Eqs. (2.3) - (2.6), are coupled differential equations. Eq. (2.3) could be reduced if the interaction between the system technology and the component technology is negligible. The parameter C_{0i} in Eq. (2.3) equals zero in this case, and Eq. (2.3) reduces to

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$$\frac{dy_0}{dt} = a_0 y_0 - b_0 {y_0}^2 \,. \tag{3.1}$$

The solution of Eq. (3.1) has the form

$$y_0 = \frac{A}{\frac{b_0}{a_0} + Be^{-a_0 t}}\,, \tag{3.2}$$

where *A* and *B* are integral constants. The logistic S-curve model is obtained from Eq. (3.2) when b_0 equals a_0 as

$$y_0 = \frac{A}{1 + Be^{-a_0 t}}\,, \tag{3.3}$$

If the technical difficulty term $b_0 y_0^2$ in Eq. (3.1) is neglected, the Lotka-Volterra ecosystem model is further reduced to

$$\frac{dy_0}{dt} = a_0 y_0 \,. \tag{3.4}$$

The solution of Eq. (3.4) is

$$y_0 = De^{a_0 t}\,, \tag{3.5}$$

where *D* is an integral constant. Eq. (3.5) models technology performance evolution as an exponential function, which is also known as Moore’s Law. Moore’s Law is a special case of the logistic S-curve model. It was proposed by Gordon E. Moore in 1965 and is widely used in the semiconductor industry [13].

The simplification from Eq. (3.1) to Eq. (3.5) shows that the Lotka-Volterra ecosystem model could be reduced to the logistic S-curve model and Moore’s Law. In other words, the logistic S-curve model and Moore’s Law are only special cases of the Lotka-Volterra ecosystem model. The ecosystem model also covers Gompertz, Bass, Non-Symmetrical Responding Logistic (NSRL) and Sharif-Kabir models [34]. Thus, the

Lotka-Volterra ecosystem model has a greater data fitting accuracy than the logistic S-curve model, Moore's Law, and the other aforementioned models.

3.2. Equilibrium Point Analysis of the Lotka-Volterra Ecosystem Model

In community ecology, the population change rate of a species equals zero at the equilibrium point. If an equilibrium point exists on the first quadrant of the phase diagram of the traditional Lotka-Volterra equations, it signifies that the population of the species reaches an upper limit value as an asymptote [35]. Similarly, the equilibrium point analysis of the Lotka-Volterra ecosystem model could help practitioners determine whether system or component technology performance reaches an upper limit as it evolves. The mathematical expression of the upper limit value also offers guidelines for practitioners on improving technology performance.

The simple case where one system technology interacts with one component technology is considered first [33]. The Lotka-Volterra ecosystem model has the form

$$\frac{dy_0}{dt} = a_0 y_0 - b_0 {y_0}^2 + C_{01} y_0 y_1 \tag{3.6}$$

$$\frac{dy_1}{dt} = a_1 y_1 - b_1 {y_1}^2 + C_{10} y_1 y_0 \tag{3.7}$$

where y_0 is the system technology performance, and y_1 is the component technology performance. The equilibrium points of Eqs. (3.6) and (3.7) are defined as

$$\frac{dy_0}{dt} = a_0 y_0 - b_0 {y_0}^2 + C_{01} y_0 y_1 = 0 \tag{3.8}$$

$$\frac{dy_1}{dt} = a_1 y_1 - b_1 {y_1}^2 + C_{10} y_1 y_0 = 0 \tag{3.9}$$

The system and the component technology performance change rates equal zero at the equilibrium points.

There are four equilibrium points in this case. The first point is at the origin of the performance phase diagram where both y_0 and y_1 equal zero. The second and third equilibrium points have the coordinates $(0, a_1/b_1)$ and $(a_0/b_0, 0)$. These three equilibrium points have little implication for technology evolution prediction and manipulation because system or component technology performance always has a positive value. Solving Eqs. (3.8) and (3.9), the coordinates of the fourth equilibrium point are

$$y_0^{(e)} = \frac{a_0 b_1 + a_1 C_{01}}{b_0 b_1 - C_{01} C_{10}} \tag{3.10}$$

$$y_1^{(e)} = \frac{a_1 b_0 + a_0 C_{10}}{b_0 b_1 - C_{01} C_{10}}. \tag{3.11}$$

The parameters a and b have positive values in general as discussed in Chapter 2.2. The case that parameter C has positive value is considered here because symbiosis and commensalism are the most common relationships between a system technology and a component technology [18]. The rare case that parameter C has a negative value is not discussed as it is outside the scope of this chapter. Thus, the fourth equilibrium point is located in the first quadrant ($b_0 b_1 > C_{01} C_{10}$ and $y_0^{(e)} > 0$, $y_1^{(e)} > 0$) or in the third quadrant ($b_0 b_1 < C_{01} C_{10}$ and $y_0^{(e)} < 0$, $y_1^{(e)} < 0$) of the performance phase diagram.

The performance phase diagram for $b_0 b_1 > C_{01} C_{10}$ is shown in Figure 3.1. The equilibrium point is located in the first quadrant ($y_0^{(e)} > 0$, $y_1^{(e)} > 0$). The initial values of the system technology performance y_0 and the component performance y_1 could be located in the four areas in Figure 3.1. The performance change rates dy_0/dt and dy_1/dt in the four areas have

Area (a) $$\frac{dy_0}{dt} > 0, \frac{dy_1}{dt} > 0 \tag{3.12}$$

Area (b) $$\frac{dy_0}{dt} < 0, \frac{dy_1}{dt} > 0 \tag{3.13}$$

Area (c) $$\frac{dy_0}{dt} < 0, \frac{dy_1}{dt} < 0 \tag{3.14}$$

Area (d) $$\frac{dy_0}{dt} > 0, \frac{dy_1}{dt} < 0\,. \tag{3.15}$$

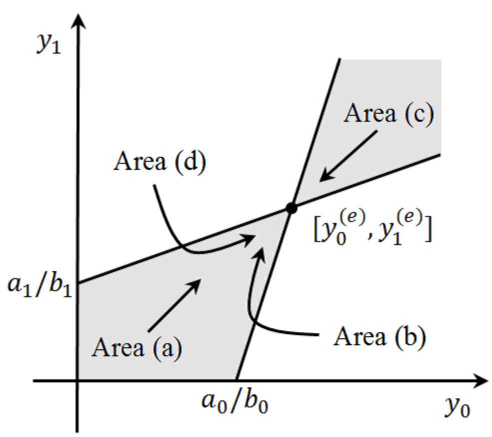

Figure 3.1 Performance Phase Diagram when $b_0b_1 > C_{01}C_{10}$

In this case, the system technology performance y_0 and the component technology performance y_1 converge to corresponding upper limit values no matter where the initial values of y_0 and y_1 are located in area (a), (b), (c), or (d). The typical evolution curves of component technology performance and system technology performance in each of the four areas are illustrated in Figure 3.2. These curves are derived using the numerical method recommended in Chapter 5.

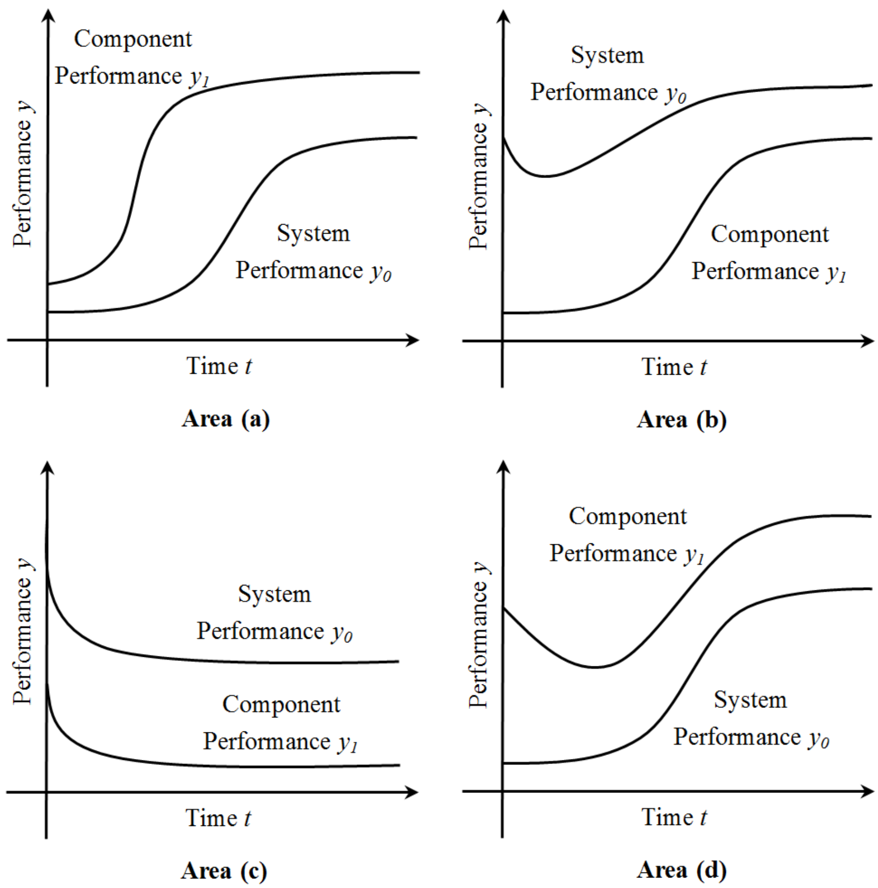

Figure 3.2 Typical Performance Evolution Curves when $b_0b_1>C_{01}C_{10}$

The performance of a component technology or a system technology has a positive value and continually increases during its evolution. Thus, only the curves in area (a) have clear interpretation in technology evolution because the curves in areas (b), (c), and (d) have decreasing periods. In area (a), the system technology performance evolution accelerates significantly when the component technology is under a certain stage of development, and both the system and the component technology performances converge to their respective upper limit values along S-shape curves. The upper limit values are the corresponding equilibrium point coordinates on the performance phase diagram (Figure 3.1). Although the curves in areas (b), (c), and (d) do not have clear interpretation in technology evolution, they are appropriate to describe product or firm interaction, where the performance metrics are sales revenue or market share. These metrics may increase or decrease with time rather than monotonically increasing [36].

Similarly, the performance phase diagram for $b_0 b_1 < C_{01} C_{10}$ is shown in Figure 3.3. The equilibrium point is located in the third quadrant ($y_0^{(e)} < 0$, $y_1^{(e)} < 0$). The initial values of the system technology performance y_0 and the component technology performance y_1 could be located in the three areas in Figure 3.3. The performance change rates dy_0/dt and dy_1/dt in the three areas have

Area (e) $$\frac{dy_0}{dt} < 0, \frac{dy_1}{dt} > 0 \tag{3.16}$$

Area (f) $$\frac{dy_0}{dt} > 0, \frac{dy_1}{dt} > 0 \tag{3.17}$$

Area (g) $$\frac{dy_0}{dt} > 0, \frac{dy_1}{dt} < 0 \tag{3.18}$$

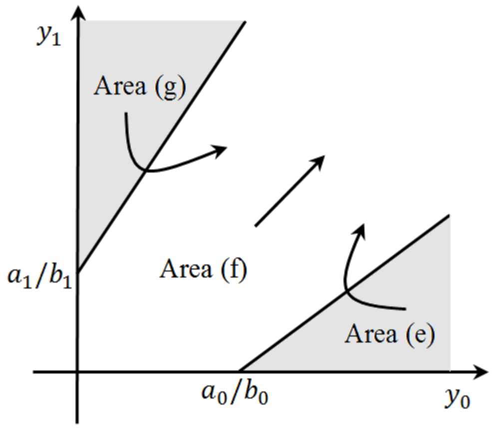

Figure 3.3 Performance Phase Diagram when $b_0b_1 < C_{01}C_{10}$

The system technology performance y_0 and the component technology performance y_1 have no upper limit values in this case. The typical evolution curves of the component technology performance and the system technology performance in areas (e), (f), and (g) are illustrated in Figure 3.4.

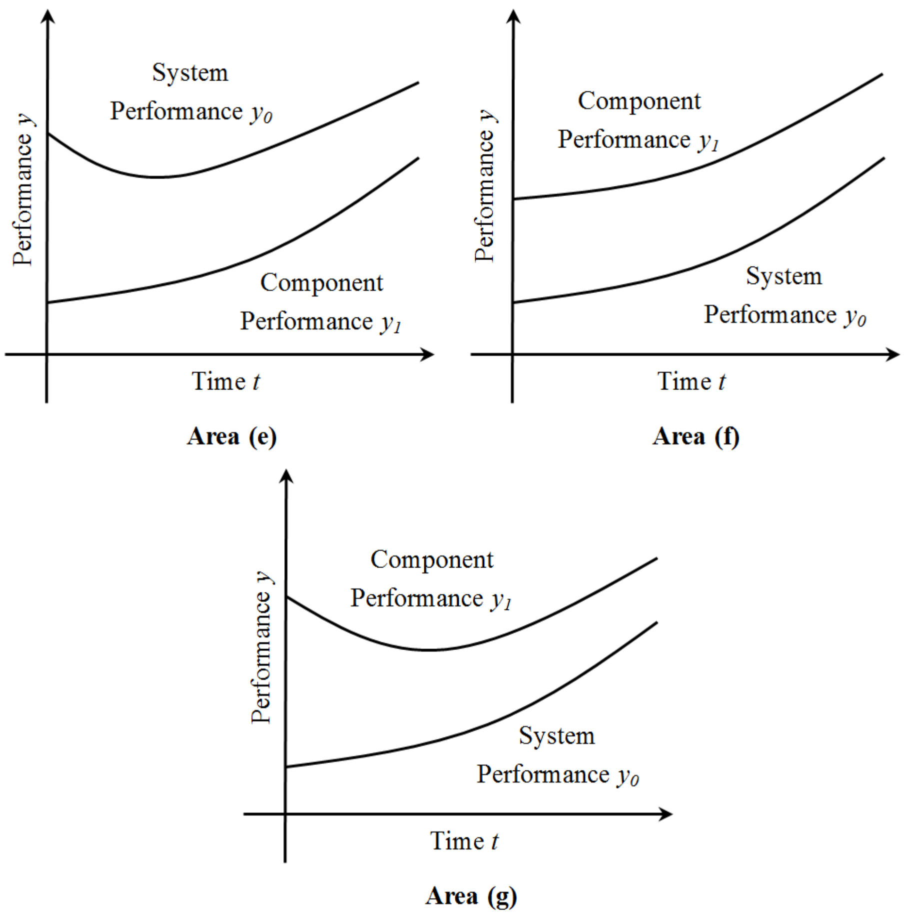

Figure 3.4 Typical Performance Evolution Curves when $b_0 b_1 < C_{01} C_{10}$

As shown in Figure 3.2 and Figure 3.4, the Lotka-Volterra ecosystem model has the ability to model component or system technology performance evolution regardless of whether the performance has an assumed upper limit. Such a model is useful when the component or the system is sufficiently new, making mature performance estimation uncertain.

The equilibrium point analysis can be extended to the general case in which one system technology interacts with *n* component technologies. In this case, the Lotka-

Volterra ecosystem model has the same form as Eqs. (2.3) - (2.6). Using the same approach as reflected by Eqs. (3.8) and (3.9), the coordinates of the equilibrium point in the general case are

$$y_0^{(e)} = \frac{a_0 + \sum_{i=1}^{n} \frac{a_i}{b_i} C_{0i}}{b_0 - \sum_{i=1}^{n} \frac{C_{i0} C_{0i}}{b_i}} \tag{3.19}$$

$$y_j^{(e)} = \frac{a_j}{b_j} \cdot \frac{b_0 + \frac{a_0 C_{j0}}{a_j} + \sum_{i=1}^{n} \left(\frac{C_{j0}}{a_j} - \frac{C_{i0}}{a_i} \right) \frac{a_i}{b_i} C_{0i}}{b_0 - \sum_{i=1}^{n} \frac{C_{i0} C_{0i}}{b_i}}. \tag{3.20}$$

Eqs. (3.19) and (3.20) reduce to Eqs. (3.10) and (3.11) if j=n=1. Similar to the simple case (one system technology interacting with one component technology), the system technology and n component technology performances do not have upper limits when the denominator of Eq. (3.19) has a negative value. In contrast, the performances converge to the upper limit values along S-shape curves when the denominator of Eq. (3.19) has a positive value. The corresponding upper limit values are determined by Eqs. (3.19) and (3.20).

3.3. Implications for Practitioners

The analysis in Chapter 3.2 offers important implications for practitioners. It helps practitioners to identify key component technologies in a system technology and also provides guidelines to improve system technology performance.

In the Lotka-Volterra ecosystem model, the parameter C describes the interaction between the system technology and the component technology in technology evolution. A larger value of parameter C indicates a higher dependency level between the component technology and the system technology. Specifically, in Eq. (2.3), a higher positive value of parameter C_{0i} indicates greater significance of component technology i performance to the system technology performance evolution. From the perspective of system design, practitioners (i.e., designers and R&D mangers) could identify the component technologies with the highest C_{0i} values as the key features of the system. For these key component technologies, practitioners may wish to develop and manufacture the key component technologies in-house. This strategy preserves the core competency of the firm. If in house development or manufacture is not feasible, the firm might consider acquiring the component technology manufacturer or at least establish a more synergistic relationship with the manufacturer through joint R&D or exclusive supply. For the component technologies with the smallest C_{0i} values, however, practitioners may consider outsourcing these component technologies. Such outsourcing strategies could reduce costs for the firm and make its product more price competitive.

The identification of key component technologies is crucial for new system technology development. For example, electric automobile practitioners cannot develop every component technology (e.g., battery, motor, steering) of the automobile in-house. They likely would want to invest their limited R&D budget on designing the component technologies that have significant impacts on electric automobile (system technology) performance. Practitioners would like to purchase the component technologies having relatively little impact on the electric automobile (system) performance from suppliers. Of note, practitioners typically make these decisions based on experience or qualitative analysis [37]. The Lotka-Volterra ecosystem model allows practitioners to quantify the significance of each component technology through the value of parameter C_{0i} and make more informed R&D and outsourcing decisions.

Moreover, the Lotka-Volterra ecosystem model not only measures the dependency between component technology and system technology, but also offers several strategies for practitioners to improve the performance of an existing system technology. As discussed in Chapter 2.2, the parameter a in the Lotka-Volterra ecosystem model denotes the independent growth rate, the parameter b represents the degree of technical difficulty, and the parameter C indicates the dependency level between the component technology and the system technology. The values of b and C are fixed once practitioners decide to integrate a system using n specific component technologies. It might be hard for practitioners to change the values of b and C after integration. However, the value of parameter a is associated with the stimulation factors such as R&D investment and government policy encouragement. Practitioners have the chance to manipulate the value of parameter a to boost system technology performance.

In practice, two accessible strategies exist for practitioners to boost system technology performance. The first strategy is to increase a_0 in Eq. (2.3) through the investment on the system technology to create superior integration of component technologies [38]. The other strategy is to subsidize component technology j or otherwise improve the independent growth rate a_j in Eq. (2.5). Eq. (3.19) specifies the upper limit value of system technology performance. By comparing the value of a_0 and a_jC_{0j}/b_j, practitioners can make an informed decision on investing system technology or component technology j. Here a_0 and a_jC_{0j}/b_j are used as indicators to evaluate the effects of different strategies (investment on the system technology or the component technology j) regardless of whether the system technology performance y_0 has an upper limit or not. Specifically, if $a_0 >> a_j C_{0j}/b_j$, the investment on the system technology is more effective to improve system technology performance than investment on the component technology j; by the same token, investment on the component technology j is preferable if $a_0 << a_j C_{0j}/b_j$.

In some cases, it may be expensive to adopt either of the two proposed strategies when system technology performance or component technology performance approaches its upper limit. In this case, large amounts of R&D investment can only lead to small improvements on the a_0 or a_j value. In such a case, practitioners have to consider innovative strategies. One alternative could be to adopt a new technology in component design [39], which can decrease the value of b_j in Eq. (2.5) and may also change the value of C_{j0} in Eq. (2.5) at the same time. Practitioners could also substitute one or more new component technologies for old component technologies in their system. This strategy alters the parameters a_j, b_j, C_{j0} and C_{0i} in Eqs. (2.3) and (2.5). As the result of these two innovative strategies, the denominator of Eqs. (3.19) and (3.20) may change its value from positive to negative. The component or system technology performance will start a new growth period due to this change. Several real cases validate the effectiveness of these innovative strategies. For instance, the traditional keyboard mobile phones approached a performance upper limit around 2005. Manufacturers such as LG, Samsung and Apple used a capacitive touch screen (a new component technology) to displace keyboard (an old component technology) on mobile phones (system technology) [40], which greatly improved the customer experience and spawned a new era in the industry.

3.4. Summary

This chapter validates the Lotka-Volterra ecosystem model as an advanced mathematical model for technology evolution prediction and manipulation through functional equivalence and equilibrium point analysis of the Lotka-Volterra ecosystem model. The functional equivalence results show that the Lotka-Volterra ecosystem model could be reduced to logistic S-curve model and Moore's Law, which are two popular descriptive models in technology evolution prediction. The equilibrium point analysis indicates that the Lotka-Volterra ecosystem model has the ability to model component or system technology performance evolution regardless of whether the performance has an assumed upper limit.

The equilibrium point analysis provided in this chapter also offers important implications for practitioners. The values of parameter C in the Lotka-Volterra ecosystem model help practitioners to identify key component technologies in a system technology. Practitioners may wish to develop and manufacture the key component technologies with the highest C_{0i} values in-house and may consider outsourcing the unimportant component technologies with the smallest C_{0i} values. In addition, based on the values of parameters a, b, and C in the Lotka-Volterra ecosystem model, practitioners can select one or more effective strategies to improve system technology performance. The proposed strategies include investment on the system technology to create superior integration of component technologies, subsidizing key component technologies or otherwise improve the independent growth rate of these component technologies, adopting a new technology in component design, and substituting one or more new component technologies for old component technologies in the system technology.

4. ANALYTIC SOLUTIONS OF THE LOTKA-VOLTERRA EQUATIONS IN COMMENSALISM AND AMENSALISM*

The Lotka-Volterra ecosystem model is a set of ordinary differential equations. It is necessary to solve these differential equations when practitioners apply the Lotka-Volterra ecosystem model to predict and manipulate future technology performance. The analytic solutions of these differential equations can ease the application process of the Lotka-Volterra ecosystem model. However, the analytic solutions of the Lotka-Volterra equations have not been reported in prior research.

Although the analytic solutions of the Lotka-Volterra equations are not available in general case, this chapter derives the analytic solution for system technology performance in technology commensalism and amensalism. Commensalism and amensalism are two special cases of technology interactions in which system technology development has a negligible influence on component technology evolution. The corresponding solutions are also derived when the component technology performance follows a logistic function or simple exponential growth. Although these analytic solutions are derived in technology evolution context, these analytic solutions also can be applied in other areas, such as community ecology and demography. The application of the analytic solutions is demonstrated through a case study of the concrete skyscraper.

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4.1. Solution of the Lotka-Volterra Ecosystem Model in Technology Commensalism and Amensalism

The Lotka-Volterra ecosystem model is shown as Eqs. (2.3) - (2.6). Each component technology performance y_i is assumed as a known function of time in Eq. (2.3) because component technology is not affected by system technology in technology commensalism and amensalism. Eq. (2.3) has the form of Bernoulli differential equation [41]. The general solution of Eq. (2.3) is as follows

$$y_0 = \frac{e^{\int\left(a_0 + \sum_{i=1}^{n} C_{0i} y_i\right) dt}}{\int b_0 e^{\int\left(a_0 + \sum_{i=1}^{n} C_{0i} y_i\right) dt} dt + D} \tag{4.1}$$

where y_0 is system technology performance, and D is an integral constant.

The solution Eq. (4.1) is valid no matter if the parameters a_0, b_0, and C_{0i} are constants or functions of time. This property is useful in real cases because the underlying meaning of parameters a_0, b_0, and C_{0i}, such as R&D investment and technical difficulty may keep changing during technology evolution. A decision maker may wish to explore the impact of changing the values of the a_0, b_0, and C_{0i} on system technology performance.

As a special case, if the system technology only interacts with one component technology, Eq. (4.1) reduces to

$$y_0 = \frac{e^{\int\left(a_0 + C_{01} y_1\right) dt}}{\int b_0 e^{\int\left(a_0 + C_{01} y_1\right) dt} dt + D} \tag{4.2}$$

where y_0 is system technology performance, y_1 is component technology performance, and D is an integral constant.

4.2. System Technology Solutions for Specific Component Technology Evolution Curves

The underlying assumption for the solution Eqs. (4.1) and (4.2) is that the impact of the system technology on the component technology is negligible. Thus, some evolution behavior for the component technology needs to be assumed. Based on the current understanding and descriptive models of technology evolution, the logistic function and the exponential function are chosen as the representative component technology performance growth curves and are substituted into Eq. (4.2). The parameters a_0, b_0, and C_{01} are assumed to be constants in this section. Other component technology evolution curves and parameter assignments in technology commensalism and amensalism can be applied in a similar manner.

4.2.1. Component Technology Follows Logistic Growth

The logistic function is the most commonly used descriptive model in technology evolution prediction [5, 42]. In this case, the component technology performance y_1 is assumed to be of the following form

$$y_1 = \frac{1}{1 + e^{-(m+nt)}} \tag{4.3}$$

where m is the "width" or "steepness" of the S-curve, and n specifies the time when the curve reaches midpoint of the growth trajectory [43].

Substituting Eq. (4.3) into the solution Eq. (4.2) of the system technology performance y_0, the integral in the numerator of Eq. (4.2) is obtained as follows

$$\int (a_0 + C_{01}y_1)dt = a_0 t + \frac{C_{01}}{n} ln(1 + e^{m+nt}) + D_1 \tag{4.4}$$

Similarly, the integral in the denominator of Eq. (4.2) becomes

$$\int e^{\int a_0 + C_{01}y_1 dt} dt = \frac{e^{c_1 + K_1 t}}{K_1}\ {}_2F_1\left(\frac{a_0}{n}, -\frac{C_{01}}{n}; \frac{n + a_0}{n}; -e^{(m+nt)}\right) + D_2 \tag{4.5}$$

where c_1, D_1 and D_2 are integral constants in Eqs. (4.4) and (4.5). ${}_2F_1$ is the Hypergeometric Function defined by [44]

$$ {}_2F_1(a, b; c; z) = \sum_{n=0}^{\infty} \frac{(a)_n (b)_n}{(c)_n} \frac{z^n}{n!} \tag{4.6}$$

Substituting Eq. (4.4) and Eq. (4.5) into Eq. (4.2) and simplifying the integral constants, the system technology performance y_0 is derived as follows

$$y_0 = \frac{e^{a_0 t + \frac{C_{01}}{b} ln\left(1 + e^{m+nt}\right) + D_3}}{\frac{b_0}{a_0} \cdot e^{a_0 t} \cdot\ {}_2F_1\left(\frac{a_0}{n}, -\frac{C_{01}}{n}; \frac{n + a_0}{n}; -e^{(m+nt)}\right) + D_4} \tag{4.7}$$

where D_3 and D_4 are integral constants and the other terms are as defined earlier.

The analytic solution Eq. (4.7) is valid only in the commensalism condition (i.e., when $C_{01} > 0$). A numerical approach should be applied in the case of amensalism (i.e., when $C_{01} < 0$). Numerical integration can be used for Eq. (4.2). The Dormand-Prince method [45], which belongs to Runge-Kutta formula family, can also be employed to solve Eq. (2.3) directly.

4.2.2. Component Technology Follows Exponential Growth

Some research shows that technology evolutions follow the simple exponential function [13, 46]. It is a special case of the logistic S-curve model when time t is much smaller than the midpoint (inflection point) t_0 of the logistic curve ($t<<t_0$). To simulate this phenomenon, the function of component technology performance y_1 is given by

$$y_1 = e^{(m+nt)} \tag{4.8}$$

Substituting Eq. (4.8) into the solution of system technology performance Eq. (4.2), the integral in the numerator of Eq. (4.2) is given by

$$\int (a_0 + C_{01}y_1)dt = a_0 t + \frac{C_{01}}{n} e^{(m+nt)} + D_5 \tag{4.9}$$

Similarly, the integral in the denominator of Eq. (4.2) is

$$\int e^{\int a_0 + C_{01}y_1 dt} dt = \frac{e^{-\frac{a_0 m}{n}}}{n}\left[-y_1^{\frac{a_0}{n}} \cdot \left(-\frac{C_{01}}{n} y_1\right)^{-\frac{a_0}{n}} \cdot \Gamma\left(\frac{a_0}{n}, -\frac{C_{01}}{n} y_1\right) + D_6\right] \tag{4.10}$$

where D_5 and D_6 are integral constants. $\Gamma(a, x)$ is the Incomplete Gamma Function and defined as follows [44]

$$\Gamma\,(a, x) = \frac{1}{\Gamma(a)} \int_0^x e^{-t} t^{a-1} dt \tag{4.11}$$

where $\Gamma(a)$ is the Gamma Function defined as follows [44]

$$\Gamma\,(a) = \int_0^\infty t^{a-1} e^{-t} dt \tag{4.12}$$

The solution of the system technology performance y_0 is obtained after simplifying integral constants. D_7 and D_8 are integral constants and the solution for y_0 has the form

$$y_0 = \frac{e^{a_0 t + \frac{C_{01}}{n} e^{(m+nt)} + D_7}}{b_0\left[e^{(m+nt)\frac{a_0}{n}} \cdot \left(\frac{C_{01}}{n} e^{(m+nt)}\right)^{-\frac{a_0}{n}} \cdot \Gamma\left(\frac{a_0}{n}, -\frac{C_{01}}{n} e^{(m+nt)}\right)\right] + D_8} \tag{4.13}$$

Because $n > 0$ in technology performance growth, the analytic solution Eq. (4.13) is only valid in the amensalism case when $C_{01} < 0$. In the commensalism condition (i.e. when $C_{01} > 0$), numerical methods have to be applied. Numerical integration or Dormand-Prince method [45] can be used as stated earlier.

4.3. Case Study of Concrete Skyscraper*

The application of the analytic solutions derived in Chapter 4.2 is demonstrated through a case study of the concrete skyscraper in this section. As with any technology evolution study, the data of interest are challenging to acquire and limited in volume. Nevertheless, this empirical application demonstrates the validity of the ecosystem model in the real world of technology interaction.

Similar to the example of steel and bridge in Chapter 2.1, concrete also has a commensalism relationship with concrete skyscraper. Concrete is the component technology which supports the system technology of concrete skyscrapers. The development of concrete skyscraper has a negligible effect on the concrete because concrete is also used to build other structures such as roads, bridges, and dams.

Compressive strength is an important performance metric of concrete. The compressive strength of concrete is also an important component technology performance measure of skyscraper construction. Looking at concrete and skyscrapers, there should be a positive performance evolution between concrete compressive strength

* Appendix A includes the data sets used in the case study of concrete skyscraper.

and skyscraper height. Thus, concrete compressive strength and skyscraper height allow us to explore a commensalism relationship between the two technologies.

A government report indicates that concrete compressive strength has an upper limit value of 200 megapascal (MPa) [47] that will be achieved in the near future. This upper limit value is used as the characteristic value of the component technology performance [18]. The concrete compressive strength history data is extracted from an ACI technical report [48]. The component technology performances data points are divided by its corresponding characteristic value (200 MPa in this case study) as a dimensionless treatment [18, 19]. The non-dimensionalized data is fitted by the logistic function. The best-fitting curve is

$$y_1 = \frac{1}{1 + e^{-(-2.1 + 0.062\, t)}} \tag{4.14}$$

The coefficient of determination R^2 for the curve fitting is 0.9685.

The height of concrete skyscraper is chosen as the metric of system technology performance as stated earlier. Eq. (4.14) is substituted into the solution of Eq. (4.2) to fit the historical data of concrete skyscraper height in the world from 1950 to 2010, which is collected from The Global Tall Building Database of the CTBUH. The characteristic value of the system technology performance y_0 is 423 meters, which is the highest value in the historical data. This value (i.e., 423 meters) is used for dimensionless treatment of the system technology performance data. The best-fitting values for parameters a_0, b_0, and C_{01} are then given by

$$\frac{dy_0}{dt} = 3.64 y_0 - 18.53 y_0^2 + 18.80 y_0 y_1 \tag{4.15}$$

The coefficient of determination R^2 for the curve fitting is 0.9708.

The curve fitting results for concrete compressive strength and concrete skyscraper height are illustrated in Figure 4.1. The dependency indicator a_0/ C_{01} equals 0.194 in this case, which shows that concrete skyscraper technology relies heavily on concrete technology as one would expect. The model also gives a prediction that the concrete skyscraper height will reach an upper limit value 505 meters by around 2050 when compressive strength of concrete increases to almost 200 MPa.

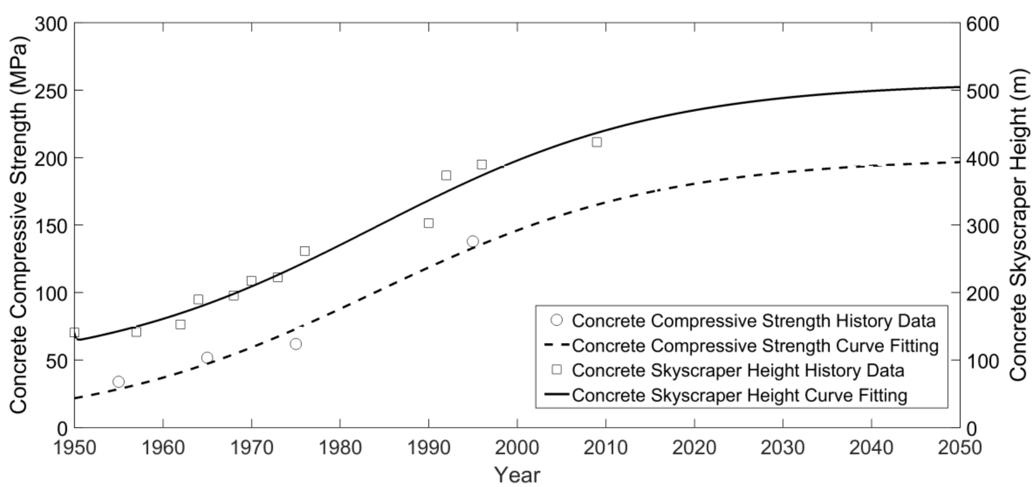

Figure 4.1 Forecasted Concrete Compressive Strength and Skyscraper Height Based on Historical Data (1950-2010)

The significant difference between the Lotka-Volterra ecosystem model and the existing descriptive models is that the ecosystem model considers the influence of the component technology. This consideration is critical for the technology evolution prediction when practitioners have an adequate understanding of the component technology evolution but lack some information on system technology. For example, the upper limit value of system technology performance is typically necessary for a logistic model extrapolation prediction. The logistic model may produce an unreasonable result if the upper limit value is set as an unknown parameter in data fitting, but the ecosystem model works well in this circumstance. The performance of the ecosystem model is verified through a holdout sample test (Figure 4.2) at the end of this section. Moreover, the linkage between system and component technologies in the ecosystem model is also helpful for long term prediction. For example, the prediction for the concrete skyscraper height from 2050 to 2150 can be made if the concrete compressive strength starts another S-shaped curve evolution at 2050 and reaches 600 MPa [49] in 2150. Importantly, the interpretation of the parameters a_0, b_0, and C_{01} in the ecosystem model also gives practitioners some practical hints to manipulate the future of a specific technology. For example, more R&D investment increases the value of a_0 in the ecosystem model. Practitioners will be able to predict the impact of their investment on system technology performance if the empirical formula between the amount of investment and the a_0 value is established for an interested system technology in future research. Specifically, if the R&D investment on the concrete skyscraper technology is doubled, which can increase the value of a_0 by 10% (this relationship is assumed to be provided by future research), the concrete skyscraper height in the year 2050 will increase from 505 meters to 513 meters as a result of this investment.

The main purpose of this empirical application is to demonstrate the ability of the Lotka-Volterra ecosystem model to explain technology commensalism. The system technology evolution curve in Figure 4.1 is close to the logistic S-curve partly because the limited data points of concrete compressive strength is fitted for the logistic function. Fitting the data points with a different mathematical function may lead to different concrete skyscraper height predictions. However, the prediction accuracy of the ecosystem model still can be compared with that of the existing descriptive models by a holdout sample test.

The concrete skyscraper height data from 1950 to 1996 is fitted through the Lotka-Volterra ecosystem model, logistic S-curve model, and simple exponential function. The results appear in Figure 4.2. The prediction errors of these three models for 2009 range from 6.1% (Lotka-Volterra ecosystem model) to 23.4% (logistic S-curve model) and to 24.8% (simple exponential model). It is clear that the prediction performance of the Lotka-Volterra ecosystem model significantly exceeds that of logistic S-curve model and simple exponential model. Moreover, logistic S-curve model and simple exponential model predict that the concrete skyscraper height will exceed 600 meters around 2020 and reach 1,000 meters during the year 2040. The reason of these unreasonable predictions is the descriptive models don’t consider the impact from component technology.

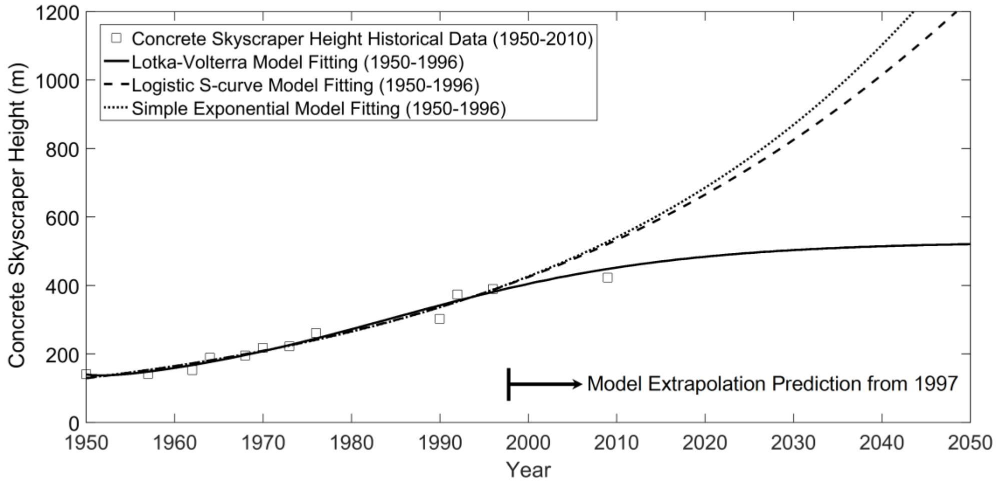

Figure 4.2 Forecasted Concrete Skyscraper Height Based on Historical Data (1950-1996)

4.4. Summary

System technology development has a negligible impact on component technology evolution if these two technologies have the relationship of commensalism or amensalism. This chapter derives the general integral form solution of the Lotka-Volterra ecosystem model as Eq. (4.1) in technology commensalism and amensalism. The corresponding solutions are also derived as Eq. (4.7) and Eq. (4.13) when the component technology performance follows a logistic function and simple exponential growth, respectively. These solutions ease the application process of the Lotka-Volterra ecosystem model in practical projects when technology commensalism or amensalism exists. In addition, these analytic solutions are also applicable in other areas, such as community ecology and demography.

A case study of concrete skyscraper is performed to demonstrate the application of the analytic solutions of the Lotka-Volterra ecosystem model, where the concrete skyscraper (system technology) has a commensalism relationship with the concrete (component technology). In the case study of concrete skyscraper, a holdout sample test shows that the prediction performance of the Lotka-Volterra ecosystem model significantly exceeds that of logistic S-curve model and simple exponential model (i.e., Moore's Law). This result validates the prediction accuracy of the Lotka-Volterra ecosystem model.

5. MODELING TECHNOLOGY EVOLUTION USING LOTKA-VOLTERRA ECOSYSTEM MODEL*

The analytic solutions of the Lotka-Volterra ecosystem model are derived in Chapter 4 when the system technology and its component technologies have the relationship of commensalism or amensalism. The analytic solution of the Lotka-Volterra ecosystem model is not available when there is a symbiotic relationship between the system technology and any of its component technologies.

This chapter begins with the discussion of the numerical methods to solve the Lotka-Volterra equations in general case. Three steps are then introduced to apply the Lotka-Volterra ecosystem model for technology evolution prediction and manipulation when the system technology and its component technologies have the relationship of symbiosis, commensalism or amensalism. The application of the Lotka-Volterra ecosystem model is illustrated using a case study of passenger aircraft fuel efficiency.

5.1. Numerical Methods for Solving the Lotka-Volterra Equations

Solving the differential equations given by Eqs. (2.3) - (2.6) is necessary to apply the Lotka-Volterra ecosystem model for technology evolution prediction and manipulation. Unfortunately, the analytic solution of the Lotka-Volterra equations is not

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available for the general case. Thus, numerical methods must be implemented to solve these equations. Employing an appropriate numerical method is crucial to apply the Lotka-Volterra ecosystem model in technology evolution, since numerical instability previously hamstrung the progress of research in this area.

The finite difference scheme developed by mathematical ecologists to solve Eqs. (2.1) and (2.2) has the following form [23, 50]

$$N(t+h) = \frac{\lambda_N^h N(t)}{1 + c_N\left(\lambda_N^h - 1\right)N(t) + c_N'\left(\lambda_N^h - 1\right)M(t)} \tag{5.1}$$

$$M(t+h) = \frac{\lambda_M^h M(t)}{1 + c_M\left(\lambda_N^h - 1\right)M(t) + c_M'\left(\lambda_N^h - 1\right)N(t)} \tag{5.2}$$

where t is time, h is step length, and

$$\lambda_N = e^{a_n} \tag{5.3}$$

$$c_N = \frac{b_n}{a_n} \tag{5.4}$$

$$c_N' = -\frac{C_{nm}}{a_n} \tag{5.5}$$

$$\lambda_M = e^{a_m} \tag{5.6}$$

$$c_M = \frac{b_m}{a_m} \tag{5.7}$$

$$c_M' = -\frac{C_{mn}}{a_m}. \tag{5.8}$$

This difference scheme is developed to model the competition between two species in an ecological community where the parameters C_{mn} and C_{nm} have negative values.

Pistorius and Utterback studied competitive, symbiotic and predator-prey relationships between two technologies using Eqs. (2.1) and (2.2) [33, 51, 52]. They simplified Pielou's approach shown in Eqs. (5.1) - (5.8) by setting h=1 to solve the Lotka-Volterra equations. The numerical solution showed oscillations in the mature phase of an S-shape curve when two technologies have symbiotic relationships, where C_{mn} and C_{nm} have positive values. Pistorius and Utterback termed the oscillatory pattern as a chaos-like state. They postulated that this state represents the nature of a symbiotic interaction between two technologies. Such oscillatory pattern and its interpretation prevented the research stream from moving forward.

One example given by Pistorius and Utterback [33, 51] is as follows

$$\frac{dN}{dt} = 0.1N - 0.01N^2 + 0.0157NM \tag{5.9}$$

$$\frac{dM}{dt} = 0.15M - 0.01M^2 + 0.005MN \tag{5.10}$$

$$N(t = 0) = 0.01 \tag{5.11}$$

$$M(t = 0) = 0.01\,. \tag{5.12}$$

The solid line in Figure 5.1 shows the numerical solution of Eqs. (5.9) - (5.12) for step length h=1. The result has oscillation around t=250.

However, the oscillation is not present if smaller step length is used. The dashed line in Figure 5.1 illustrates the result with the same numerical approach as shown in Eqs. (5.1) and (5.2) for step length h=0.1. The performances $N(t)$ and $M(t)$ converge to upper limit values when $t \to \infty$, and the chaos-like state vanishes. Similarly, the oscillatory pattern also does not appear in other cases [33] if smaller step length is used.

Of note, the difference scheme illustrated by Eqs. (5.1) - (5.8) is a first order one-step method for solving ordinary differential equations. Researchers has proved that the one-step method solution converge to exact solution when step length $h \rightarrow 0$ [53]. When the step length h is too large, the convergence problem results in an oscillatory pattern. Researchers need to choose appropriate step length when they use the one-step numerical approach to solve the Lotka-Volterra equations. In addition, the approach is a first order difference scheme. The truncation error of the approach is $O\ (h^2)$. This dissertation recommends high order Runge-Kutta methods such as Dormand-Prince method [45] to improve efficiency and accuracy for solving the Lotka-Volterra equations. The mathematical theories of these methods are well established [54]. The Runge-Kutta methods can be applied to solve Eqs. (2.3) - (2.6) without convergence concern.

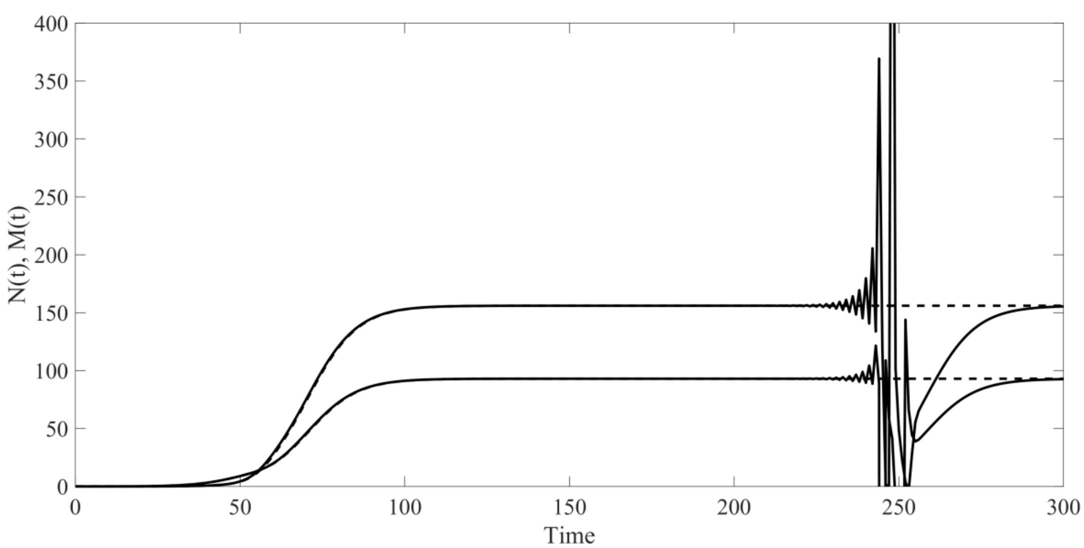

Figure 5.1 Numerical Solution of Eqs. (5.9) - (5.12)

5.2. Application of the Lotka-Volterra Ecosystem Model in Technology Evolution

The mathematical analysis in Chapter 3 demonstrates the Lotka-Volterra ecosystem model as an advanced model for technology evolution prediction and manipulation. The ecosystem model covers a variety of mathematical functions and thus has improved data fitting accuracy. The Lotka-Volterra ecosystem model also considers the interaction between the system technology and its component technologies through the interaction C terms in the ecosystem model. Moreover, the parameters a, b, C in the Lotka-Volterra ecosystem model are associated with their respective causal factors (e.g., R&D investment and government policy change), which offers guidelines for practitioners to identify the key component technologies in a system technology and develop strategies to improve system technology performance. In addition, the numerical methods to solve the Lotka-Volterra equations are also discussed in Chapter 5.1. The cause of numerical instability that hamstrung the progress of research in this area is identified and thus the reasonableness of the Lotka-Volterra ecosystem model for technology evolution understanding is reinforced.

In this section, three steps to apply the Lotka-Volterra ecosystem model for technology evolution prediction and manipulation are developed. Practitioners could follow these steps to make system and component technology performance prediction. Through this approach, practitioners could also evaluate different strategies to improve future system technology performance.

5.2.1. Component Technology Selection and Data Collection

The definition of the system technology and its component technologies is crucial for the successful application of the Lotka-Volterra ecosystem model. Practitioners first define the system technology performance of interest. A system technology often has more than one performance metric [55, 56]. Practitioners should determine one specific performance metric they want to predict and list all the component technologies that may impact this system technology performance. The component technologies can include tangible hardware and intangible software.

To avoid omitting any component technology, practitioners are recommended to first list all component technologies that constitute the system technology and select the component technologies that have a significant impact on the system technology performance for incorporation into the model. In this process, team effort is preferred and practitioners could use design tools such as a relationship table [19] to identify the appropriate component technologies. The knowledge of industry experts also could be involved in the process. Once the component technologies are selected, practitioners determine a performance metric for each component technology. The performance metric should be a typical indicator of component technology evolution (e.g., clock speed of CPU), and the performance data should be available for the modeling time interval.

Practitioners then collect performance data of the system technology and the component technologies for the modeling time interval. The time interval usually starts from a past time period and ends in the current time period. The typical time unit of performance evolution is a year. In some cases, the time unit could be a quarter or a month for fast developing component or system technology. More than one performance data point may exist during a specific sampled time period. For example, there are currently CPUs with slower and faster clock speed. In this case, practitioners use the data point with highest value as it represents the current state of CPU performance evolution. Practitioners also need to remove a data point if its performance value is smaller than that of any previous data points because each data point should represent the best system or component technology performance during the time period. This data screening process is illustrated using passenger aircraft fuel efficiency data in Chapter 5.3.

Moreover, dimensionless treatment is necessary for every component and system technology performance evolution data set because each performance metric can be measured by several different units (e.g., kilogram and pound for weight). Practitioners should divide system technology performance y_0 and component technology performance y_j by their maximum performance value Y_0 and Y_j for the modeling interval respectively. The dimensionless treatment normalizes system and component technology performance data within the same range (0, 1]. In this way, each data point has the same weight in the following data fitting process.

5.2.2. The Lotka-Volterra Ecosystem Model Development and Data Fitting

It is assumed that practitioners select n component technologies that have significant impact on system technology performance in the first step given by Chapter

5.2.1. In this case, practitioners develop the Lotka-Volterra ecosystem model as Eqs. (2.3) - (2.6). The system technology equation given by Eq. (2.3) has (n+2) parameters (a_0, b_0, and C_{0i}) and each component technology equation given by Eq. (2.5) has 3 parameters (a_j, b_j, and C_{j0}). There are (4n+2) parameters in the Lotka-Volterra ecosystem model. Practitioners should determine the range of each parameter in the Lotka-Volterra ecosystem model before the subsequent data fitting process.

As discussed in Chapter 2.2, the parameter a represents independent growth rate in technology evolution. The value of the parameter a is associated with stimulation factors such as R&D investment and government policy encouragement. The parameter a generally has a positive value and thus its data fitting range is (0, +∞).

The parameter b denotes technical difficulty in technology evolution. The value of the parameter b sets the performance upper limit value. The parameter b also has a positive value and its data fitting range is (0, +∞).

The parameter C describes the interaction between the component technology and the system technology. The data fitting range of the parameter C could be set as (-∞, +∞) in a general case. To improve the data fitting efficiency and utilize available expert knowledge, practitioners could also determine the data fitting range of each parameter C based on the interaction mode (symbiosis, commensalism, or amensalism) between the component technology and the system technology.

Practitioners could evaluate the application of a component technology to identify a commensalism or an amensalism relationship between the component technology and the system technology. If the component technology serves a variety of system technologies, the impact from a single system technology on the component technology may be negligible. Commensalism or amensalism is appropriate to describe the interaction between the component technology and the system technology under this circumstance. The parameter C_{j0} in Eq. (2.5) equals zero, the data fitting range of the parameter C_{j0} in Eq. (2.3) is $(0, +\infty)$ in commensalism and $(-\infty, 0)$ in amensalism.

Practitioners also could determine the range of the parameter C by analyzing the component technology performance evolution curve with the help of industry experts. Three typical performance evolution curves are shown in Figure 5.2.

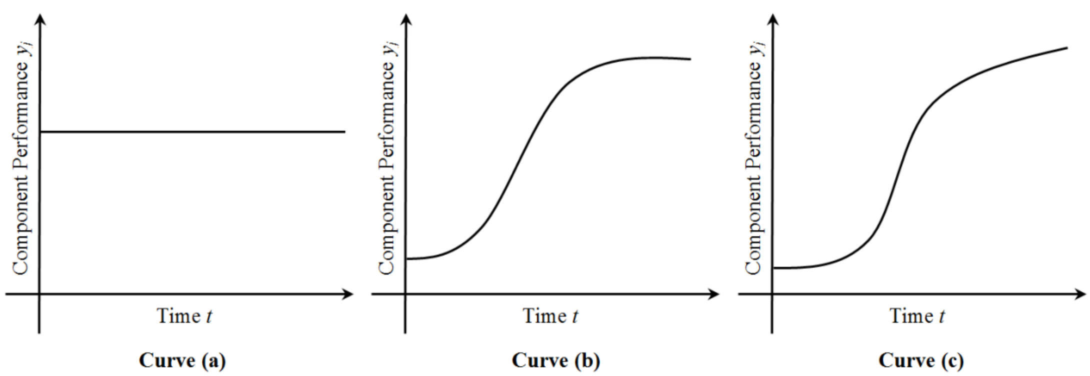

Figure 5.2 Three Typical Performance Evolution Curves

If the component technology performance y_j exhibits insignificant improvement during the modeling time interval, its evolution curve is a straight line as curve (a) in Figure 5.2. In this case, the interaction term $C_{0j}y_0y_j$ in Eq. (2.3) is reduced to $C_{yj}y_0$ where constant C_{yj} equals $C_{0j}y_j$. The term $C_{yj}y_0$ could be further combined with the independent growth term a_0y_0, eliminating the interaction term $C_{0j}y_0y_j$ in Eq. (2.3). This mathematical reduction shows that practitioners could remove the component technology j from the

Lotka-Volterra ecosystem model if the performance evolution curve of the component technology j is a straight line during modeling time interval.

Sometimes, the component technology performance may evolve along an S-shape curve such as curve (b) shown in Figure 5.2. The component technology performance almost reaches its upper limit at the current time. Practitioners could use the logistic S-curve model to describe the component technology performance evolution in this case. The equation of the component j in the Lotka-Volterra ecosystem model has the form

$$\frac{dy_j}{dt} = a_j y_j - b_j {y_j}^2 \tag{5.13}$$

The solution of Eq. (5.13) is the logistic S-curve model as discussed in Chapter 3.1. Here, the system technology has negligible impact on the component technology performance. The component technology j has a commensalism or an amensalism relationship with the system technology, and the parameter C_{j0} in Eq. (2.5) equals zero.

If the component technology performance evolution curve is similar to curve (c) in Figure 5.2, practitioners have to interpret the relationship between the component technology and the system technology as symbiosis because the logistic S-curve model cannot cover this curve shape. Therefore, the data fitting ranges of the parameters C_{0j} in Eq. (2.3) and C_{j0} in Eq. (2.5) are $(0, +\infty)$.

Once practitioners determine the range of $(4n+2)$ parameters in the Lotka-Volterra ecosystem model, they fit the dimensionless system and component technology performance data with the ecosystem model as Eqs. (2.3) - (2.6). Of note, the initial value of each $(n+1)$ equations (e.g., the value of y_0 $(t=0)$ for Eq. (2.3)) is also necessary for the data fitting process. Practitioners could use the first data point (the earliest known component or system technology performance) in each data set as the initial value of Eqs. (2.3) - (2.6). To improve the accuracy of data fitting, practitioners also could set the initial values as unknown parameters. This treatment brings (n+1) extra parameters to the Lotka-Volterra ecosystem model, and the model has (5n+3) unknown parameters at the beginning of the data fitting process.

The purpose of data fitting is to search the parameter space (range) in order to determine the parameter values that minimize the sum of squared errors between the technology performance data sets and the solutions of Eqs. (2.3) - (2.6). Several optimization algorithms (e.g., genetic algorithms, trust region, and simulated annealing) are available for this purpose [57]. Practitioners could utilize available expert knowledge to find a good initial value for each parameter from where to start the optimization iteration. Of note, practitioners have to solve Eqs. (2.3) - (2.6) numerically at each optimization iteration step. As discussed in Chapter 5.1, high order Runge-Kutta methods such as the Dormand-Prince method [45] are recommended to solve the Lotka-Volterra equations in the data fitting process.

5.2.3. Analysis of Results

The data fitting process produces the optimal values of the parameters in the Lotka-Volterra ecosystem model. Practitioners could make component and system technology performance evolution prediction via mathematical extrapolation of the ecosystem model. Of note, the parameters a, b, and C are assumed to be constants in the

Lotka-Volterra ecosystem model. This assumption implies that the endogenous and exogenous factors that impact component and system technology evolution stays the same during the extrapolation time interval. This assumption may not hold true in some cases such as an economic crisis or a dramatic regulation change. Practitioners have to adjust the value of the corresponding parameter and update the prediction results to cover these cases. For example, a potential economic crisis will lead to less R&D investment. In order to predict the component technology and the system technology performances under such adverse circumstances, practitioners could decrease the values of a_0 in Eq. (2.3) and a_j in Eq. (2.5) to derive more conservative prediction results.

As stated in Chapter 3.3, practitioners could quantify the importance of each component technology through the data fitting results of Eq. (2.3). Practitioners would like to develop the component technologies with the highest C_{0i} values in-house or build a synergistic relationship with the suppliers. In contrast, practitioners consider outsourcing the component technologies with the lowest C_{0i} or purchase the component technologies in the market with competitive prices.

Practitioners could also evaluate the most effective strategies to boost system technology performance through the values of parameters in the Lotka-Volterra ecosystem model. Practitioners could establish the empirical function between the system technology performance boosting strategy and the parameter value based on prior data. For example, if practitioners establish the empirical function between R&D investment and the value of the parameter a_0 in Eq. (2.3) and a_j in Eq. (2.5), they can predict the investment return (on technology performance) of different strategies through the Lotka-Volterra ecosystem model and determine the most effective strategy. If the prior data are not available, practitioners can compare the values of a_0 and a_jC_{0j}/b_j as a basis for their decision. If $a_0 >> a_jC_{0j}/b_j$, the investment on the system technology is more effective to improve system technology performance than investment on the component technology j; similarly, investment on the component technology j is more favorable if $a_0 << a_jC_{0j}/b_j$.

In some cases, it may be hard to improve either parameter a_0 or a_j. For example, when both the component and the system technology performances are near their upper limits, even a large amount of R&D investment will likely result in small performance improvements. In such cases, practitioners have to consider innovative strategies, such as adopting new technology in component design or substituting one or more new component technologies for old component technologies in the system. These innovative strategies are typically more risky and expensive than traditional strategies, but they may produce a cutting-edge product.

5.3. Case Study of Passenger Aircraft Fuel Efficiency*

Three steps to apply the Lotka-Volterra ecosystem model are developed in Chapter 5.2. In this section, passenger aircraft fuel efficiency is used as a case study to illustrate each step, which can be applied in similar fashion to other application scenarios. The system technology (passenger aircraft fuel efficiency) interacts with three

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* Appendix B includes the data sets used in the case study of passenger aircraft fuel efficiency.

component technologies (aerodynamics, weight reduction, and aero-engine fuel efficiency) in this case study. The results of this specific case study demonstrate that the system technology and the three component technologies almost exhaust their growth potential at 2018. To improve passenger aircraft fuel efficiency significantly in the future, practitioners may spend extra funding to develop sophisticated system optimization techniques or consider adopting one or more new technologies to reduce the weight of the passenger aircraft. A holdout sample test is also used to show the improved prediction accuracy of the Lotka-Volterra ecosystem model compared with those of extant descriptive models.

5.3.1. Component Selection and Data Collection

Passenger aircrafts have several performance metrics such as speed, passenger capacity, range, and fuel efficiency. This section focus on the fuel efficiency of passenger aircrafts. Because the fuel efficiency of the same passenger aircraft varies with flight range [58], the aircraft fuel efficiency for specific length trip of 3 000 nautical miles (5 556 kilometers) is considered, which is a typical transatlantic distance (e.g., from New York to London). Here, the maximum passenger capacity is divided by the fuel consumption of 3 000 nautical mile flight [59] as the definition of passenger aircraft fuel efficiency.

A passenger aircraft has thousands of component technologies. Aerodynamics, weight reduction, and aero-engine fuel efficiency are chosen as three major component technologies because they have significant impact on passenger aircraft fuel efficiency

[60, 61]. These three component technologies correspond to the three major disciplines (i.e., aerodynamics, structures, and propulsion) in aerospace. Passenger aircraft aerodynamics is often summarized in terms of either the lift-over-drag ratio or the drag coefficient. Often, this data is considered proprietary, and is thus unavailable. As a proxy for these more traditional performance metrics for aerodynamics, the wing aspect ratio is used, which correlates well with lift-to-drag ratio. The performance metric of weight reduction is defined as passenger aircraft maximum payload divided by the typical airline operating empty weight (OEW). The performance metric of aero-engine fuel efficiency is engine rated output divided by fuel consumption per landing and take-off (LTO) cycle [62].

With the exception of the EEA and EASA data mentioned above, the passenger aircraft performance data (e.g., maximum passenger capacity, first flight year, wing aspect ratio, payload, and OEM) was compiled from multiple volumes of Jane's All the World's Aircraft and WIKIPEDIA. The system technology and the component technologies' performance data from 1970 to 2017 are collected. The peak performance data every year are then selected for the modeling. For example, there are 33 passenger aircraft 3 000 nautical miles (nmi) fuel efficiency data points as shown on Figure 5.3. Among these 33 data points, only 7 data points (dots in Figure 5.3) are selected to represent the evolution of passenger aircraft 3 000 nmi fuel efficiency during 1970 - 2017.

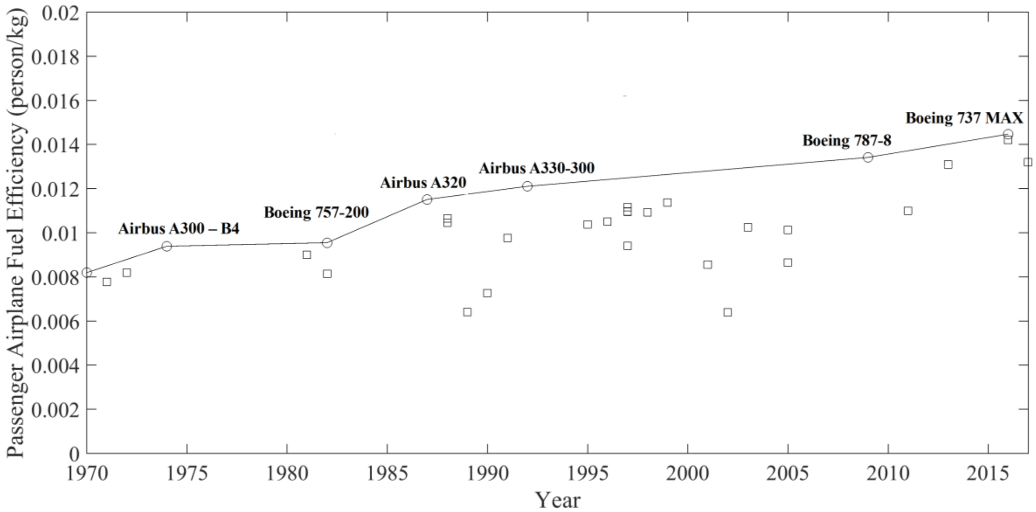

Figure 5.3 Passenger Aircraft 3 000 nmi Fuel Efficiency Data (1970-2017)

Each data point is also divided by its corresponding maximum performance value during modeling time interval. The value of every component technology and system technology data point is within the range (0, 1] after the dimensionless treatment.

5.3.2. The Lotka-Volterra Ecosystem Model Development and Data Fitting

It is observed that the performances of wing aspect ratio and weight reduction almost reach their upper limit by 2017. Their evolution curves (Figure 5.5 and Figure 5.6 in Chapter 5.3.3) are similar to curve (b) in Figure 5.2. The evolution curve of aero-engine fuel efficiency (Figure 5.7 in Chapter 5.3.3) is similar to curve (c) in Figure 5.2. Thus, the first two component technologies (aerodynamics and weight reduction) have an assumed commensalism relationship with the system technology (passenger aircraft fuel efficiency), and the third component technology (aero-engine fuel efficiency) has an assumed symbiotic relationship with the system technology (passenger aircraft fuel efficiency). The Lotka-Volterra ecosystem model is built based on these interaction modes as

$$\frac{dy_0}{dt} = a_0 y_0 + b_0 y_0^2 + C_{01} y_0 y_1 + C_{02} y_0 y_2 + C_{03} y_0 y_3 \tag{5.14}$$

$$\frac{dy_1}{dt} = a_1 y_1 + b_1 y_1^2 \tag{5.15}$$

$$\frac{dy_2}{dt} = a_2 y_2 + b_2 y_2^2 \tag{5.16}$$

$$\frac{dy_3}{dt} = a_3 y_2 + b_3 y_2^2 + C_{30} y_3 y_0 \ , \tag{5.17}$$

where y_0 is passenger aircraft fuel efficiency (maximum passenger capacity/3 000 nmi fuel consumption), y_1 is aircraft wing aspect ratio, y_2 is weight reduction parameter (maximum payload/typical airline operating empty weight),and y_3 is aero-engine fuel efficiency (engine rated output/fuel consumption per LTO cycle). Of note, the above simplification is used to illustrate the methodology developed in Chapter 5.2. The same data fitting result is derived when the ranges of parameters C_{10}, C_{20}, and C_{30} are set as (-∞, +∞) in this case study.

The data fitting range of the parameters *a*, *b*, and *C* in Eqs. (5.14) - (5.17) is (0, +∞). The initial values of each equation are set as unknown parameters with the range (0, 1). In total, there are 16 unknown parameters in Eqs. (5.14) - (5.17).

The trust region reflective algorithm [63] is used to search the parameter space (range). In each search step, the Dormand-Prince method [45] is employed to solve Eqs. (5.14) - (5.17) numerically. The values of 16 parameters are derived, which minimize the sum of squared errors between passenger aircraft performance data sets and the solutions of Eqs. (5.14) - (5.17). The parameter values are plugged into Eqs. (5.14) - (5.17) and have

$$\frac{dy_0}{dt} = 0.0243y_0 - 0.0524y_0^2 + 5.02 \cdot 10^{-6} y_0 y_1 + 0.0314 y_0 y_2 + 2.92 \cdot 10^{-5} y_0 y_3 \tag{5.18}$$

$$\frac{dy_1}{dt} = 0.0855y_1 - 0.0826y_1^2 \tag{5.19}$$

$$\frac{dy_2}{dt} = 0.114y_2 - 0.114y_2^2 \tag{5.20}$$

$$\frac{dy_3}{dt} = 0.372y_3 - 2.17y_3^2 + 1.81y_3y_0 \tag{5.21}$$

$$y_0(t = 0) = 0.577 \tag{5.22}$$

$$y_1(t = 0) = 0.672 \tag{5.23}$$

$$y_2(t = 0) = 0.759 \tag{5.24}$$

$$y_3(t = 0) = 0.00394\,. \tag{5.25}$$

5.3.3. Results Analysis

The performances of the system technology and the three component technologies in the years 2018-2030 are predicted through a mathematical extrapolation of the Lotka-Volterra ecosystem model as Eqs. (5.18) - (5.25). It is assumed that the endogenous and exogenous factors (e.g., economics and government policy) that impact component and system technology evolution stay the same, so that the parameters *a*, *b*, *C* remain the same during 2018-2030. The modeling result of passenger aircraft 3 000 nmi fuel efficiency is shown on Figure 5.4. It is observed that the aircraft fuel efficiency increases slowly from 2018 to 2030. By 2030, the fuel efficiency will become 0.0149 person/kg, a 2.6% improvement from Boeing 737 MAX's in 2016. The upper limit of passenger aircraft fuel efficiency could be estimated from Eq. (3.19). That upper limit is 0.0154 person/kg and passenger aircraft fuel efficiency will reach 99% upper limit around 2055.

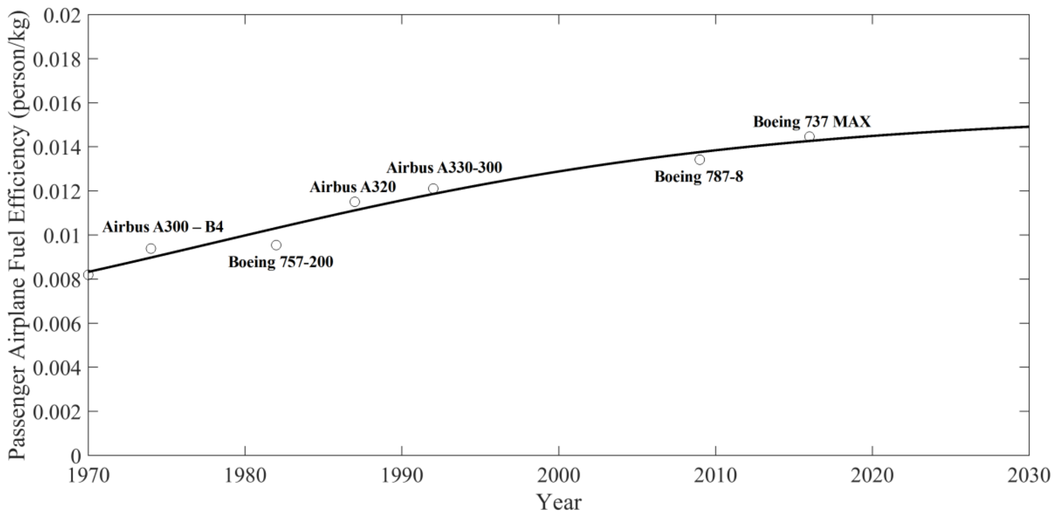

Figure 5.4 Passenger Aircraft 3 000 nmi Fuel Efficiency Modeling (1970-2030)

The wing aspect ratio and weight reduction parameter (maximum payload/OEW) of passenger aircraft will reach their upper limits soon. The modeling results are shown in Figure 5.5 and Figure 5.6 respectively. In 2030, the wing aspect ratio will reach 10.48, which is 99.6% of its upper limit of 10.52. The weight reduction parameter will touch 0.497 (99.9% upper limit) in 2030, only a 0.2% improvement from Boeing 787-9's in 2013.

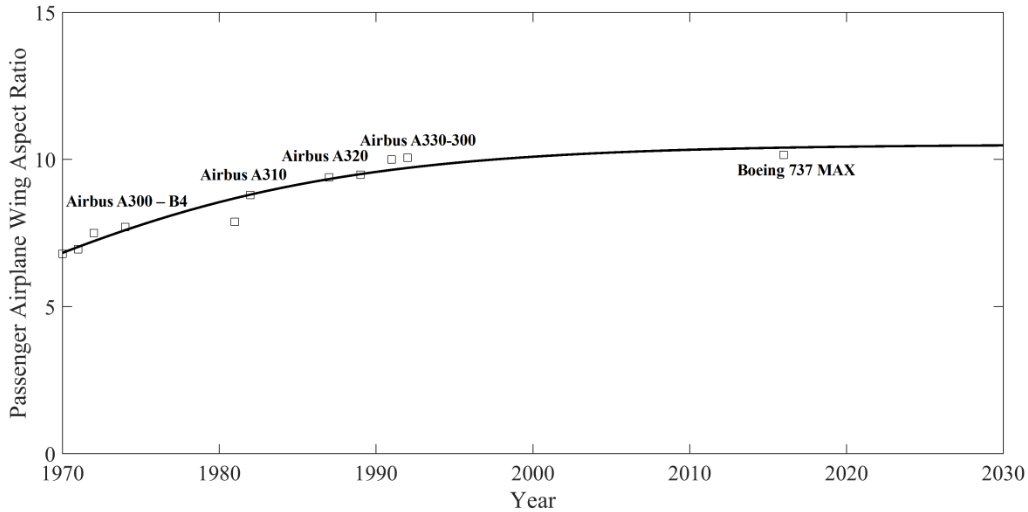

Figure 5.5 Passenger Aircraft Wing Aspect Ratio Modeling (1970-2030)

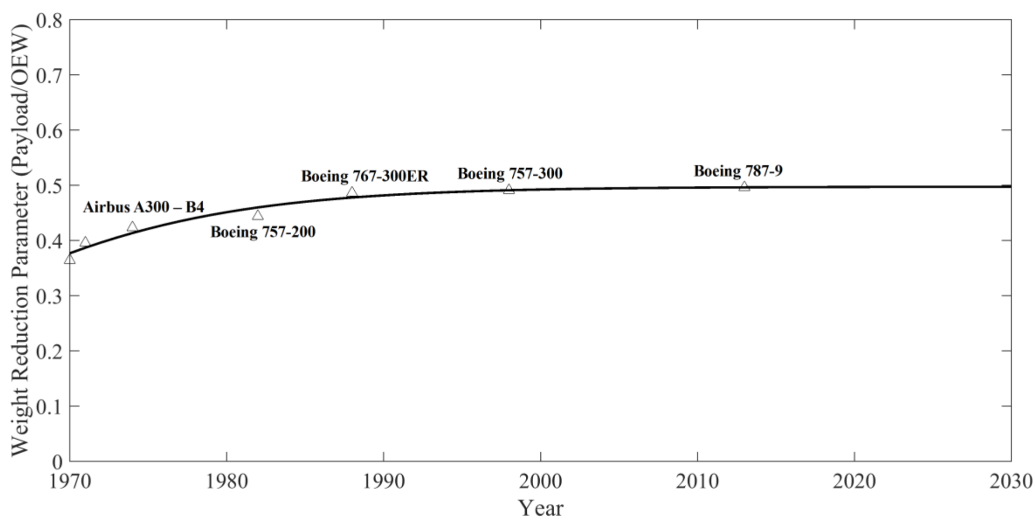

Figure 5.6 Passenger Aircraft Weight Reduction Modeling (1970-2030)

As a component technology, aero-engine fuel efficiency has better growth potential than aerodynamics and weight reduction. Estimated from Eq. (3.20), the upper limit of aero-engine fuel efficiency is 0.417 kN/kg. The fuel efficiency performance of

Pratt & Whitney PW1133G-JM in 2014 is 0.393 kN/kg, which is 94.2% of the upper limit. The aero-engine fuel efficiency will rise to 0.404 kN/kg (97.0% of the upper limit) in 2030 and reach 99% of the upper limit around 2050. The modeling result of aero-engine fuel efficiency is shown in Figure 5.7.

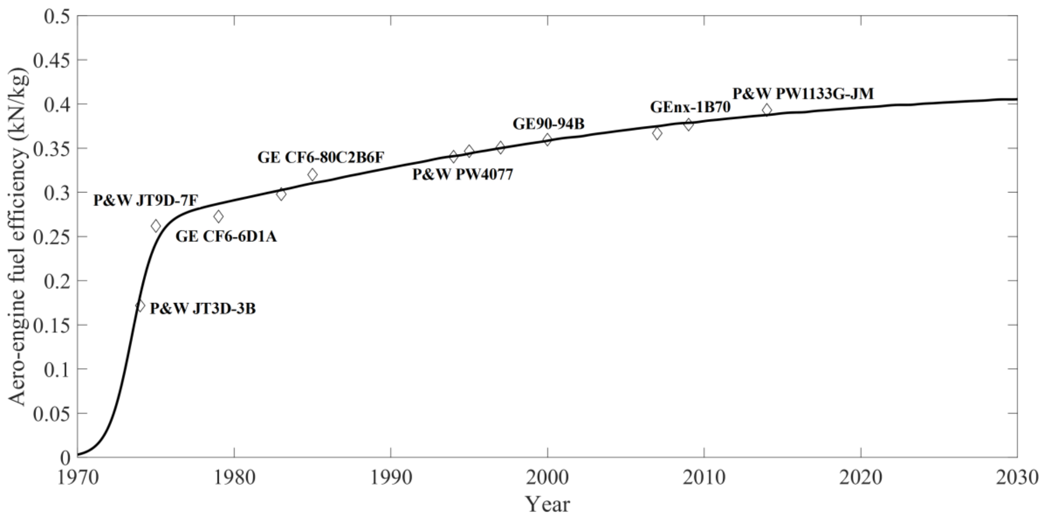

Figure 5.7 Aero-engine Fuel Efficiency Modeling (1970-2030)

The importance of the three component technologies is evaluated from parameter C values in Eq. (5.18). It is observed that the value of C_{02} is three orders higher than C_{01} and C_{03}, which means that the weight reduction has a more significant impact on passenger aircraft fuel efficiency than those of the other two component technologies (aerodynamics and aero-engine fuel efficiency). The result suggests that passenger aircraft designers and R&D managers may focus on R&D projects (e.g., new material development) to reduce the weight of the passenger aircraft. Meanwhile, they may consider outsourcing the R&D (e.g., wind tunnel test) and manufacture (e.g., aero-engine manufacture) of the other two components.

Figures 5.4 -5.7 show that both the system technology and the three component technologies almost exhaust their growth potential at 2018. To improve passenger aircraft fuel efficiency significantly in the future, practitioners have to find effective stimulation strategies. Since the historical R&D investment data of the system technology and the three component technologies are not available, the empirical relationship between R&D expenditures and the parameter values in the ecosystem model cannot be established. However, as discussed in Chapter 5.2.3, the values of a_0 and a_jC_{0j}/b_j in Eqs. (5.18) - (5.21) can be compared to provide a basis for passenger aircraft practitioners. The comparison result is shown in Table 5.1, which indicates the most effective strategies are investing on the passenger aircraft (system technology) or on weight reduction (component technology 2) based on the discussion in Chapter 3.3 and Chapter 5.2.3. Specifically, the strategies discussed in Chapter 3.3 and Chapter 5.2.3 could be applied to improve the system technology performance. In this case, three effective strategies are an increase of a_0 through R&D investment, one or more new technology adoption(s) in key component (weight reduction) design, and a component technology substitution in the system technology.

Table 5.1 The Comparison of a_0 and a_jC_{0j}/b_j values in Eqs. (5.18) - (5.21)

Passenger Aircraft a_0	Aerodynamics a_1C_{01}/b_1	Weight reduction a_2C_{02}/b_2	Aero-engine a_3C_{03}/b_3
0.0243	$5.19 \cdot 10^{-6}$	0.0315	$5.03 \cdot 10^{-6}$

The value of the parameter a_0 will increase if practitioners spend extra R&D funding on the passenger aircraft system design. Practitioners could use the funding to develop sophisticated optimization techniques to pursue an improved fuel efficiency design. For example, Boeing is trying to further stretch the fuselage of 737 for competing with Airbus A321neo [64]. This current R&D strategy of Boeing is consistent with the aforementioned guideline. If practitioners could improve the value of a_0 by 10%, the passenger aircraft fuel efficiency will increase from 0.0149 person/kg to 0.0155 person/kg in 2030.

The weight reduction parameter (maximum payload/OEM) almost reaches its upper limit at 2018. It will be hard to increase the value of the parameter a_2 under this circumstance. Practitioners have to consider adopting one or more new technologies to further reduce the weight of the passenger aircraft. A major effort of weight reduction until now is the gradual replacement of aluminum by composite materials on passenger aircraft structure [65]. The potential weight reduction approach in the future may be innovative airborne equipment (e.g., generator) and passenger cabin design (e.g., CPI windowless fuselage), which decrease the non-essential weight of passenger aircraft [61].

Practitioners could also consider the strategy of component technology substitution to improve passenger aircraft fuel efficiency. It represents a disruptive evolution of aerodynamics or aero-engine. The substitution from piston aero-engine to turbofan aero-engine around 1960s is a typical example of passenger aircraft component technology substitution. The example of Virgin Galactic is a recent approach of component technology substitution. The aircraft would travel outside of the Earth's atmosphere and enter orbit, using gravitational forces to travel at incredibly fast speeds [66]. This approach could shift the design restriction (parameter b in the Lotka-Volterra ecosystem model) of both the system technology and the three component technologies and also change the interaction (parameter C in the ecosystem model) between them.

5.3.4. Holdout Sample Test

The prediction capability of the Lotka-Volterra ecosystem model is validated through a holdout sample test. The performance evolution of passenger aircraft 3 000 nmi fuel efficiency during 1970 - 2000 is modeled using the Lotka-Volterra ecosystem model as Eqs. (5.14) - (5.17), Moore’s Law as Eq. (3.5), and the logistic S-curve model as Eq. (3.3). The system performance in the following years is derived through model extrapolation, and the predicted system performance is compared with the actual fuel efficiency data. The data fitting and prediction results appear in Figure 5.8. The prediction accuracy of the Lotka-Volterra ecosystem model exceeds those of Moore’s Law and the logistic S-curve model. The prediction errors of the three models for Boeing 737 MAX 3 000 nmi fuel efficiency in 2016 range from 12.2% (the Lotka-Volterra ecosystem model) to 24.7% (the logistic S-curve model) to 26.1% (Moore’s Law). The improved prediction accuracy of the Lotka-Volterra ecosystem model is a result of modeling the interactions between a system technology and its component technologies. The ecosystem model takes into account the impact from the three component technologies (aerodynamics, weight reduction, and aero-engine fuel efficiency) on the system technology (passenger aircraft fuel efficiency).

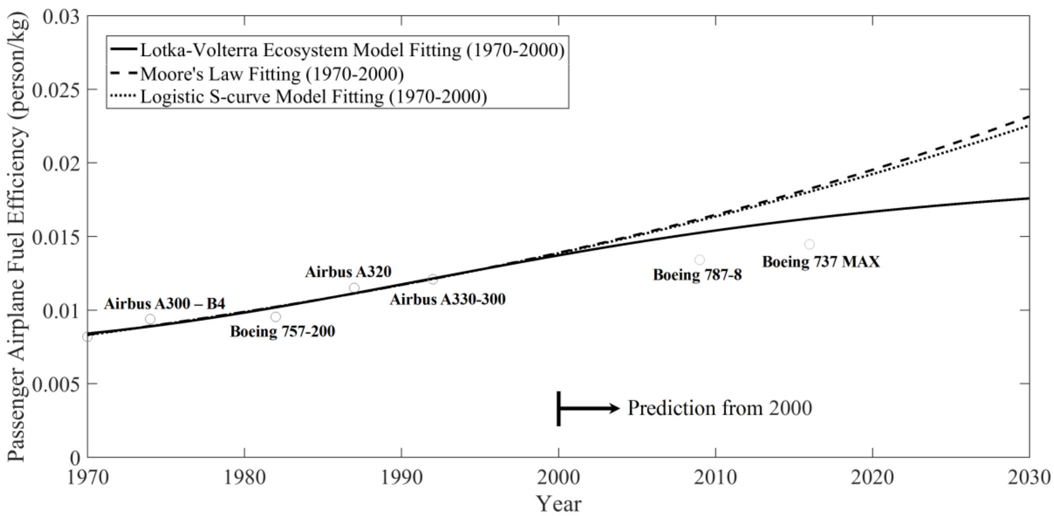

Figure 5.8 Predicted Passenger Aircraft Fuel Efficiency on Historical Data (1970-2000)

5.4. Summary

This chapter discusses the numerical methods to solve the Lotka-Volterra equations at the beginning. Because of the convergence concern, high order Runge-Kutta methods such as Dormand-Prince method are recommended for solving the Lotka-Volterra equations. To apply the Lotka-Volterra ecosystem model in practical projects, three steps (i.e., component technology selection and data collection, the Lotka-Volterra ecosystem model development and data fitting, and analysis of results) are developed for practitioners to predict and manipulate the performances of the system technology and its component technologies.

Passenger airplane fuel efficiency is used as a case study to illustrate these three steps. The system technology (passenger airplane fuel efficiency) interacts with three component technologies (aerodynamics, weight reduction, and aero-engine fuel efficiency) in the case study. The modeling results show that the system technology and the three component technologies almost exhaust their growth potential at 2018. To improve passenger aircraft fuel efficiency significantly in the future, practitioners may spend extra funding to develop sophisticated system optimization techniques or consider adopting one or more new technologies to reduce the weight of the passenger aircraft. A holdout sample test is also used to compare the prediction accuracy of the Lotka-Volterra ecosystem model with those of extant descriptive models. The test result suggests that the prediction accuracy of the Lotka-Volterra ecosystem model exceeds those of Moore's Law and the logistic S-curve model.

6. PREDICTION INTERVALS GENERATION FOR TECHNOLOGY EVOLUTION*

The prediction results generated by existing models (e.g., exponential function, logistic function, and Lotka-Volterra equations) of technology evolution prediction are expressed as single numbers, which are called point forecasts. Practitioners often want to supplement point forecasts by computing interval forecasts to assess future uncertainty and make contingency plans accordingly [21, 67]. For example, it is often necessary for practitioners to estimate the earliest and the latest time at which the technology of interest would achieve an expected performance. A comprehensive R&D plan is usually developed based on such estimation. However, prediction intervals generation for technology evolution has received scant attention in the literature. Researchers have used continuous mathematical functions or differential equations (e.g., exponential function, logistic function, and Lotka-Volterra equations) to model the performance change of a technology over time but seldom supplemented their point forecast results for future technology performance with prediction intervals [13, 19, 42].

This chapter introduces a broadly applicable method to generate prediction intervals for technology evolution. The prediction interval generation method can be applied to any model that predicts technology performance changes. To ease the implementation of this method in practical projects of technology evolution prediction,

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four steps are summarized to implement the method. The application of the prediction intervals generation method is illustrated using case studies of CPU and passenger aircraft.

6.1. Uncertainty in Technology Evolution Prediction

There are three primary types of uncertainty encountered in prediction problems [68]. These uncertainties are often referred to as model uncertainty, parameter uncertainty, and data uncertainty. Model uncertainty comes from the structure of the model. Considerable error may occur if a prediction model is not appropriate for the problem [68, 69]. Parameter uncertainty is rooted in the estimation of the model parameters. Researchers usually assume that the model parameters are constants during a data fitting process. However, the value of each parameter may change over time [19, 21], and the variation of each parameter may lead to prediction error. Data uncertainty covers the observed data's random variations that are not explained by model uncertainty and parameter uncertainty. The random variation is often represented by a random error (or white noise) term, ε, in prediction models [21, 70-72]. Of note, researchers often categorize the sources of uncertainty as either aleatory or epistemic in engineering modeling for risk and reliability analysis [73]. Here, the model uncertainty and the parameter uncertainty belong to the epistemic category; the data uncertainty is characterized as aleatory.

Researchers have considered these three types of uncertainty and developed several methods to construct prediction intervals for time series problems [21, 72, 74].

Although time series models are not commonly used in technology evolution prediction, these methods associated with time series models could provide a framework for new methods in uncertainty estimation of technology evolution prediction. A typical time series prediction model has the following mathematical form

$$y_t = F_t\left(y_{t-1}, y_{t-2}, \cdots y_{t-p}; \boldsymbol{\theta}\right) + \varepsilon_t \;, \tag{6.1}$$

where y_t is the variable of interest at time t, F is a function that takes arguments y at previous time t-1, t-2, …, t-p and potential parameters $\boldsymbol{\theta}$, and ε is an independent random error term. Typical time series data (e.g., yearly United States oil production) are uniformly spaced. One data point is given at each time period (e.g., monthly or yearly). The current value of the series, y_t, can be explained as a function of p consecutive past y values y_{t-1}, y_{t-2}, …, y_{t-p}, and other variables $\boldsymbol{\theta}$ (e.g., q past error ε values ε_{t-1}, ε_{t-2}, …, ε_{t-q} in a mixed autoregressive moving average model [72]).

To mitigate the model uncertainty and improve the robustness and efficiency of statistical models, researchers select an optimal prediction model from a wide range of time series models by minimizing a statistic such as Akaike's Information Criterion (AIC) or Schwarz Bayesian Information Criterion (BIC) [68, 70]. Several procedures have been established to select an optimal model, which include but are not limited to, the Box-Jenkins procedure for autoregressive integrated moving average (ARIMA) models and the Holt-Winters procedure for exponential smoothing models [68, 70, 75, 76]. Model uncertainty is generally neglected once the optimal prediction model is selected via one of these procedures.

Many times, the parameter uncertainty is underemphasized in time series analysis. However, parameter uncertainty cannot be overlooked in a model with many parameters or when the number of observed data points is small [21]. Researchers often perform sensitivity analysis to assess parameter uncertainty [77]. Bayesian approach has also been widely adopted in time series problems to quantify parameter uncertainty [78].

Data uncertainty is described by the random error term, ε, in Eq. (6.1). Researchers often assume the random error is an independent variable that follows a parametric distribution. Assumptions of normality are commonly used for the random error term ε [21] but no complete consensus exists among researchers regarding this choice. Harvey suggested the use of a *t*-distribution to describe the random error for a Gaussian time series model [76]. Williams and Goodman analyzed six time series of residences and the number of business main telephones in service on the last day of the month for three Michigan cities [79]. They found that the absolute values of the prediction error approximately follow a gamma distribution [79].

If current time is defined as t, and researchers want to predict the value of variable y at time $t+k$ as y_{t+k}, the general form of a 100(1-α) % prediction interval for y_{t+k} in a time series analysis is [21]

$$F_{t+k} \pm z_{\alpha/2}\sqrt{var(\varepsilon_{t+k})}\,, \tag{6.2}$$

where F_{t+k} is the value of the function F at time $t+k$, $z_{\alpha/2}$ is the $\alpha/2$ percentage point of the parametric distribution of the random error ε, var (ε_{t+k}) is the variance of random error ε at time $t+k$. In practice, researchers often set confidence level α=0.05 and compute the 95% prediction intervals for their problem. Eq. (6.2) also assumes the model prediction, F_{t+k}, is unbiased with expected mean squared prediction error. The analytic form of var (ε_{t+k}) could be derived for several time series modes. For example, the random walk with drift model has the form [72]

$$y_{t+1} = \delta + y_t + \varepsilon_{t+1} , \tag{6.3}$$

where the constant δ is called drift. The variance of the random error, ε, at time $t+k$ has the form

$$var(\varepsilon_{t+k}) = k\sigma_\varepsilon^2 , \tag{6.4}$$

where σ_ε^2 equals var (ε_{t+1}), which is the variance of the one step ahead prediction error [21, 80]. For the time series models for which the analytic form of var (ε_{t+k}) is not available, researchers have to use approximate formulas [80] or numerical approaches (e.g., Monte Carlo simulation or bootstrapping) to estimate the variance [21, 81]. Of note, typical time series models (e.g., ARIMA and exponential smoothing [70]) represented by Eq. (6.1) require uniformly spaced data. Advanced time series models (e.g., ACD-GARCH model [82]) exist for time series data with non-uniform spacing.

Time series models and the associated prediction interval generation methods have been successfully applied in several areas such as econometrics, demography, marketing, and medical science [70, 72, 74]. However, time series models are not commonly used in technology evolution prediction. Researchers often believe that an underlying law governs the technology performance change in technology evolution that involves a dominant design [14, 83, 84]. Such law is usually described by continuous mathematical functions or differential equations involving time rather than time series models. Moreover, a typical technology evolution problem involves fewer than 30 data points. Statistical theorems, such as the central limit theorem, are not applicable with such a small sample size. It is also hard to validate a parametric distribution assumption for the error term ε because a parametric distribution test (e.g., normality test) has less power to reject the null hypothesis due to the small sample size [85].

Popular technology evolution prediction models include but are not limited to, Moore's Law, the logistic S-curve model, and the Lotka-Volterra ecosystem model [5, 13, 19]. Researchers have fitted these models to non-uniformly spaced data and predict technology performance through mathematical extrapolation. However, researchers seldom supplemented their point forecast results with prediction intervals. The limited publications that consider uncertainty in technology evolution prediction include the works from Farmer & Lafond [3], Arendt, McAdams, & Malak [86], Naim & Lewis [56] and Nagy, Farmer, Bui, & Trancik [4]. Farmer & Lafond modified Moore's Law as a correlated geometric random walk with drift model and constructed the prediction intervals through an approximate approach [3]. However, the model and the approach developed by Farmer & Lafond only work for uniformly spaced time series data. Arendt et al. fitted technology evolution data by an Erto-Lanzotti S-curve model and considered the parameter uncertainty through a Monte Carlo simulation [86]. The method provided by Arendt et al. is valuable for decision making in design, but the method cannot be applied to the technology evolution that does not follow the Erto-Lanzotti S-curve model. Naim & Lewis introduced an *n*-dimensional growth model for engineering system performance evolution [56]. They considered the uncertainty of one parameter (performance upper limit) through a Monte Carlo simulation. The data uncertainty and the uncertainty pertaining to other parameters in their model were neglected. Nagy et al. tested six technology evolution models in their paper [4]. The technology performance Nagy et al. discussed was production or price rather than technical performance metrics (e.g., speed or capacity) that are of primary interest to the audience of this dissertation.

6.2. Prediction Intervals Generation Using a Bootstrap Method

Based on the capability void discussed in Chapter 6.1, a generic method is introduced to generate prediction intervals for technology evolution prediction. The generic method can be applied to any technology evolution prediction model that describes the incremental change in technology performance. The discussion of more fundamental or radical technological changes (e.g., changes in system configuration or functionality, and disruptive innovations) is beyond the scope of this dissertation. The three types of uncertainty in technology evolution prediction are discussed. The empirical probability distributions of parameter uncertainty and data uncertainty are established through bootstrapping. A holdout sample analysis is also presented to determine the confidence level, α, for prediction intervals generation. In addition, the probability distribution of each parameter in a prediction model is constructed. Of note, practitioners also could transform the non-uniformly spaced technology evolution data to uniformly spaced data through an interpolation approach. Typical time series models (e.g., ARIMA or exponential smoothing [70]) could then be used for technology evolution prediction. However, the interpolation approach introduces artificial data points that bring fresh uncertainty in technology evolution prediction, and this new uncertainty is hard to address in prediction intervals generation.

As a generic problem of technology evolution prediction, there are n technology performance data points from start time, T_1, to current time, T_2. Practitioners want to predict the technology performance from current time, T_2, to future time, $T_2+\tau$, with prediction intervals. The n technology performance data at time $t_1, t_2, \ldots, t_n$ are denoted by $y_1, y_2, \ldots, y_n$ respectively. A technology evolution prediction model $M(t; \boldsymbol{\varphi})$ is chosen to fit the data, where t is time and $\boldsymbol{\varphi}=(A, B, C, \ldots)$ represents the constant parameters in the model M. Each technology performance data point is expressed as

$$y_i = M(t_i;\ \boldsymbol{\varphi_0}) + \varepsilon_i\ , \tag{6.5}$$

where $i \in \{1, 2, \ldots, n\}$, $\boldsymbol{\varphi_0}=(A_0, B_0, C_0, \ldots)$ denotes estimated parameters derived from a data fitting process, and ε_i is the deviation from the model at each data point.

The point forecast of technology performance at time t_e, where $T_2 < t_e < T_2+\tau$, is obtained by mathematical extrapolation as $M(t_e; \boldsymbol{\varphi_0})$. An optimal prediction model should be selected to minimize the model uncertainty. It is a challenging task to select an optimal model from a wide range of technology evolution prediction models. Such discussion is beyond the scope of this dissertation. $M(t; \boldsymbol{\varphi})$ is assumed to be the optimal model and the model uncertainty is not considered here. To incorporate the model uncertainty, practitioners could review the work of Chatfield [69], Meade & Islam [5], Young [17], and Draper [87].

The parameter uncertainty is estimated using a bootstrap method. The bootstrap method, also called bootstrapping or the resample method, was introduced by Efron in

1977 [24]. The method has been used to construct prediction intervals for regression, time series, and growth curve models [25, 26, 81, 88, 89]. Here, an original sample is comprised of the deviation terms in Eq. (6.5) as $\boldsymbol{E_0}$=(ε_1, ε_2, …, ε_n). A resample $\boldsymbol{E_1}$ of size n is created by drawing elements from the original sample, $\boldsymbol{E_0}$, with replacement. Each element in sample $\boldsymbol{E_0}$ has an equal probability of $1/n$ to be drawn. The resampling process is repeated R times to generate R resamples as

$$\boldsymbol{E_j} = (\varepsilon_1^j, \varepsilon_2^j, \cdots, \varepsilon_n^j)\ , \tag{6.6}$$

where $j \in \{1, 2, \ldots, R\}$. Typically, R is at least 1,000 for prediction intervals generation [25]. Each resample is made up of the elements in the original sample ($\varepsilon_i^j \in \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n\}$). The R bootstrapped technology performance data sets are then derived as $\boldsymbol{Y_j}$=(y_1^j, y_2^j,…, y_n^j) where

$$y_i^j = M(t_i;\ \boldsymbol{\varphi_0}) + \varepsilon_i^j\ . \tag{6.7}$$

The model parameters can be estimated using a specified data fitting method (e.g., ordinary least squares) for the bootstrapped technology performance data sets $\boldsymbol{Y_j}$ as $\boldsymbol{\varphi_j}$=(A_j, B_j, C_j, …). An empirical probability distribution $\boldsymbol{M_e}(t_e;\ \boldsymbol{\varphi})$ at time t_e is built by setting the same probability, $1/R$, at each point $M(t_e;\ \boldsymbol{\varphi_1})$, $M(t_e;\ \boldsymbol{\varphi_2})$,…, $M(t_e;\ \boldsymbol{\varphi_R})$ [90]. The empirical probability distribution $\boldsymbol{M_e}(t_e;\ \boldsymbol{\varphi})$ describes the parameter uncertainty in technology evolution prediction. Here, the empirical probability distribution of each parameter can also be built in the prediction model M from $\boldsymbol{\varphi_j}$. For example, an empirical probability distribution $\boldsymbol{A_e}$ for parameter A can be built by setting the same probability, $1/R$, at each point A_1, A_2,…, A_R. If the parameters have a clear interpretation in technology evolution context (e.g., technology performance upper limit in the logistic S-curve model or technology interaction in the Lotka-Volterra ecosystem model), the probability distributions of the parameters built here could be a key reference for practitioners to make R&D and outsourcing decisions, which is illustrated by the passenger aircraft case study in Chapter 6.4.2.

The data uncertainty is represented by the deviation term, ε. The deviation is assumed to be an independent random variable that is applied to any technology performance data from T_1 to $T_2+\tau$. It is hard to assume any parametric distribution (e.g., normal distribution) for the random variable $\boldsymbol{\varepsilon}$ because a typical technology evolution problem has less than 30 data points. An empirical probability distribution $\boldsymbol{E_e}$ (ε) is constructed from the sample $\boldsymbol{E_0}$=(ε_1, ε_2,…, ε_n) by setting the same probability of $1/n$ to each element in the sample $\boldsymbol{E_0}$ [90]. The empirical probability distribution, $\boldsymbol{E_e}(\varepsilon)$, describes the data uncertainty in technology evolution prediction.

Above all, the prediction intervals could be generated using the empirical probability distributions $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ and $\boldsymbol{E_e}(\varepsilon)$. The percentile method is used because of its convenience [26]. A 100(1-α) % prediction interval for technology performance y at time t_e is given by

$$[M_e^{\alpha/2} + \varepsilon_e^{\alpha/2},\ M_e^{1-(\alpha/2)} + \varepsilon_e^{1-(\alpha/2)}]\ , \tag{6.8}$$

where $M_e^{\alpha/2}$ and $M_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{M_e}$ (t_e; $\boldsymbol{\varphi}$) distribution, $\varepsilon_e^{\alpha/2}$ and $\varepsilon_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{E_e}$ (ε) distribution. For example, a 95% prediction interval (α=0.05) for technology performance at time t_e is

$$[M_e^{2.5\%} + \varepsilon_e^{2.5\%},\ M_e^{97.5\%} + \varepsilon_e^{97.5\%}]\ . \tag{6.9}$$

Of note, a 100(1-α) % prediction interval does not cover 100(1-α) % possible technology performance in a future time period [21, 79, 80]. The value of α is considered a practitioner's choice. It is of significance for practitioners to determine an appropriate value for the confidence level α to generate reasonable prediction intervals. Such reasonable prediction intervals should capture the uncertainty of future technology performance in a modest range rather than an exaggerated wide range. In practice, researchers often follow the convention in statistical hypothesis testing and take α=0.05 to generate 95% prediction intervals. However, the 95% prediction intervals sometimes are too wide in technology evolution prediction (e.g., Figure 6.2 and Figure 6.3 in Chapter 6.4), and such wide intervals are not useful for practitioners to make R&D decisions. This dissertation suggests using holdout sample analysis to determine an appropriate value for the confidence level α and generate reasonable prediction intervals accordingly. The suggested holdout sample analysis gives an appropriate value of α based on prior technology performance evolution data rather than a constant value of α. This strategy considers the difference between diverse technologies on evolution trend and the associated uncertainty. First, the same model M is used to fit the data points from start time T_1 to time T_2-τ. The empirical probability distributions $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ and $\boldsymbol{E_e}(\varepsilon)$ at time t_e, where $T_2-\tau < t_e < T_2$, can be derived following the preceding procedure. There are k known data points from time T_2-τ to time T_2, from which the narrowest prediction intervals that just cover the k data points can be identified. The confidence level α_e associated with the narrowest prediction intervals is used as the appropriate value of confidence level. The appropriate confidence level α_e is then used to generate the prediction intervals from current time, T_2, to future time, $T_2+\tau$. The underlying assumption of this method is that the prediction uncertainty from time T_2 to time $T_2+\tau$ is smaller than or equal to the uncertainty from time $T_2-\tau$ to time T_2. This assumption is validated through two case studies of CPU and passenger aircraft evolution predictions in Chapter 6.4. It is shown that the prediction intervals generated by the confidence level α_e suffice to cover every actual data point in the holdout sample tests. Meanwhile, the 95% prediction intervals are much wider than the prediction intervals generated by the confidence level α_e.

6.3. Four Steps to Generate Prediction Intervals for Technology Evolution Prediction

In Chapter 6.2, a method is presented to generate prediction intervals for a generic problem of technology evolution prediction. In this section, the procedure to implement the method is summarized in four steps. Practitioners can follow these guidelines to supplement point forecasts with prediction intervals in technology evolution prediction.

Step 1 - Data collection and pretreatment. Practitioners first collect the technology performance data for a time interval of interest. The time interval usually begins with a past time, T_1, and ends in current time, T_2. There may be more than one data point in a specific time period (e.g., several CPUs with different transistor counts are introduced in the same year). Practitioners retain only the greatest performance value in each time period because that data point represents the best available technology performance at the time. Practitioners also delete performance values that are lower than those during previous time periods. The remaining data points are used for technology evolution prediction. Practitioners can transform (e.g., a log transformation) or normalize (e.g., dimensionless treatment) the data if necessary.

Step 2 - Model selection. Practitioners select a technology evolution prediction model for their specific problem. Descriptive models (e.g., S-curve models or Moore's Law) are simple mathematical functions that are applicable for fundamental technology evolution prediction in which technology interaction is ignored. If technology interaction needs to be considered, a system model (e.g., the Lotka-Volterra ecosystem model) is preferable [18, 19]. Of note, the best fit model usually is not the best prediction model [69]. The model selection should be based on the results from several holdout sample tests as well as the advice from domain or subject matter experts.

Step 3 - Confidence level determination. Practitioners conduct a holdout sample analysis using the technology evolution data from time T_1 to time T_2-τ. The technology evolution prediction model selected in Step 2 is estimated using the holdout data set, and the empirical probability distributions for model prediction $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ and deviation $\boldsymbol{E_e}(\varepsilon)$ at time t_e, where $T_2-\tau < t_e < T_2$, are derived as described in Chapter 6.2. Practitioners calculate a confidence level α associated with each data point during time interval (T_2-τ, T_2). The smallest value of confidence level α corresponds to the narrowest prediction intervals that can cover every data point during time interval (T_2-τ, T_2). The smallest confidence level is then used as the appropriate value α_e in the next step.

Step 4 - Prediction intervals generation. Practitioners predict technology performance and generate prediction intervals in the future time interval (T_2, $T_2+\tau$) using data from start time, T_1, to current time, T_2. The technology evolution prediction model selected in Step 2 is estimated using the entire data set. Of note, the parameter estimates derived from the data fitting process are not the same as the parameter estimates from the holdout sample analysis in Step 3. Practitioners obtain the empirical probability distributions for model prediction $\boldsymbol{M_e}(t_e;\ \boldsymbol{\varphi})$ and deviation $\boldsymbol{E_e}(\varepsilon)$ in the future time interval (T_2, $T_2+\tau$) through the method developed in Chapter 6.2. The probability distribution of each parameter in the model also could be built if necessary. The upper and lower limits of the prediction intervals are generated by Eq. (6.8) using confidence level α_e derived in Step 3. Practitioners should substitute the latest technology performance (y_n in Chapter 6.2) for the lower limit(s) of the prediction intervals generated by Eq. (6.8) if the lower limit(s) is smaller than the latest technology performance because technology performance monotonically increases over time.

6.4. Case Studies of CPUs and Passenger Aircrafts

In this section, CPU and passenger aircraft are used as two case studies to illustrate the four steps of the process outlined in Chapter 6.3. In the holdout sample tests of these two case studies, the prediction intervals generated by the method developed in this dissertation cover every actual data point. These results validate the method and the associated assumptions.

The holdout sample analysis also shows that the 95% prediction intervals are much wider than the 100(1-α_e) % prediction intervals generated by the method developed in this chapter. In practice, this dissertation suggests that practitioners use 100(1-α_e) % prediction intervals for R&D planning and decision making. Practitioners also could estimate the earliest and the latest time at which the technology of interest would achieve the expected performance level using the 100(1-α_e) % prediction intervals. The 95% prediction intervals can be used as a reference to make contingency plans if necessary.

The prediction intervals generation method developed in this chapter also provides the probability distribution of each parameter in a prediction model. In the passenger aircraft case study, the probability distributions of the parameters C_{01} and C_{10} in the Lotka-Volterra ecosystem model indicate the interaction between the system technology (passenger aircraft) and its component technology (turbofan aero-engine). The probability distributions help practitioners to make more informed R&D and outsourcing decisions.

6.4.1. CPU Transistor Count Evolution Prediction[*]

The prediction of CPU transistor count is important in the semi-conductor industry. The prediction results are critical for high technology companies in R&D

[*] Appendix C includes the data set used in the case study of CPU.

planning [13]. To validate the method developed in Chapter 6.2, the CPU transistor count data from 1970 to 2014 is used to generate prediction intervals during 2014-2018.

The CPU transistor count data during 1970-2018 are collected from Wikipedia first. There are 118 data points in total as shown in Figure 6.1. The top performance data point of each year is chosen, and then the data points that are lower than any previous data point are removed. Only 30 data points (dots in Figure 6.1) are selected to represent the CPU performance evolution from 1970 to 2018. As is common in the semi-conductor industry, the natural logarithm of the 30 performance values is taken because of fast improvements in CPU performance.

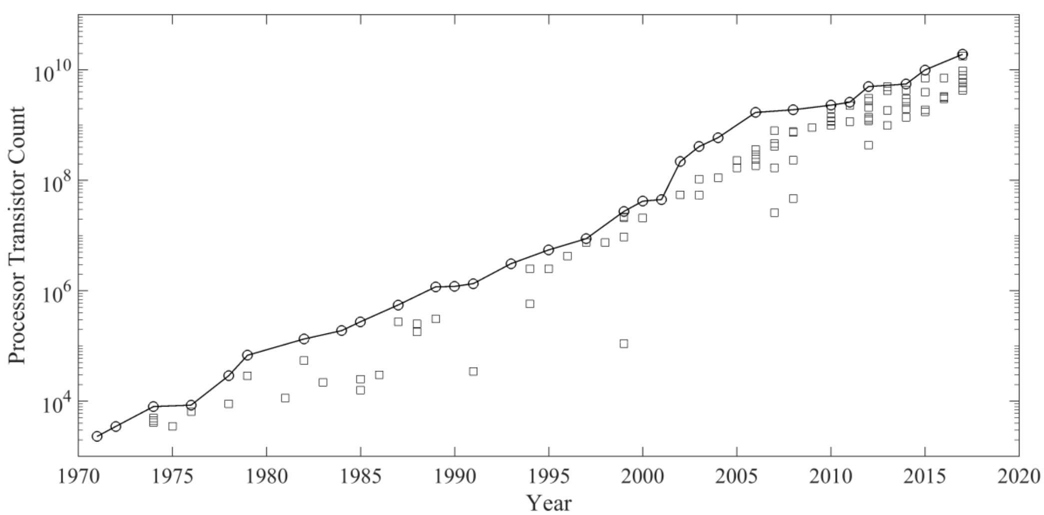

Figure 6.1 CPU Transistor Count Data during 1970-2018

Moore’s Law is used as the technology evolution prediction model for CPU performance evolution. Moore’s Law is the most influential model used widely in the semi-conductor industry to predict the performances of CPU and dynamic random-access memory (RAM) [13]. The mathematical model is given by

$$y = e^{A+Bt} \tag{6.10}$$

where y is technology performance, t is time, and A and B are constant parameters. A natural logarithm transformation is made to Eq. (6.10) and a simple regression model is obtained as

$$z = A + Bt \ , \tag{6.11}$$

where z=ln(y). Eq. (6.11) is a linear model that is used to fit the natural logarithm transformed data set.

To validate the prediction intervals generation method developed in this chapter, a holdout sample test is conducted. In this test, it is checked whether the prediction intervals cover the actual data points in the following years. Imagine practitioners are in 2014 and want to predict the CPU transistor count evolution in the subsequent four years (τ=4) using the data from 1970 to 2014 (T_1=0, T_2=44).

To determine an appropriate value for confidence level α_e, a holdout sample analysis is performed using the CPU transistor count data from 1970 to 2010 (T_1=0, T_2-τ=40). The 25 data points (n=25) is fitted to minimize the sum of squared errors. The fitted model is

$$z_i = 7.183 + 0.3607 t_i + \varepsilon_i \ , \tag{6.12}$$

where $i \in \{1, 2, \ldots, 25\}$, z_i is the natural logarithm transformed transistor count, t_i is time, where $T_1 \le t_i \le T_2 - \tau$, and ε_i is the deviation at each data point. An original sample is created from the deviation term of Eq. (6.12) as $\boldsymbol{E_0}$=(ε_1, ε_2, …, ε_{25}). Resamples with size

n=25 are generated by drawing elements from sample $\boldsymbol{E_0}$ with replacement. Each element in sample $\boldsymbol{E_0}$ has a probability of 1/25 to be drawn. 1,000 resamples (R=1,000) are created as

$$\boldsymbol{E_j} = \left(\varepsilon_1^j, \varepsilon_2^j, \cdots, \varepsilon_n^j\right) , \tag{6.13}$$

where $j \in \{1, 2, \ldots, 1000\}$. 1,000 bootstrapped CPU transistor count data sets are then derived as $\boldsymbol{Z_j}=(z_1^j, z_2^j, \ldots, z_{25}^j)$ where

$$z_i^j = 7.183 + 0.3607 t_i + \varepsilon_i^j . \tag{6.14}$$

Bootstrapped model parameters A_j and B_j for each bootstrapped CPU transistor count data set $\boldsymbol{Z_j}$ are estimated as $\boldsymbol{\varphi_j}=(A_j, B_j)$. An empirical probability distribution $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ at time t_e ($40< t_e <44$) is built by setting probability 1/1000 at each point $M(t_e; \boldsymbol{\varphi_1})$, $M(t_e; \boldsymbol{\varphi_2}), \ldots, M(t_e; \boldsymbol{\varphi_{1000}})$ where

$$M\left(t_e;\, \boldsymbol{\varphi_j}\right) = A_j + B_j t_e . \tag{6.15}$$

The empirical probability distribution $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ describes the parameter uncertainty in CPU transistor count prediction.

To estimate data uncertainty in CPU transistor count prediction, an empirical probability distribution $\boldsymbol{E_e}(\varepsilon)$ is constructed from the sample $\boldsymbol{E_0}=(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{25})$ by setting a probability of 1/25 to each element in the sample $\boldsymbol{E_0}$.

Above all, a 100(1-α) % prediction intervals is derived for natural logarithm transformed CPU transistor count z at time t_e ($40< t_e <44$) by

$$[M_e^{\alpha/2} + \varepsilon_e^{\alpha/2},\ M_e^{1-(\alpha/2)} + \varepsilon_e^{1-(\alpha/2)}] , \tag{6.16}$$

where $M_e^{\alpha/2}$ and $M_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{M_e}(t_e; \boldsymbol{\varphi})$ distribution, $\varepsilon_e^{\alpha/2}$ and $\varepsilon_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{E_e}(\varepsilon)$ distribution. The actual data points exist in 2011, 2012, and 2014 (t_e=41, 42, and 44). The distribution percentile P% could be determined that overlap these actual data points at time t_e=41, 42, and 44. The three values of confidence level α associated with each prediction interval can be calculated by 1-|1-P/50|. A 100(1-α) % prediction interval corresponds to each α value. The results of the distribution percentile, the confidence level, and the prediction interval at each actual data point are listed in Table 6.1.

Table 6.1 Distribution Percentile, Confidence Level, and Prediction Interval at 2011, 2012, and 2014 of CPU Transistor Count Evolution

Year	Distribution Percentile (%)	Confidence Level α	Prediction Interval
2011	36.0	0.720	28.0%
2012	56.0	0.880	12.0%
2014	24.1	0.482	51.8%

Table 6.1 shows that the 51.8% prediction intervals cover the three data points during 2010-2014, resulting in corresponding confidence level of α_e=0.482 which is used to generate prediction intervals in the next step.

As the final step, the 28 data points of CPU transistor count (n=28) from 1970 to 2014 (T_1=0, T_2=44) is fitted with Eq. (6.11). The ordinary least-squares estimation produces the fitted model as follows

$$z_i = 7.242 + 0.3568t_i + \varepsilon_i \ . \tag{6.17}$$

Following the same procedure as stated earlier in this section, 51.8% prediction intervals are generated for CPU transistor count from 2014 to 2018. The results are shown in Figure 6.2. The 51.8% prediction intervals create a grey area that covers the two actual data points (rhombuses in Figure 6.2) at 2015 and 2017. The 95% prediction intervals (α=0.05) are also shown in Figure 6.2. The Figure 6.2 shows that 95% prediction intervals are much wider than the 51.8% prediction intervals on the log coordinates.

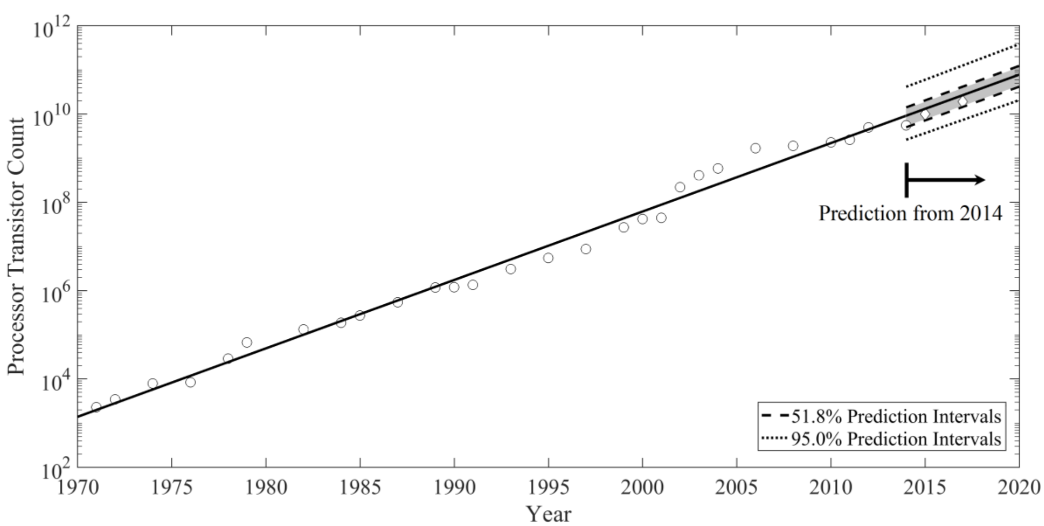

Figure 6.2 CPU Transistor Count Evolution Prediction Intervals from 2014 to 2018

6.4.2. Passenger Aircraft Overall Performance Evolution Prediction*

The evolution of the passenger aircraft has led to airliners with higher passenger capacity, faster speed, and longer range over time. The aircraft engine (hereafter referred to as the aero-engine) is a major component technology of the passenger aircraft. The interaction between the passenger aircraft and the aero-engine should be considered in the passenger aircraft performance evolution prediction [19]. Thus, the Lotka-Volterra ecosystem model [19] is used to model the technology interaction and predict the passenger aircraft performance evolution. Here, the passenger aircraft is the system technology. Passenger capacity·speed·range (km^2/h) is taken as the overall performance metric of the system technology. The turbofan aero-engine is the component technology. Take-off thrust (kN) is used as the performance metric of the component technology. The point forecasts of the passenger aircraft and the turbofan aero-engine performance evolutions are found in a previous publication [19]. Prediction intervals generation is focused on in this section. To test the method developed in Chapter 6.2, the performance evolution data of the passenger aircraft and the turbofan aero-engine from 1960 to 2004 is used to generate prediction intervals during 2004-2008.

The performance evolution data of the passenger aircraft and the turbofan aero-engine during 1960-2008 are collected [2, 91, 92]. The top performance data point of each year is chosen and then the data points that are lower than any previous data point are removed. 10 data points are selected that represent the passenger aircraft

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* Appendix D includes the data sets used in the case study of passenger aircraft overall performance.

performance evolution, and 15 data points are selected that represent the turbofan aero-engine performance evolution from 1960 to 2008. To create dimensionless metrics, these data values are divided by the corresponding characteristic values [19]. The latest performance in a specified time interval is used as the characteristic value for each technology.

In this case study, the simplified Lotka-Volterra equations are

$$\frac{dy_0}{dt} = a_0 y_0 - b_0 {y_0}^2 + C_{01} y_0 y_1 \tag{6.18}$$

$$\frac{dy_1}{dt} = a_1 y_1 - b_1 {y_1}^2 + C_{10} y_1 y_0 \tag{6.19}$$

where y_0 is the dimensionless passenger aircraft performance, y_1 is the dimensionless turbofan aero-engine performance, and a_0, b_0, C_{01}, a_1, b_1, and C_{10} are constant parameters.

Again, a holdout sample test is conducted to validate the prediction intervals generation method developed in this chapter. In the holdout sample test, it is checked whether the prediction intervals cover the actual data point(s) in the following years. It is assumed that practitioners are in 2004 and want to predict the passenger aircraft performance evolution for the subsequent four years (τ=4) using the data from 1960 to 2004 (T_1=0, T_2=44).

To determine an appropriate value for confidence level α_e, a holdout sample analysis is performed using the performance evolution data of the passenger aircraft and the turbofan aero-engine from 1960 to 2000 (T_1=0, T_2-τ=40). The 23 data points (n=23) is fitted to minimize the sum of squared errors using the trust region reflective algorithm

[63]. In the data fitting process, the simplified Lotka-Volterra equations, shown in Eqs. (6.18) and (6.19), are solved using high order Runge-Kutta method [45, 54]. The fitted model is

$$\frac{dy_0}{dt} = 0.280y_0 - 0.616{y_0}^2 + 0.481y_0y_1 \tag{6.20}$$

$$\frac{dy_1}{dt} = 0.0509y_1 - 0.0319{y_1}^2 + 2.33 \cdot 10^{-14}y_1y_0 \tag{6.21}$$

$$y_0(t = 0) = 0.0796 \tag{6.22}$$

$$y_1(t = 0) = 0.241 \tag{6.23}$$

where t=0 represents the start year of 1960. Here, the technology performances at the start year are treated as unknown parameters in the data fitting process. The deviation term, ε_i, is derived by subtracting the corresponding solution of Eqs. (6.20) - (6.23) from the actual data at each data point, where $i \in \{1, 2, \ldots, 23\}$. Here, the deviation terms of two technologies (the passenger aircraft and the turbofan aero-engine) are not treated differently in the following bootstrapping process because every data point is normalized in the same range (0, 1] by the dimensionless treatment. The cluster bootstrapping approach in technology evolution prediction using a system model may be explored in future research. Thus, an original sample from the deviation term is created as $\boldsymbol{E_0}$=(ε_1, ε_2, …, ε_{23}). Resamples with size n=23 are generated by drawing elements from the sample $\boldsymbol{E_0}$ with replacement. Each element in the sample $\boldsymbol{E_0}$ has a probability of 1/23 to be drawn. 1,000 resamples (R=1,000) are created as

$$\boldsymbol{E_j} = \left(\varepsilon_1^j, \varepsilon_2^j, \cdots, \varepsilon_n^j\right), \tag{24}$$

where $j \in \{1, 2, \ldots, 1000\}$. 1,000 bootstrapped passenger aircraft and turbofan aero-engine data sets are then derived as $\boldsymbol{Y_j}=(y_1^j, y_2^j, \ldots, y_{23}^j)$ by adding the bootstrapped deviation term ε_i^j to the corresponding solutions of Eqs. (6.20) - (6.23) for each data point.

Bootstrapped model parameters $\boldsymbol{\varphi_j}=(y_{t0}^j, a_0^j, b_0^j, C_{01}^j, y_{t1}^j, a_1^j, b_1^j, C_{10}^j,)$ for each bootstrapped technology performance data set $\boldsymbol{Y_j}$ are estimated, where $y_{t0}=y_0(t=0)$ and $y_{t1}=y_1(t=0)$. An empirical probability distribution $\boldsymbol{MP_e}(t_e; \boldsymbol{\varphi})$ at time t_e ($40< t_e <44$) is built by setting a probability of 1/1000 at each point $MP(t_e; \boldsymbol{\varphi_1})$, $MP(t_e; \boldsymbol{\varphi_2}),\ldots, MP(t_e; \boldsymbol{\varphi_{1000}})$, where $MP(t_e; \boldsymbol{\varphi_j})$ is the solution of Eqs. (6.18) and (6.19) for the passenger aircraft dimensionless performance y_0 at time t_e with eight parameter values given by $\boldsymbol{\varphi_j}$. The empirical probability distribution $\boldsymbol{MP_e}(t_e; \boldsymbol{\varphi})$ describes the parameter uncertainty in the passenger aircraft performance prediction. The empirical probability distribution $\boldsymbol{MA_e}(t_e; \boldsymbol{\varphi})$ for the dimensionless turbofan aero-engine performance could be derived in the same manner.

To estimate data uncertainty, an empirical probability distribution $\boldsymbol{E_e}(\varepsilon)$ is constructed from the sample $\boldsymbol{E_0}=(\varepsilon_1, \varepsilon_2,\ldots, \varepsilon_{23})$ by setting a probability of 1/23 to each element in the sample $\boldsymbol{E_0}$.

Above all, a 100(1-α) % prediction intervals for the dimensionless passenger aircraft performance y_0 at time t_e ($40< t_e <44$) is derived by

$$[MP_e^{\alpha/2} + \varepsilon_e^{\alpha/2},\ MP_e^{1-(\alpha/2)} + \varepsilon_e^{1-(\alpha/2)}]\,, \tag{6.25}$$

where $MP_e^{\alpha/2}$ and $MP_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{MP_e}(t_e; \boldsymbol{\varphi})$ distribution, $\varepsilon_e^{\alpha/2}$ and $\varepsilon_e^{1-(\alpha/2)}$ are the $\alpha/2$ and 1-$\alpha/2$ percentiles of the $\boldsymbol{E_e}(\varepsilon)$ distribution.

Similarly, the 100(1-α) % prediction intervals for the dimensionless turbofan aero-engine performance y_1 at time t_e (40< t_e <44) could be derived as

$$[MA_e^{\alpha/2} + \varepsilon_e^{\alpha/2},\ MA_e^{1-(\alpha/2)} + \varepsilon_e^{1-(\alpha/2)}]\,. \tag{6.26}$$

There is one turbofan aero-engine data point at 2002 (t_e= 42). The distribution percentile 87.0% overlaps that actual data point at 2002. The 87.0% distribution percentile corresponds to 74.0% prediction interval. The confidence level α associated with the 74.0% prediction interval equals 0.260. Thus, the confidence level α_e=0.260 is used to generate prediction intervals in the next step.

As the final step, the 24 data points of the passenger aircraft and the turbofan aero-engine performance evolutions (n=24) from 1960 to 2004 (T_1=0, T_2=44) are fitted with Eqs. (6.18) and (6.19). The ordinary least-squares estimation produces the fitted model as follows

$$\frac{dy_0}{dt} = 0.267y_0 - 0.612{y_0}^2 + 0.580y_0y_1 \tag{6.27}$$

$$\frac{dy_1}{dt} = 0.0346y_1 - 1.71 \cdot 10^{-8}{y_1}^2 + 4.32 \cdot 10^{-10}y_1y_0 \tag{6.28}$$

$$y_0(t = 0) = 0.0797 \tag{6.29}$$

$$y_1(t = 0) = 0.224 \tag{6.30}$$

Following the procedure described earlier in this section, 74.0% prediction intervals (α_e=0.260) are generated for the passenger aircraft performance evolution from 2004 to 2008. The results are shown on Figure 6.3. The 74.0% prediction intervals create a grey area that covers the actual data point (rhombuses on Figure 6.3) in 2005. The 95% prediction intervals (α=0.05) are also shown in Figure 6.3. Again, the Figure 6.3 shows that the 95% prediction intervals are much wider than the 74.0% prediction intervals generated by the method developed in this case study.

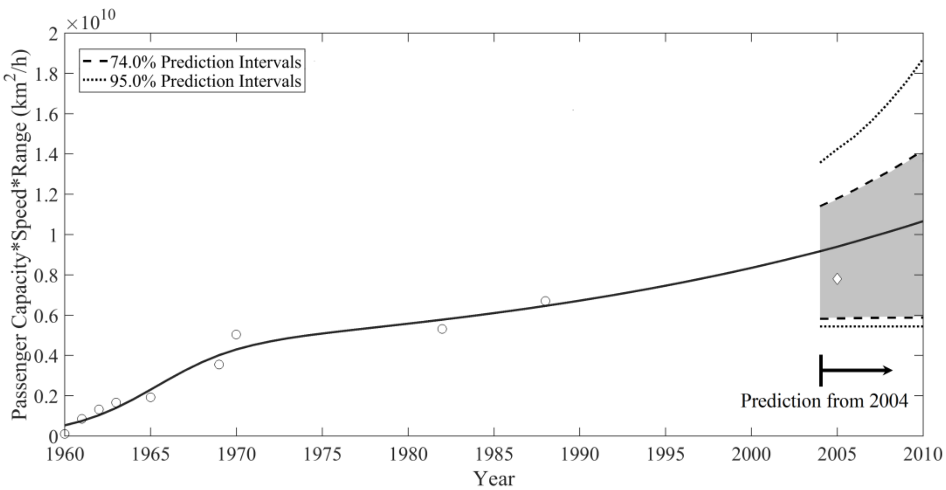

Figure 6.3 Passenger Aircraft Performance Evolution Prediction from 2004 to 2008

Of note, the lower limits of 74.0% prediction intervals are smaller than the latest passenger aircraft performance (the passenger aircraft performance at 1988) during 1960-2004. In this case, practitioners should substitute the latest system technology performance for the lower limits of the prediction intervals generated by the method because technology performance monotonically increases over time. Although some technology performances in future periods may not exceed the top technology performance in the past, practitioners usually ignore these performances and focus on the better performance that a technology may achieve in a future period.

The Lotka-Volterra ecosystem model allows practitioners to predict the performance of system and component technologies with improved accuracy. The ecosystem model also quantifies the interaction between the technologies [19]. For example, the parameter C_{01} in Eq. (6.18) captures the impact of the turbofan aero-engine on the passenger aircraft performance evolution; the parameter C_{10} in Eq. (6.19) reflects the impact of the passenger aircraft on the turbofan aero-engine performance evolution. Importantly, the method presented in this chapter provides the probability distribution of each parameter in a prediction model. For system models, practitioners could evaluate the interaction between the technologies from the probability distribution and make more informed R&D and outsourcing decisions. For example, empirical probability distributions for the eight parameters in Eqs. (6.20) - (6.23) can be constructed from $\boldsymbol{\varphi_j}$. The histograms of C_{01}/a_0 and C_{10}/a_1 are shown on Figure 6.4 and Figure 6.5. The results indicate that the development of turbofan aero-engine has considerable impact on the passenger aircraft evolution because the value of C_{01}/a_0 has a median of 1.44 and a probability of 80.8% that $C_{01}/a_0 > 0.1$. Meanwhile, the advancement of passenger aircraft performance has limited impact on the turbofan aero-engine evolution. The value of C_{10}/a_1 has a median of 0.337 and a probability of 54.7% that $C_{01}/a_0 > 0.1$. Thus, in order to improve the passenger aircraft performance, the first priority is to invest in the R&D of the turbofan aero-engine. However, the opposite is not true. Investment in the R&D of the passenger aircraft is unlikely to be an effective strategy to improve the performance of the turbofan aero-engine.

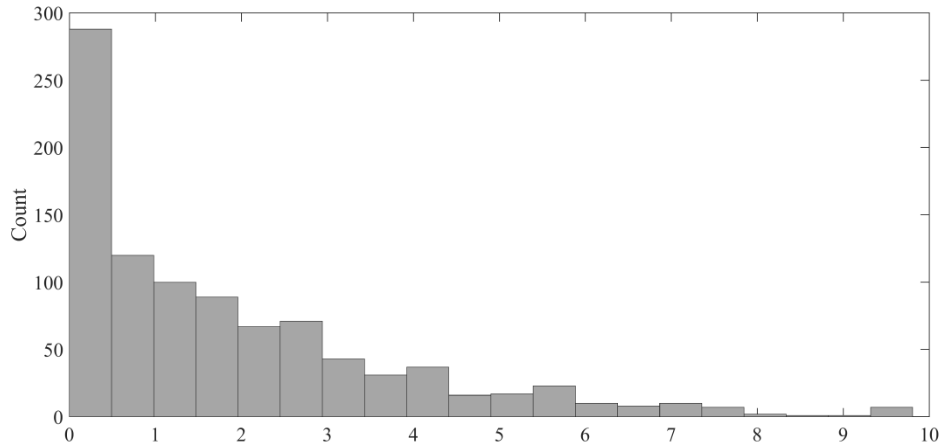

Figure 6.4 Histogram of C_{01}/a_0 Distribution in Eq. (6.20)

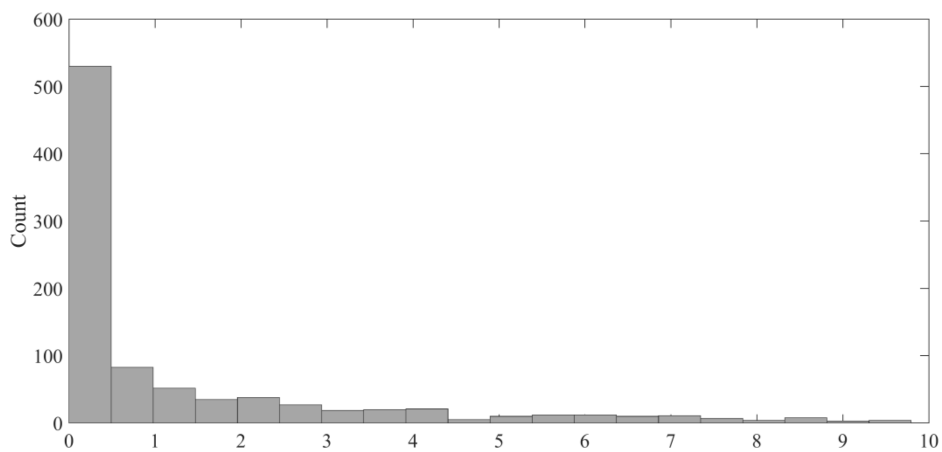

Figure 6.5 Histogram of C_{10}/a_1 distribution in Eq. (6.21)

This passenger aircraft case study models only the interaction between one system technology and one component technology. In the case of one system technology interacting with multiple component technologies, practitioners could use a system model associated with this method to identify the key component technologies that have significant impact on the system technology evolution (e.g., through the probability distributions of parameters C in the Lotka-Volterra ecosystem model [19]). Practitioners would consider developing and manufacturing these key component technologies in-house, or establish a partner relationship (e.g., through joint R&D, cross-shareholding, or exclusive supply) with the suppliers of these component technologies. Meanwhile, other component technologies that have limited impact on the system technology evolution may be considered for outsourcing [19].

6.5. Summary

This chapter introduces a general method that uses bootstrapping to generate prediction intervals for technology evolution prediction. The method can be applied to any technology evolution prediction model based on mathematical functions or differential equations involving time that predicts the incremental change in technology performance. Parameter uncertainty and data uncertainty are considered and their empirical probability distributions are established in the method. The appropriate confidence level α required to generate prediction intervals is determined using a holdout sample analysis rather than setting α=0.05 as is frequently done in previous research. In addition, this general method provides the probability distribution of each parameter in a prediction model. Four steps are outlined for practitioners to generate prediction intervals in technology evolution prediction in practice.

The prediction intervals generations of CPU and passenger aircraft are used as two case studies to illustrate these steps and validate the method. These case studies show that the prediction intervals generated by the method cover every actual data point in the holdout sample tests. These results validate the effectiveness of this method to assess future technology evolution uncertainty.

7. CONCLUSIONS AND FUTURE WORK*

This dissertation establishes a quantitative ecological based theory to model the technical performance changes of technologies and to predict and manipulate future technology performance. The quantitative ecological based theory consists of a Lotka-Volterra ecosystem model and a generic method for prediction intervals generation. The Lotka-Volterra ecosystem model and the prediction intervals generation method provide practically useful prediction intervals for the trend that technology evolution is expected to follow. The ecosystem model and the prediction intervals generation method also help practitioners to develop effective strategies to improve future technology performance. These prediction intervals and technology performance boosting strategies are important for practitioners (e.g., designers, R&D mangers, and policy makers) to establish stable product architecture, set reasonable R&D targets, and develop effective incentive policies.

As the last chapter of this dissertation, this chapter summarizes the contributions of this research. Future research directions in the areas of technology technical performance evolution, technology functional evolution, and technology architectural evolution are also discussed.

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7.1. Research Contributions

The general contribution of this research is to introduce an ecosystem approach in technology evolution. Prior research assumes that every technology evolves in isolation and the interaction between technologies is not considered. This research creates a quantitative ecological based theory to model the technical performance changes of system technology and its component technologies simultaneously. The quantitative ecological based theory considers the interaction between technologies in the relationships of symbiosis, commensalism, and amensalism. Moreover, the quantitative ecological based theory helps practitioners to assess future technology evolution uncertainty, to discern the causality of technology evolution, and to develop effective strategies to improve technology performance accordingly. The quantitative ecological based theory consists of a Lotka-Volterra ecosystem model and a generic method for prediction intervals generation. The Lotka-Volterra ecosystem model and the generic method for prediction intervals generation have several specific contributions, respectively.

The Lotka-Volterra ecosystem model comprises a set of differential equations that is extended from Lotka-Volterra equations in community ecology. Every parameter in the Lotka-Volterra ecosystem model is associated with its causal factors, such as R&D investment and technical difficulty. Importantly, the values of parameter C in the ecosystem model represent the symbiosis, commensalism, or amensalism relationship between system technology and its component technologies. The values and interpretations of parameter C help practitioners to identify the key component technologies in a system technology and make informed R&D investment and outsourcing decisions accordingly. The mathematical analysis of the Lotka-Volterra ecosystem model and the interpretation of other parameters (parameter a and b) in the ecosystem model offer practitioners guidelines on effective strategies to boost system technology performance. To apply the Lotka-Volterra ecosystem model in practical projects, a three-step procedure is developed for practitioners to predict and manipulate the performances of the system technology and its component technologies. Passenger aircraft fuel efficiency is used as a case study to illustrate the three steps procedure. The system technology (passenger aircraft fuel efficiency) interacts with three component technologies (aerodynamics, weight reduction, and aero-engine fuel efficiency) in the case study.

The generic method for prediction intervals generation helps practitioners to supplement point forecasts by computing interval forecasts. Practitioners rely on the interval forecasts to assess future technology evolution uncertainty and make contingency plans accordingly. The novelty of this method is in the application of bootstrapping to estimate parameter and data uncertainty for technology evolution prediction and in determining confidence level α from a holdout sample analysis. The method can be applied to any technology evolution prediction model based on mathematical functions or differential equations involving time that predicts the incremental change in technology performance. Parameter uncertainty and data uncertainty are considered in the method and the empirical probability distributions of these uncertainties are established. The appropriate confidence level α required to generate prediction intervals is determined using a holdout sample analysis rather than setting α=0.05 as is frequently done in previous research. In addition, the method provides the probability distribution of each parameter in a prediction model. Four steps are outlined for practitioners to generate prediction intervals in technology evolution prediction in practice. CPU and passenger aircraft prediction intervals generations are used as two case studies to illustrate these steps and validate the method.

7.2. Recommendations for Future Work

As stated in Chapter 1, research in technology evolution tracks the historical technical performance and the functional and architectural changes of existing technologies, and also studies how and why these changes occur and searches for patterns behind these evolutions. This dissertation focuses on the technical performance changes of technologies and creates a quantitative ecological based theory for technology technical performance evolution prediction and manipulation. This research has several limitations that offer opportunities for future research in technology technical performance evolution. Moreover, it is promising to study the functional and architectural evolution of various technologies in future work.

7.2.1. Technology Technical Performance Evolution

The historical technical performance data of three representative technologies (i.e., concrete skyscraper, passenger aircraft, and CPU) are used to illustrate the application of the quantitative ecological based theory in this dissertation. Researchers could apply the quantitative ecological based theory in various technologies (e.g., automobile [93] and computer [94]) in the future. Such application may derive compelling prediction results and help practitioners generate effective strategies to boost technology performance. To facilitate technology evolution research, technical performance evolution data of several system technologies and their component technologies are collected from various sources, and a database is established. The database currently includes 90 data sets that belong to 27 performance metric categories of 6 system technologies (i.e., passenger aircraft, orbital launch system, automobile, computer, refrigerator, and lamp) and their corresponding component technologies. Table E.1 in Appendix E lists the performance metric categories of this database[*]. One category sometimes contains several data sets. For example, the category of passenger aircraft speed contains two data sets including propeller aircraft speed and jet aircraft speed. Importantly, most of these data sets have not been used for technology evolution research so far.

Moreover, the Lotka-Volterra ecosystem model introduced in this dissertation only considers the interaction between system technology and its component technologies. The Lotka-Volterra ecosystem model may still oversimplify the technology ecosystem. Researchers may find appropriate mathematical formulas to build advanced technology evolution models through an ecosystem analogy in future work. These advanced technology evolution models may have more than two layers. Figure 7.1 shows a typical hierarchical technology ecosystem that includes a system layer, a

[*] Please contact the author (glzhang85@hotmail.com) to access these data sets.

component layer, and a fundamental layer. The system technology of interest represents the system layer. The system technology is realized through the integration of multiple hardware and software elements, commonly referred to as component technologies. These component technologies support the system technology but usually cannot fulfill end users' functional requirements separately. These component technologies establish a component layer in the ecosystem. Further, fundamental technologies enable the invention of these component technologies. Each component technology consists of several fundamental technologies that constitute the fundamental layer in the ecosystem. For example, a microprocessor is a key component technology of a smartphone system technology. Improvements in microprocessor performance enable enhanced smartphone performance. In turn, this performance enhancement of the microprocessor relies on the advancement of lithographic technology that belongs to the fundamental layer of the smartphone technology ecosystem.

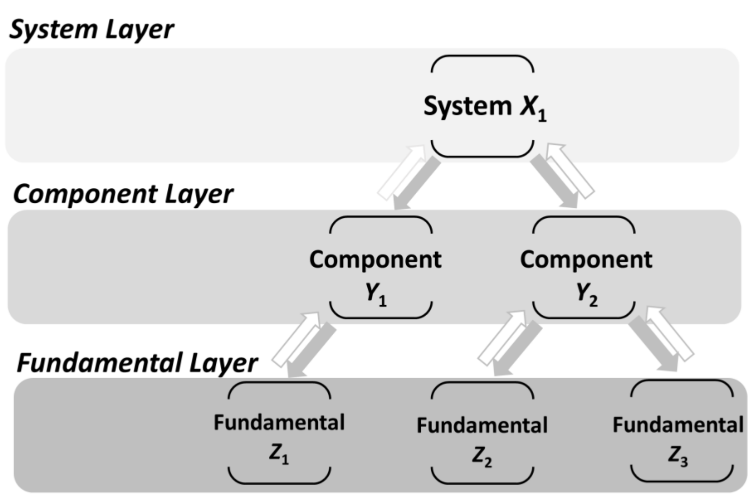

Figure 7.1 A Typical Hierarchical Technology Ecosystem

Importantly, such advanced ecosystem models cannot replace descriptive models. In many cases, descriptive models are still the best choice to model the technical performance changes of technologies. For example, practitioners may only have one historical data set available when they want to predict the future system or component technology performance. Sometimes, it may be legitimate to neglect the interactions in a technology ecosystem. In these cases, it is a challenging task for practitioners to select an appropriate model among many candidates. Methodologies have been developed to select appropriate models for technological forecasting that focus on business indicators, such as cost, price, production, sales revenue, and profit [5, 17]. Using the database mentioned in this section, future research could test whether these methodologies are effective in technology evolution with a focus on technical performance (e.g., speed, capacity, and energy efficiency) of technologies or could develop new model selection methodologies. There are also research opportunities to develop new descriptive models for technology evolution. The classical models in other areas (e.g., ecology, marketing, economics, and finance) may inspire new model development in technology technical performance evolution [23, 36, 82, 95].

7.2.2. Technology Functional Evolution

The functions that a system technology achieves usually change as the system technology evolves. For example, cell phones have undergone significant functional evolution since their commercial inception in the 1980s, as shown in Figure 7.2. The first commercial cell phone introduced wireless calling to consumers in 1983. Several years later, cell phones had text messaging capabilities and the integration of cameras allowed users to store photos on their devices. In 2007, cell phone users were able to access the mobile web and use their device for music streaming. GPS navigation technology was eventually integrated which allowed users to rely on their cell phones for directions rather than separate navigation devices or printed maps.

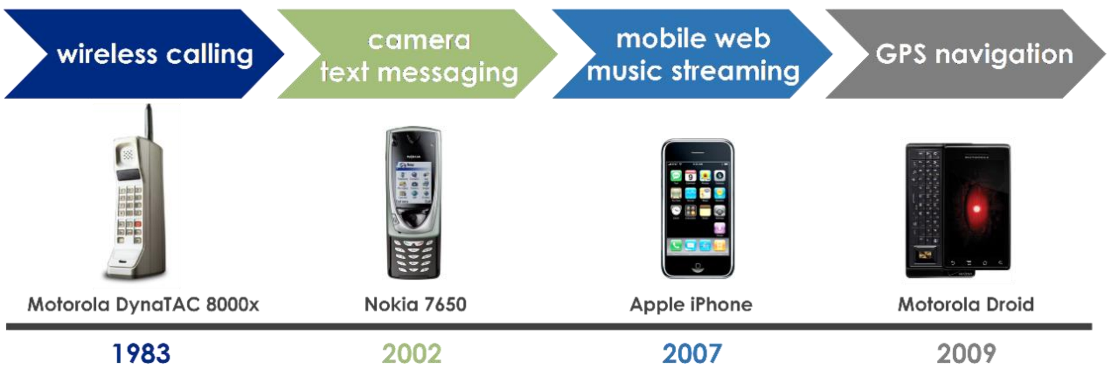

Figure 7.2 Cell Phone Functional Evolution

Understanding the functional evolution of system technologies can help designers establish system technology functional requirements at the beginning of the design process. It is risky to develop the functional requirements of a system technology through customer interviews and surveys only. The typical users for a current system technology may not be the early adopters of the new system technology [84]. For example, the early computers were designed for the military rather than household consumers. Moreover, revolutionary functional changes cannot be informed by any current users. For instance, nearly every function addition in Figure 7.2 was not expected by the previous cell phone users. Future research in technology functional evolution has potential to fill this gap. R&D managers and designers can decide when and how to add one or more new functions into a system technology based on the research results of technology functional evolution.

To my knowledge, the functional evolution of system technologies has received scant research attention in the past. Although functional models [96, 97] have been developed and applied in engineering design since 2000, there are no research efforts that study the evolution of a functional model as its corresponding system technology evolves. Future research can also study why the new function was added into the system technology at the time. Based on these research results, new methods that can predict future functional requirements of a system technology may be developed. In addition, the functional change of a system technology often alters the human-system interaction in the meantime. Users typically operate the system in a different way when a new function is added into the system. For example, text messaging capabilities in cell phones began in the 1990s but did not experience complete integration until the early 2000s. During the early days of text messaging development, designers and investors did not foresee this alternative form of communication competing with wireless calling. However, as text messaging technology advanced, cell phone users began using text messaging more frequently. By 2007, consumers on average used the text messaging function more than the wireless calling function [98]. Therefore, text messaging changed the way cell phone users communicate and operate their devices. Future research could also track the evolution of the activity diagram [15] or the action-function diagram [99] as a system technology evolves. The evolution of human-system interaction will guide designers for new system technology development.

7.2.3. Technology Architectural Evolution

Unlike technology functional evolution, technology architectural evolution has attracted research attention in recent years [12]. Such consideration is known as evolvable design [100]. The purpose of evolvable design is to reduce development time and cost for possible future system technologies through reusing current system technology architecture and associated processes (e.g., manufacturing) [101].

The guideline for evolvable design is clear. Designers should include a component technology into the system technology in a modular fashion if the component technology will evolve rapidly [12]. If the component technology is mature, designers need to include that component technology into the system technology in an integral way. Although the guideline is in place, the method for achieving this objective is challenging. Very few practical methodologies are available to achieve evolvable design in system architecture. The limited publications that develop evolvable design methodologies include the works from Tackett et al., Lim, and van Heerden et al. Tackett et al. introduced evolvability measures that designers can take into account in system architecture [102]. These evolvability measures are based on system excess and capacity. Lim developed a systematic approach for aircraft evolvable design [103]. The systematic approach builds on the premise that the commonality between current system architecture and possible future system architectures are specified. van Heerden et al.

developed a method that considers the evolution of airframe and subsystems at the same time [101]. Their method is able to predict commonality according to the scenario planning and technology roadmap of aircraft.

There are many remaining research questions in this research field. Current evolvable design methodologies rely on system development roadmaps, also called technology roadmaps [104], which includes possible system architectures in the future. To my knowledge, there is no general applicable method that can generate possible future system architectures based on the technical performance and functional evolution prediction of the technology. Moreover, designers can benefit from practical methodologies to achieve evolvable design in system architecture when possible future system architectures are not available. In addition, future research could study the historical architectures of system technologies. For example, researchers can observe how designers define module boundaries in different cell phones throughout history and discover system architectures that achieve evolvable design successfully. The lessons learned from history can improve designers' ability to architect new systems in the future.

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APPENDIX A

TECHNICAL PERFORMANCE DATA SETS USED IN CONCRETE SKYSCRAPER CASE STUDY

Appendix A includes two data sets that are used in the concrete skyscraper case study in Chapter 4.3. The historical data of concrete compressive strength is shown in Table A.1. The concrete compressive strength data is extracted from an ACI technical report [48]. The historical data of concrete skyscraper height is shown in Table A.2. The concrete skyscraper height data is collected from The Global Tall Building Database of the CTBUH (http://www.skyscrapercenter.com/).

Table A.1 Concrete Compressive Strength Evolution Data

Year	Compressive Strength (MPa)
1955	34
1965	52
1975	62
1995	138

Table A.2 Concrete Skyscraper Height Evolution Data

Year	Concrete Skyscraper Name	Concrete Skyscraper Height (m)
1950	Edificio Alas	141
1957	Torre de Madrid	142
1962	Sheraton New York	153
1964	Tour de la Bourse	190
1968	Lake Point Tower	196
1970	One Shell Plaza	218
1973	Carlton Centre	223
1976	Water Tower Place	262
1990	Two Prudential Plaza	303
1992	Central Plaza	374
1996	CITIC Plaza	390
2009	Trump International Hotel & Tower	423

APPENDIX B

TECHNICAL PERFORMANCE DATA SETS USED IN PASSENGER AIRCRAFT FUEL EFFICIENCY CASE STUDY

Appendix B includes four data sets that are used in the passenger aircraft fuel efficiency case study in Chapter 5.3. These data sets are collected from Air Pollutant Emission Inventory Guidebook [59], ICAO Aircraft Engine Emissions Databank [62], Wikipedia and multiple volumes of Jane's All the World's Aircraft.

Table B.1 Passenger Aircraft Fuel Efficiency Evolution Data

Aircraft Name	**First Flight Year**	**Passenger Capacity**	**Fuel Burn per 3,000 nmi (kg)**	**Fuel Efficiency (1000*person/kg)**
MD-10 series 10	1970	380	46360	8.20
Airbus A300 – B4	1974	345	36726	9.39
Boeing 757-200	1982	239	25014	9.55
Airbus A320	1987	195	16932	11.52
Airbus A330-300	1992	440	36333	12.11
Boeing 787-8	2009	381	28391	13.42
Boeing 737 MAX	2016	230	15890	14.47

Table B.2 Passenger Aircraft Wing Aspect Ratio Evolution Data

Aircraft Name	First Flight Year	Wing Aspect Ratio
MD-10 series 10	1970	6.8
Boeing 747-200	1971	6.96
MD-10 series 30&40	1972	7.5
Airbus A300 – B4	1974	7.71
Boeing 767-200	1981	7.89
Airbus A310	1982	8.8
Airbus A320	1987	9.4
Tupolev TU 204	1989	9.49
Airbus A340-200/300	1991	10
Airbus A330-300	1992	10.06
Boeing 737 MAX	2016	10.16

Table B.3 Passenger Aircraft Weight Reduction Evolution Data

Aircraft Name	First Flight Year	Payload (kg)	OEW (kg)	Payload/OEW
MD-10 series 10	1970	40600	111300	0.365
Boeing 747-200	1971	67360	170100	0.396
Airbus A300-B4	1974	37495	88505	0.424
Boeing 757-200	1982	25970	58440	0.444
Boeing 767-300ER	1988	43800	90011	0.487
Boeing 757-300	1998	31600	64340	0.491
Boeing 787-9	2013	63958	128850	0.496

OEW - Typical Airline Operating Empty Weight

Table B.4 Aero-Engine Fuel Efficiency Evolution Data

Manufacturer	Engine	Test Finish Year	Rated Output/Fuel LTO
Pratt & Whitney	JT3D-3B	1974	0.1718
Pratt & Whitney	JT9D-7F	1975	0.2620
GE Aircraft Engines	CF6-6D1A	1979	0.2727
GE Aircraft Engines	CF6-80A3	1983	0.2979
GE Aircraft Engines	CF6-80C2B6F	1985	0.3202
Pratt and Whitney	PW4077	1994	0.3403
GE	GE90-92B	1995	0.3466
GE	GE90-92B	1997	0.3506
GE	GE90-94B	2000	0.3598
GE	GE90-94B	2007	0.3667
GE Aviation	GEnx-1B70	2009	0.3766
Pratt & Whitney	PW1133G-JM	2014	0.3932

APPENDIX C

TECHNICAL PERFORMANCE DATA SET USED IN CPU CASE STUDY

Appendix C includes one data set that is used in CPU transistor count case study in Chapter 6.4.1. This data set is collected from Wikipedia (https://en.wikipedia.org/wiki/Transistor_count).

Table C.1 CPU Transistor Count Evolution Data

Processor	Date of Introduction	Transistor Count
Intel 4004	1971	2300
Intel 8008	1972	3500
TMS 1000	1974	8000
Zilog Z80	1976	8500
Intel 8086	1978	29000
Motorola 68000	1979	68000
Intel 80286	1982	134000
Motorola 68020	1984	190000
Intel 80386	1985	275000
TI Explorer's 32-bit Lisp machine chip	1987	553000
Intel 80486	1989	1180235
68040	1990	1200000
R4000	1991	1350000
Pentium	1993	3100000
Pentium Pro	1995	5500000
AMD K6	1997	8800000
Pentium II Mobile Dixon	1999	27400000
Pentium 4 Willamette	2000	42000000
Pentium III Tualatin	2001	45000000
Itanium 2 McKinley	2002	220000000
Itanium 2 Madison 6M	2003	410000000
Itanium 2 with 9 MB cache	2004	592000000
Dual-core Itanium 2	2006	1700000000
Six-core Xeon 7400	2008	1900000000
8-core Xeon Nehalem-EX	2010	2300000000
10-core Xeon Westmere-EX	2011	2600000000
61-core Xeon Phi	2012	5000000000
18-core Xeon Haswell-E5	2014	5560000000
32-core SPARC M7	2015	10000000000
32-core AMD Epyc	2017	19200000000

APPENDIX D

TECHNICAL PERFORMANCE DATA SETS USED IN PASSENGER AIRCRAFT OVERALL PERFORMANCE CASE STUDY

Appendix D includes two data sets that are used in passenger aircraft overall performance case study in Chapter 6.4.2. These data sets are collected from three data books [2, 91, 92], Wikipedia, and multiple volumes of Jane's All the World's Aircraft.

Table D.1 Passenger Aircraft Performance Evolution Data

Year	Name	Passenger Capacity	Speed (km/h)	Range (km)
1960	Tupolev Tu-124	56	970	2100
1961	Convair 990 Coronado	149	1000	5785
1962	Vickers VC10	151	933	9412
1963	Ilyushin IL-62	186	900	10000
1965	DC-8-Super 60 Series	259	895	8334
1969	Boeing 747-100	366	1136	8560
1970	Boeing 747-200	366	1136	12150
1982	Boeing 747-300	400	1136	11720
1988	Boeing 747-400	416	1136	14200
2005	Airbus A380-800	544	945	15200

Table D.2 Aero-engine Performance Evolution Data

Year	Aero-engine	Rated Output (lb)
1960	Pratt & Whitney TF33 (JT3D-1)	17000
1961	Pratt & Whitney JT3D-3	18000
1962	Pratt & Whitney JT3D-11	22000
1963	Bristol Siddeley BS.100-3	38000
1967	Pratt & Whitney JT9D-1	42000
1968	General Electric TF39-1	43300
1969	Pratt & Whitney JT9D-3A	48500
1972	General Electric CF6-50C	52500
1974	Pratt & Whitney JT9D-59A	53000
1983	General Electric CF6-80C2	62000
1991	Pratt & Whitney PW4073	77000
1995	Pratt & Whitney PW4084	86760
1996	Rolls-Royce Trent 890	92000
1998	Rolls-Royce Trent 800	114500
2002	General Electric GE90-115B	127900

APPENDIX E

PERFORMANCE METRIC CATEGORIES OF TECHNOLOGY EVOLUTION DATABASE

Table E.1 lists the performance metric categories of the technology evolution database mentioned in Chapter 7.2.1. Please contact the author (glzhang85@hotmail.com) to access these data sets.

Table E.1 Performance Metric Categories of 6 System Technologies

System Technology	Performance Metric	Data Set	Time Span
Passenger Aircraft	Aircraft Speed	2	1913-2017
	Aircraft Passenger Capacity	2	1913-2017
	Aircraft Range	2	1913-2017
	Aircraft Fuel Consumption	16	1960-2017
	Aircraft Emission	32	1960-2005
	Aircraft Wing Aspect Ratio	1	1969-2017
	Aircraft Payload	1	1970-2017
	Aircraft Typical Airline Operating Weight Empty	1	1970-2017
	Aero-engine Rated Output	1	1960-2018
	Aero-engine Bypass Ratio	1	1970-2018
	Aero-engine Pressure Ratio	1	1970-2018
	Aero-engine Emission	8	1970-2018
	Aero-engine Fuel Consumption	1	1970-2018
Orbital Launch System	Payload	3	1957-2018
Automobile	Automobile Speed	1	1894-2017
	Automobile Fuel Efficiency	3	1984-2019
Computer	CPU Transistor Count	1	1970-2018
	GPU Transistor Count	1	1997-2018
	FPGA Transistor Count	1	1997-2018
	Hard Disk Drive Areal Density	1	1955-2015
	Hard Disk Drive Moment	1	1950-2010
	Hard Disk Drive Grain Diameter	1	1997-2016
	Hard Disk Drive Head-medium Spacing	4	1990-2015
	Flash Areal Density	1	1990-2015
Refrigerator	Refrigerator Volume	1	1972-2010
	Refrigerator Energy Consumption	1	1972-2010
Lamp	Lamp Energy Efficiency	1	1880-1980