Research-Technology Management

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/urtm20

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To cite this article: Alexander Kott, Philip Perconti, & Nandi Leslie (2021) Anticipating the Next Technology, Research-Technology Management, 64:4, 48-56, DOI: 10.1080/08956308.2021.1922017

To link to this article: https://doi.org/10.1080/08956308.2021.1922017

Published online: 30 Jun 2021.

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This case study of armaments presents a generalizable model and shows how companies can create a quantitative view of future capabilities to make long-term R&D investment decisions.

Alexander Kott, Philip Perconti, and Nandi Leslie

OVERVIEW: Moore's Law has driven innovation in computing for decades by providing a future target and set of expectations that drives innovation. In this paper, we study whether a similar law might be developed and prove useful in different fields—for example, in armaments. We find that it can be, if we develop a composite measure that incorporates several dimensions of merit. We call this a figure of regularity (FoR). We use this case study of armaments to develop a generalizable model and find that it fits well with historical data. We then apply the model to estimate expected capabilities that will be required in 2050. A similar approach can be used in other industries to create a quantitative view of future capabilities, which companies can use to make long-term R&D investment decisions.

KEYWORDS: Technology trends, Long-range forecast, Small arms, Long term R&D, R&D investment

Trend-based approaches are valuable tools for technology analysis; they are important for making decisions about R&D investments, especially for long-term investments in early R&D (Kott and Perconti 2018). Exponential trends in technology growth have been observed for many decades and have been explained in part by action-reaction behaviors of market competitors (Seamans 1969). Nagy et al. (2011) describe exponential laws for 62 different technologies. Moore's Law is a well-known example (Moore 1965; Schaller 1997; Gelsinger 2006; Koomey et al. 2011)—so much so that exponential trends in technology are often called simply generalized Moore's laws. Although exponential models tend to be popular, researchers have also studied super-exponential models (Nagy et al. 2011; Sandberg 2013) and other alternatives to understand technology trends (Sood et al. 2012).

To identify a technology trend of a class of devices, one needs to formulate a measure—a quantity that describes the state of technology at a given time—that exhibits a trend over time (Martino 1993a; Coccia 2005). The literature on such trends commonly assumes a measure of performance (MoP) and plots the measure as a function of time—for example, the year when the technology first appeared. Often, such plots exhibit regularity in the sense that all MoP points fall close to a single curve depicting the growth of the MoP over time, despite representing different products from different manufacturers and different design approaches. In addition, the curve often offers intuitive appeal, being explainable and parsimonious in the underlying equation—for example, an exponential or super-exponential.

Our research focuses on those technologies—which we believe are common in many industries—for which the formulation of an MoP does not appear amenable to either an intuitive assumption or an approximate analytical model. This situation is common, especially with technologies

Alexander Kott is the Chief Scientist of the US Combat Capabilities Development Command Army Research Laboratory (ARL). He is also the Army Senior Research Scientist (ST) for Cyber Resilience, focusing on future technologies critical to the Army. Prior to becoming the Chief Scientist of ARL, he held positions of the Chief of the Network Science Division at ARL, and a program manager at the Defense Advanced Research Projects Agency (DARPA). He earned his PhD in mechanical engineering from the University of Pittsburgh. He has published more than 100 technical papers and has been the coauthor and editor of 12 books. alexander.kott1.civ@mail.mil

Philip Perconti is the US Deputy Assistant Secretary of the Army for Research and Technology and Army Chief Scientist. He is responsible for policy and oversight of the Army's Research and Technology program, which spans 16 laboratories and research, development, and engineering centers, and employs nearly 12,000 scientists and engineers. Previously, he was director of the US Army Research Laboratory (ARL). He holds a DSc in electrical and computer engineering degree from The George Washington University. He has published extensively on many aspects of military sensing, machine learning, and countermine/counter IED technology. He has authored and coauthored more than 50 publications. philip.perconti.civ@mail.mil

Nandi Leslie is an Engineering Fellow at Raytheon Technologies and has more than 20 years' experience as an applied mathematician. Her current research interests are machine learning, stochastic processes, data science, and cybersecurity. She has published more than 50 journal articles, conference papers, and technical reports on these topics. She received her BS in mathematics from Howard University. She earned her PhD in applied and computational mathematics from Princeton University. nandi.o.leslie@raytheon.com

DOI: 10.1080/08956308.2021.1922017

characterized by multiple competing, heterogeneous attributes, used in a broad range of conditions, and by users with diverse preferences.

As an example, we study the history of infantry small arms, a complex group of several technology families with a common function. Because the time frame we use for identifying the technology trend is over 800 years long, such weapons include bows, crossbows, harquebuses, muskets, rifles, repeating rifles, and assault rifles.

Although such technologies are the subject of in-depth engineering disciplines and literature—for example, McCoy (2009) and Carlucci and Jacobson (2018)—we are not aware of an established MoP of a kind that would be suitable for technology trend analysis. It is difficult to discern a property of small arms, or a combination of properties, that exhibits a consistent growth typical of technologies that comply with a Moore's law or its variations.

One metric might be muzzle kinetic energy (the kinetic energy of a projectile as it departs the weapon [Kott 2020]), but this property of small arms changed over time in a complex manner that is hardly consistent with an exponential, super-exponential, or other obvious regular trend (Figure 1). In such cases, it is desirable to find some other measure—let us call it a figure of regularity (FoR)—that is a function of a technology's relevant attributes and exhibits a regularity often found in the temporal evolution of an MoP.

Our notion of an FoR revisits the pioneering idea of Alexander and Nelson (1973), who found a useful correlation between the date of introduction of a product (in their case, jet engines) and a weighted sum of logarithms of the product's attributes. That sum served, in effect, as a substitute for a performance measure, as Martino (1993b) suggested. In this paper, we refer to this idea as Alexander and Nelson Regression (ANR).

We generalize the ANR approach and explore it empirically in a particularly challenging context that includes technologies spanning over 800 years that are functionally related but as technologically diverse as medieval bows and modern assault rifles. Further, we show the application of the resulting solution to common challenges of strategic technology management—for example, the forecasting of the long-term (30 years) increase in FoR and the assessment of whether certain research directions might support such an increase.

Trends in product attributes are not always obvious. For example, over the last 10 centuries, the kinetic energy of small-arms projectiles (arrows, bolts, balls, bullets) exhibited

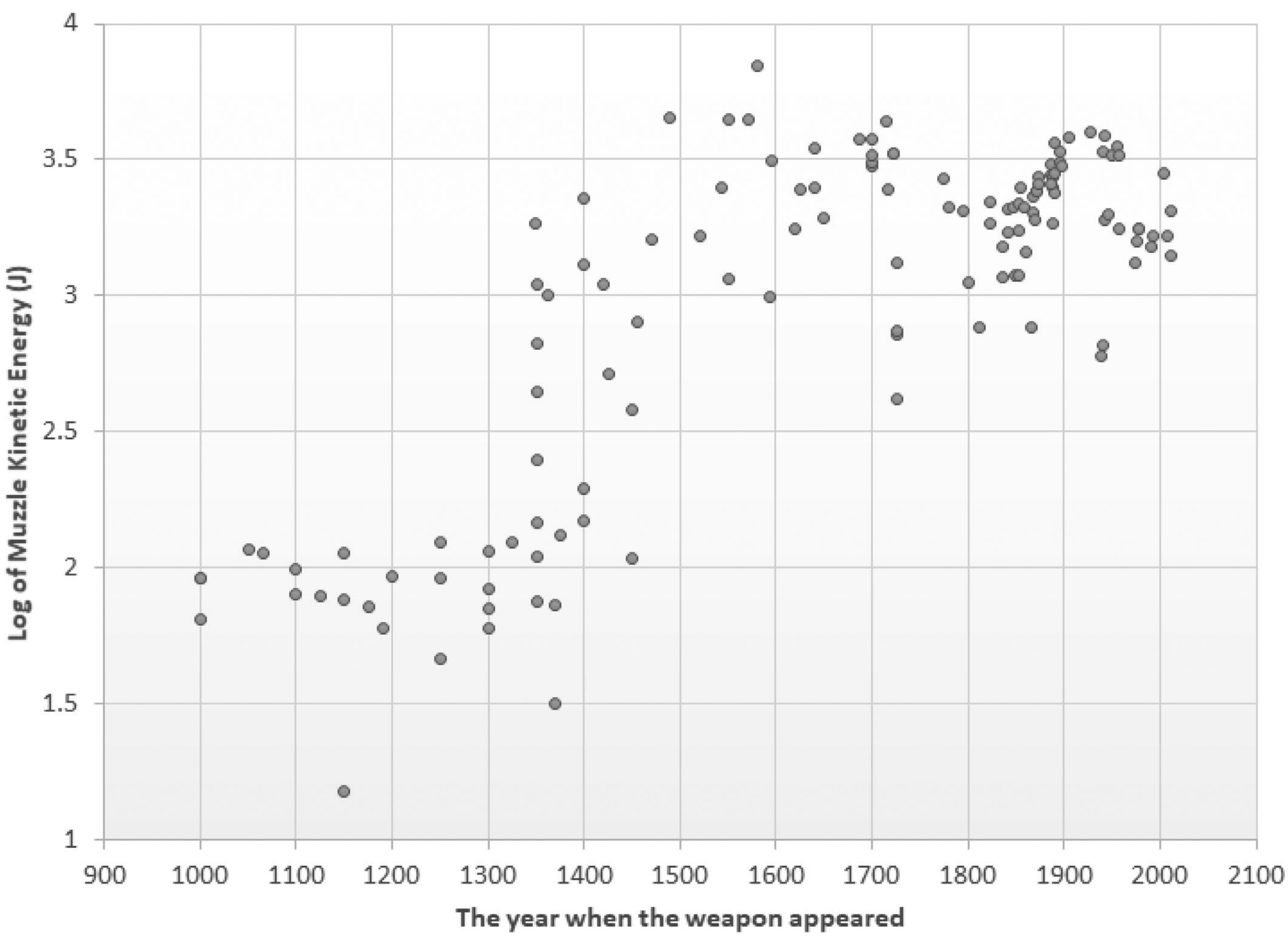


FIGURE 1. Muzzle kinetic energy of infantry small arms, 1200–2018

Many product areas evolve with multiple key attributes improving at different rates and with trade-offs among them.

a complex pattern of changes. Although an important characteristic of small arms, it does not seem to follow any exponential or super-exponential trend.

Case Study: Defining a Figure of Regularity for Small Arms

Alexander and Nelson (1973) were the first to note and study a correlation between the date of a technology introduction—for example, the year of appearance of a certain jet fighter or an engine—and a function that combines several attributes of technology. Like them, we find it convenient to use the general form of an FoR (see "Modeling the FoR"). Unlike them, however, we formulate a more general problem (Eq. 1) with the explicit recognition that different laws of temporal dynamics may need to be considered, and the search for the best fitting of the temporal dynamics should be conducted simultaneously with the search for the FoR model. Many product areas evolve with multiple key attributes improving at different rates and with trade-offs among them. This modeling approach may, therefore, have general applicability.

Extensive research exists on exponential and super-exponential models for technology trends, their empirical evidence, and theoretical explanations. Seamans (1969) proposes a mechanism—a sequence of competitive actions and reactions—that lead to an exponential trend. Martino (1993a) provides a comprehensive monograph covering many topics of technological forecasting, including exponential trends, and Martino (1993b) presents and compares approaches to forming composite measures of technologies. Nagy et al. (2013) demonstrates the broad applicability of exponential trends to multiple technologies. Super-exponential models—for example, Nagy et al. (2011) and Sandberg (2010)—may also apply. These works generally rely on an *a priori* assumption of a certain MoP, which may not be available in some technology domains. Instead, our approach uses empirical data to derive an FoR that behaves in a regular fashion like an MoP might.

The ANR approach is the pioneering idea of Alexander and Nelson (1973). It has been elaborated upon by Martino (1993a, 1993b) and more recently discussed in Inman, Anderson, and Harmon (2006). Our work differs by generalizing ANR to temporal growth models other than exponential. Because this paper explores a strategic, long-term analysis of technology, we should mention examples of long-range forecasts such as Albright (2002) or forecasts specifically about military technologies, such as Newman (1996), Vickers (1996), and O'Hanlon (2000). The accuracy of such forecasts can be quite high, about 70–80 percent (Kott and Perconti 2018).

Problem Definition and Solution Outline

First, we determine relevant attributes of a technology, vector x, and collect empirical data on how those attributes changed over time—that is, $x_i = x(t_i)$. This determination of the most important attributes, inevitably, is domain specific. For example, in our case study, we describe the variables that characterize small arms—projectile mass, maximum rate of fire, maximum effective range, and muzzle velocity—further in later sections. For other technologies, naturally, the set of attributes will be different, although the problem formulation would remain similar. Then we define a metric f (referred to as the FoR throughout our paper) to provide a single composite measure of a technology described as

$$f(x) = k\prod_{i=1}^{n} x_i^{\alpha_i}, \quad (1)$$

where $k > 0$ and $\alpha_i \geq 0$ for $i = 1,\ldots,n$ are constants derived from empirical data as we illustrate later.

Besides knowing how FoR comprises the technology attributes, we also need to determine how *f* changes with time—that is, the temporal dynamics of FoR. One common hypothesis is that the FoR increases exponentially with time t_i, which is the original ANR model. Later in this paper, for the sake of additional rigor, we present four additional models, which we consider reasonable examples of alternatives to this exponential trend. Coefficients in the model of temporal dynamics are also derived from empirical data.

Finally, to select among the models, we score the alternatives with one of the many statistics based on the maximized log likelihood of the data, the Bayesian Information Criterion (BIC). In addition, we explore other goodness-of-fit statistics, mean absolute percentage error (MAPE), and R^2.

The Solution Approach: The Case of Small-Arms Technologies

We explain our modeling and solution approach with a case study: the evolution of infantry small arms from the year 1200 to the year 2018.

Empirical Data

We begin by selecting relevant attributes of a technology and collecting empirical data on how these attributes changed over time. For this case study, we extracted the dataset of 120 points from Kott (2020) (Table 1).

Each data point can be described by $(t_1, x_1),\ldots,(t_M, x_M)$, where each $x_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$, and t_i is an unevenly spaced discrete time series representing the approximate year (from 1200 to 2018) in which the weapon was introduced or designed. Here, x_{i1} is the muzzle velocity or the projectile velocity at separation from the weapon—for example, the arrow velocity as it exits the bow or the bullet velocity when

Problem Formulation Details

The basic mathematical problem considers a real-valued vector x for the attributes of technology artifacts measured or observed at a set of times t_i, with time-series data $\{x(t_i), i = (1,\dots,M)\}$, for assessing attributes, where $x_i = x(t_i)$. In addition, we define a metric f (also referred to as the FoR throughout our paper) to provide a single csomposite measure of small-arms features modeled such that $f : \mathbb{R}^n \to \mathbb{R}$, described as

$$f(x) = k\prod_{i=1}^{n} x_i^{\alpha_i}, \tag{1}$$

where $k > 0$ and $\alpha_i \geq 0$ for $i = 1,\dots,n$ are constants.

We also seek to predict how f changes with time. We define a set of models (in our case study, a set of five) $F = \{\hat{f}^k(t_i); i = (1,\dots,M), k = (1,\dots,5)\}$, where $\hat{f}_i^k = \hat{f}^k(t_i)$ approximates f at each time step t_i, and $\hat{f}_i^k$ provide alternative models of the FoR over time.

One possible hypothesis used in our case study is the exponential model, $y_i^1 = \hat{f}^1(t_i) = \exp(\theta_2 + \theta_1 t_i)$, where $\theta = (\theta_1, \theta_2) \in \mathbb{R}^2$ are the fixed parameters of the model, $\ln(\hat{f}^1(t_i))$ is a linear regression model, and the maximum likelihood estimate of θ is given by $\hat{\theta}$. In the "Models of Temporal Dynamics" section, we define four additional models as alternatives to this exponential trend. For further details, see Kott, Perconti, and Leslie (2019).

For model selection, we score the alternatives with one of the many statistics based on the maximized log likelihood of the data, $L = \sum_{i=1}^{n} \ln(\Pr_{\hat{\theta}}(y_i^k))$, the Bayesian Information Criterion (BIC), which has a penalty applied to avoid overfitting

$$BIC = -2\ln(L) + 2k\ln(n), \tag{2}$$

where k is the number of free model parameters and n is the number of data points (Friedman, Hastie, and Tibshirani 2016). Under the Gaussian model, BIC for a model is estimated by

$$BIC = \frac{n}{\hat{\sigma}_e^2}\overline{err} + \frac{k}{n}\hat{\sigma}_e^2 \ln(n), \tag{3}$$

where $\hat{\sigma}_e^2$ is the variance and the error $\overline{err}$ is defined as $\overline{err} = \frac{1}{n-1}\sum_{i=1}^{n}(y_i^k - \hat{f}_i^k)^2$ (Friedman, Hastie, and Tibshirani 2016). In addition, we explore other goodness-of-fit statistics, mean absolute percentage error (MAPE), and R^2.

TABLE 1. Examples of data (full data set and notes on sources available in Kott, Perconti, and Leslie [2019])

Weapon	Year (CE)	Projectile mass (kg)	Max rate of fire (1/min)	Max effective range (m)	Muzzle velocity (m/s)
Longbow	1180	0.1023	5	75	47
Harquebus	1455	0.0278	1	50	240
Brown Bess musket	1722	0.0321	3	75	457
M27 assault rifle	2008	0.0041	700	550	900

it exits the muzzle. We denote the maximum effective range with x_{i2}—that is, the distance at which an infantryman can fire the weapon with an acceptable probability of hitting and disabling the targeted adversary. The mass of the projectile x_{i3} is another important feature in the data. Finally, the x_{i4} represents the maximum rate of fire as a feature in the data—that is, the maximum number of projectiles per minute that an infantryman can fire from the weapon.

Modeling the FoR

As mentioned earlier, we need to formulate a set of models F, where each model f_i describes how the technology's FoR depends on the attributes x_i. To constrain the scope of this research, we consider the single model in Eq. 1. The form of the model is similar to the one in Alexander and Nelson (1973) and Martino (1993b). Many product classes evolve with multiple key attributes improving at different rates and with trade-offs among them. This modeling approach may, therefore, have general applicability, even though here we illustrate it in the case of the particular product class infantry small arms.

Models of Temporal Dynamics

Our next step is to hypothesize the set of models F that describe how the technology's FoR changes with time. Each model $\hat{f}_i^k$ is parametrized with a set of parameters $\hat{\theta}_j^k$, where $i=1,\ldots,m$, $j=1,\ldots,p$, and $k=1,\ldots,5$.

Model A: Exponential Growth—This model $\hat{f}_i^1$ is the most common form of Moore's law (Nagy et al. 2013) and also underlies the original ANR. This form of temporal dynamics implies the hypothesis that the FoR increases by a constant fraction per unit of time such that

$$\hat{f}_i^1 = \exp(\theta_2 + \theta_1 t_i).$$

Model B: Quadratic Exponential—If the rate at which the FoR increases is a fraction that is not constant, but increases over time, then a parsimonious hypothesis would be that the fraction is a linear function of time. This leads us to suggest the model

$$\hat{f}_i^2 = \exp\,[\theta_2 \bullet (t_i - \theta_1)^2].$$

Model C: Cubic Exponential—Continuing the same logic, if the fraction is a quadratic function of time, then one other model could be

$$\hat{f}_i^3 = \exp\,[\theta_2 \bullet (t_i - \theta_1)^3].$$

Model D: Double Exponential—Following the hypothesis of Kurzweil (2001), we may assume that the fraction itself grows exponentially over time. Then a model could be

$$\hat{f}_i^4 = \exp\left[\theta_1 + \exp(\theta_2 + \theta_3 t_i)\right].$$

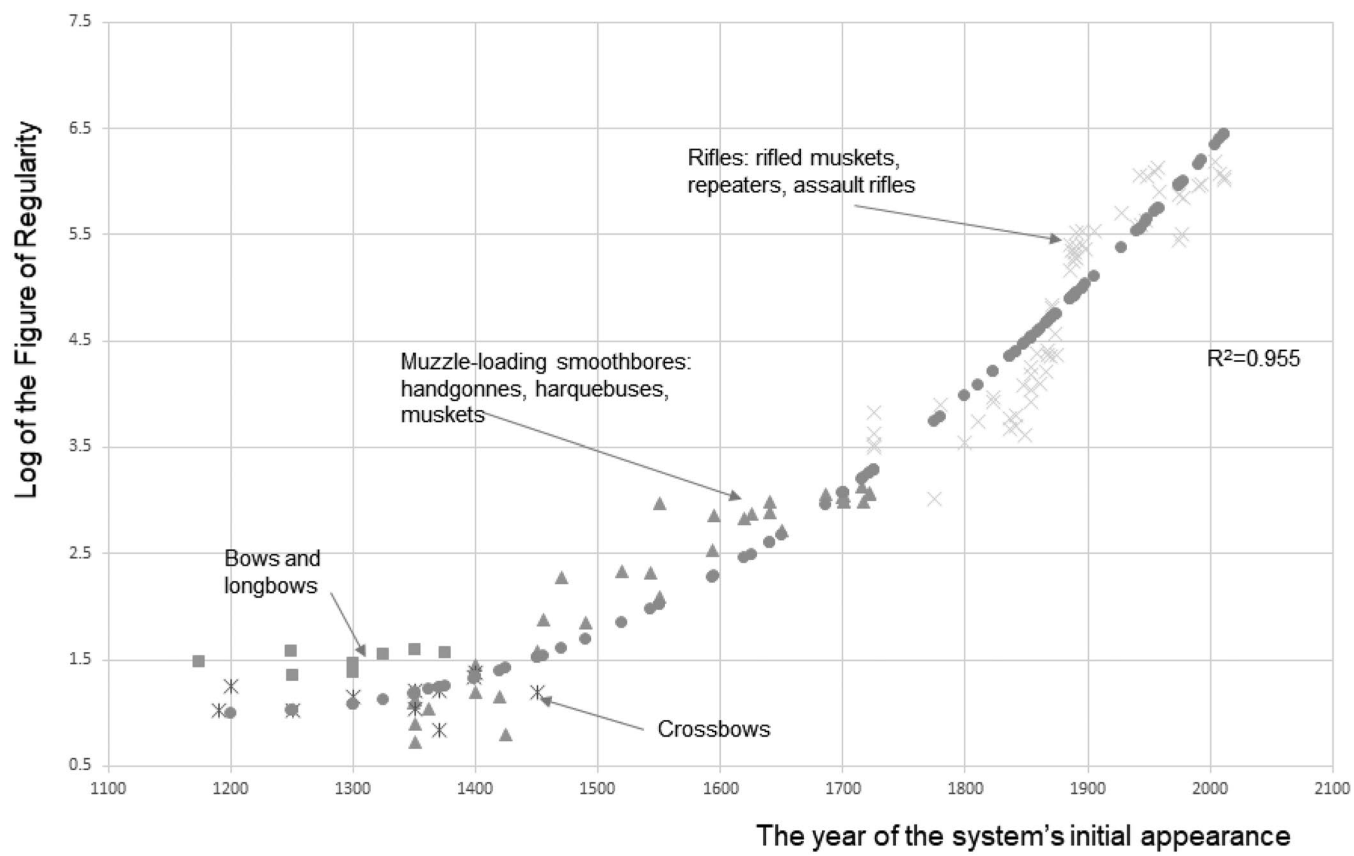
Model E: Piecewise Exponential—This model is inspired by in part by the piecewise model of Nagy et al. (2011) and in part by Lienhard (1979), who argued that a drastic change in the rate of technological dynamics occurred in the year 1832. The model is

$$\hat{f}_i^5 = \begin{cases} \exp(\theta_2 + \theta_1 t_i), if\ t_i \le 1832 \\ \exp(\theta_3 + \theta_4 t_i), if\ t_i > 1832 \end{cases}$$

where $\theta_4 > \theta_1$.

Fitting the Models

For each of the five models of temporal dynamics, we performed linear regression on the data, seeking the best least-squares fit between the values of the time-series model and the FoR model. This yields the values of



Note: Figure of Regularity fits well with the empirical data. The logarithm of the composite measure, log(FoR), is closely approximated by a quadratic function of time (circles) $1.0+8.27(10)^{-6}$ (Year-1200)^2. Here log(FoR) = –5.96 + 2.0logV + 2.35logD + 0.39logR + 0.61logM.

FIGURE 2. Figure of Regularity

TABLE 2. Summarized results of model fitting

		Models of Temporal Dynamics				
		A	B	C	D	E
FoR model parameters						
	α_1	2.00	2.00	2.00	2.00	2.00
	α_2	1.81	2.35	2.70	2.20	1.64
	α_3	0.50	0.61	0.61	0.56	0.33
	α_4	0.02	0.39	0.92	0.37	0.65
Goodness of fit						
	R^2	0.942	0.955	0.950	0.955	0.961
	BIC	−303	−326	−315	−318	−334
	MAPE	0.133	0.112	0.179	0.114	0.153

parameters θ_k for the FoR temporal dynamics model. To give the FoR function a domain-relevant interpretation, we aim to relate the FoR to the kinetic energy of the projectile and therefore scale all parameters so that $\alpha_1 = 2.0$ (more on the interpretation later). Furthermore, we scaled all parameters so that $\hat{f}_i^K = 1.0$ at $t_i = 1200$. This scaling does not affect the goodness of fit.

We illustrate the fit between the temporal evolution for Model B and the corresponding values of the FoR model (Figure 2). Note that the parameters of the FoR models may differ depending on the temporal evolution model assumed, as should be expected.

We summarize the results, together with characterization of fit (Table 2):

- Parameter α_1 was held constant at the value of 2.0 by appropriate rescaling. This serves to provide a domain-appropriate interpretation of the FoR, as discussed in the next section.
- Parameters $\alpha_2, \alpha_3, and\, \alpha_4$ differ for alternative temporal dynamics models, as expected.
- BICs differ between the models for temporal dynamics, in part because the models had different numbers of parameters.
- MAPE is the average of MAPE values computed for three centuries—that is, we computed the MAPE for the years 1800–1900, while using the FoR parameters fitted only to the data that would be available to a hypothetical forecaster in the year 1800, etc.

Discussion

In a general case, at this point in the analysis process, the analyst would select one of the models and proceed to explore the implications of the specific parameter values associated with that model. To illustrate, consider how we do this in our case of small arms. To make the discussion more domain-specific, we rename our four attributes in a more mnemonic fashion, specifically, we use V to refer to the muzzle velocity x_{i1}, D for the maximum effective range with x_{i2}, M for the mass of the projectile x_{i3}, and R for the maximum rate of fire x_{i4}.

Although the five temporal evolution models differ relatively little in the goodness of fit between the model and the empirical data, we assess the results associated with Model B as the best overall, in terms of parsimony of the model, BIC, R2, and MAPE. Model B is more parsimonious (in terms of the number of parameters in the model—two) than models D and E, and comparable to A and C. The R2 of Model B is better (higher) or comparable to all other models except Model E. The BIC (briefly, an estimate of the information lost in the model, which also accounts for undesirable overfitting) of Model B is better (lower) than all other models except Model E. And the MAPE (briefly, a measure of forecasting errors made by a model, as a percentage of the value being forecasted) of Model B is the best (lowest) than all other models.

Therefore, we focus on the FoR model parameters obtained in conjunction with model B.

With these parameters, the FoR model (see Eq. 1) becomes the following formula:

$$FoR = (1.1 * 10^{-6}) V^{2.0} D^{2.35} M^{-0.39} R^{0.39}, \tag{4}$$

where the velocity V is in meters per second, effective range D is in meters, bullet mass M is in kilograms, and rate of fire R is in number of rounds per minute.

The parameters of the temporal evolution model B, optimized jointly with those of the FoR model, are given in the following formula (here we elected to start the values of the FoR at 1.0 in the year 1200) If so we need to add one in Equation 5 and delete the comma at the end of Equation 6:

$$\log\left(f_i^2\right) = 1.0 + 8.27{*}10^{-6}\left(t_i - 1200\right)^2 \tag{5}$$

To give Eq. 4 a more intuitive interpretation, let us rewrite it as follows:

$$FoR = (2.2 * 10^{-6})(0.5 * MV^{2.0}) D^{2.35} M^{-0.39} R^{0.39}, \tag{6}$$

The second factor in the formula is simply the muzzle kinetic energy in joules. The remaining three factors can be considered as "corrections" for the effective range, mass of the projectiles, and rate of fire.

The results, obtained with ANR, fit well the empirical data over a great span of history and diversity of technologies and are consistent with domain-specific expectations of these technologies.

Specifically, the third factor in Eq. 6 can be interpreted as the correction for effective range. The exponent for this correction is 2.35, indicating a strong influence of the effective range on the FoR. An increased engagement range is a trend consistent throughout the history of warfare.

The fourth factor of Eq. 6 can be interpreted as the correction for the mass of the projectile. The exponent is negative, indicating that greater mass (other than the one already included in the kinetic energy) is undesirable as it limits the amount of ammunition the infantryman can carry and use in the battle.

Finally, the fifth factor of Eq. 6 can be interpreted as the correction for the maximum rate of fire. The exponent is positive, indicating, as expected, that a higher rate of fire is a positive contributor to the FoR.

Overall, these results, obtained with ANR, fit well the empirical data over a great span of history and diversity of technologies and are consistent with domain-specific expectations of these technologies. Although our example is specific to small arms, a similar process may apply to other classes of products.

Using the Models for Analysis and Forecasts

Here we consider how a technology analyst could use the FoR models. Let's continue to use the illustrative results we derived in the preceding sections.

First, the analyst may ask how much will a product (small arms in our particular example) improve by the year 2050. The temporal dynamics model, Eq. 5, gives us the value of *log*FoR = 6.97 in the year $t_m = 2050$. It is convenient here to use the logarithm of the FoR. The highest *log*FoR found in our data for currently known weapons is 6.18. This means that *log*FoR is likely to grow by about 0.80.

The next question: are the currently known directions of R&D in this product class (small arms) likely to raise *log*FoR by 0.80? To answer this question, consider the FoR model, Eq. 5, and begin with the term that refers to muzzle velocity. There are expectations (South 2020) that the Army near-future rifle will exhibit a higher muzzle velocity than current rifles. Assuming a plausible increase of 10 percent and using Eq. 5, this would yield an increase of $2.0 \cdot log(1.1) = 0.08$ in the value of *log*FoR.

The next variable term of Eq. 5 refers to the effective range of a weapon. Here we note developments toward computerization (with elements of artificial intelligence) of aiming and fire control of an infantryman weapon (Task and Purpose 2019). Assuming a 70 percent increase in D, *log*FoR would increase by an increment of $2.35 \cdot log(1.7) = 0.54$.

The third variable term of Eq. 5 refers to the projectile mass. Recent years have seen a move toward a heavier bullet, such as the 6.8mm round (Task and Purpose 2019), with the bullet mass perhaps 80 percent greater than in the current NATO-standard 5.56×45mm cartridge. Then *log*FoR would increase by an increment of $0.61 \cdot log(1.8) = 0.16$.

Finally, the fourth variable term of Eq. 5 has to do with the cyclic rate of fire. Based on the current literature, an increase in this rate is an unlikely contributor toward the growth of the FoR by the year 2050.

We can summarize that the currently known developments in small-arms technology might yield a total potential increment of *log*FoR about $0.08+0.54+0.16=0.78$. This is very close to the total increment of 0.80 we forecast based on the long-term trend.

Therefore, the analysis shows that 2050 expectations for the FoR are likely to be met with current technology trajectories, and offers support to the current directions of R&D efforts, with associated investments. What if this were not the case? What if the analyst were to determine that the currently planned R&D efforts are insufficient to meet the anticipated increase in *log*FoR? Clearly, this would be problematic—the analyst's organization may be heading towards a weak competitive position. The organization should reconsider the current R&D portfolio, explore opportunities in new, disruptive technology approaches, and assess risks and investments of alternative strategies.

A similar analysis may apply to other product classes, particularly where multiple key attributes improve at different rates over time, and exhibit complex and time-dependent trade-offs among them.

Recommendations

The lessons from our research lead us to offer several recommendations to technology analysts and R&D managers. One insight is that longer-term trend analysis may be beneficial, as it is likely to reveal the appropriate, more generally applicable attributes of the relevant technology families. It may also help avoid a bias toward particular design features or development directions that happen to dominate a shorter-term history.

On a related note, analysts should consider exploring a broader range of functionally similar families of systems, even if the underlying mechanisms are different. For example, the relevance of crossbows or smoothbore muskets may not be obvious to a study of trends for modern assault rifles. Nevertheless, broadening the historical period and the set of underlying technologies may yield insights that are more robust.

In presenting results to senior management, an analyst does not have to delve into the mathematics of the approach, but rather stress its similarity to Moore's Law—a study of how a characteristic of a product class (in our case, not a single characteristic but a composite one) consistently progresses over time. Although the model proposed in this paper—a generalization of ANR—is somewhat more complex, it does have the advantage of being conceptually related to the well-known Moore's Law. And while no guarantees can ever be given about the future, exponential and similar trends in technology growth have persisted for many decades and even centuries, in many technology classes.

Using approaches such as the one we discussed, technology analysts should attempt to validate their forecasts with a quantitative assessment of whether a portfolio of research efforts—actual or proposed—is likely to reach the forecasted improvements in an FoR or key performance attributes of the technology in question.

Conclusion

We empirically explore an approach—a generalization of ANR—to deriving a technology's FoR from the data of the technology's history. An FoR follows a regular temporal trend and as such is useful for technological analysis and strategic forecasting, particularly for those technologies for which a suitable measure of performance cannot be formulated. The small arms example we study in this paper is by no means unique. In many industries and many technology families, MoP is often complex, depends on multiple heterogeneous attributes, and is difficult to define with any certainty. The ANR approach helps derive—not assume or postulate—an FoR that substitutes for MoP. ANR is conceptually and computationally parsimonious, with results that are visually clear and explainable, an important aspect in communicating with technology management. Long-term technology trends—crucially important for managing early R&D investments—must not be seen as unpredictable mysteries. Paradoxically, taking a longer-term perspective can give clearer, quantitative insights in such trends.

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