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Forecasting Electric Vehicle Costs with Experience Curves

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ABSTRACT: The future costs of electric-drive vehicles, like those of any new technology, are uncertain. One method for forecasting cost reductions uses the concept of the 'experience' curve. Experience curves take into account scale economies, technological improvements in production processes, improvements in product design, and improved efficiency of workers and production management. Here we analyze the future manufacturing cost of a brushless permanent magnet electric vehicle drivetrain using experience curves and a Monte Carlo simulation technique. Our preliminary forecast is a drop in manufacturing cost from today's \$13,000 (with about 2,000 units of cumulative production) to a cost of about \$1200 when full scale economies and 'learning' have been realized. In an ongoing study at the University of California, Davis, experience curves are being integrated with a detailed vehicle cost model to develop more sophisticated cost forecasts for complete electric vehicles.

1. INTRODUCTION

The dramatic surge in interest in electric vehicles (EVs) during the past decade has resulted in much technological advancement, and the impending introduction of advanced, purpose-built, and high quality EVs. Dramatic improvements in EV technology are made possible by revolutionary advances in electrical and materials engineering, computer-aided manufacturing, microprocessor controls, and electrochemistry. Despite these advances, however, important questions remain regarding the costs of these new technologies and how these costs are likely to evolve over time. There remains uncertainty about market response, scale and success of research and development, materials costs, and other variables. Due to the nascent state of most EV technologies, there will be a significant level of uncertainty involved in forecasting future EV technology costs for some time.

Here we use a Monte Carlo experience curve framework to integrate uncertain variables into the technology cost analysis. This technique assures that uncertainty effects are not masked and results are not presented in a manner that conveys an artificial level of cost certainty. Following a brief review of learning and experience curve theory, we apply this framework to forecast the manufacturing costs of a brushless permanent magnet (BPM) EV drive system.

2. EXPERIENCE AND LEARNING CURVES

The concept of the learning curve has been applied to manufacturing settings since at least 1936, when T.P. Wright discovered an interesting relationship between the labor hours needed to manufacture an airframe and the total number of airframes built. Wright found that each time the total quantity of airframes produced doubled, the

labor hours required to assemble the airframe decreased by a stable percentage [1]. Since this early work, thousands of studies have been conducted on the nature and variability of experience curves in industries as diverse as electric power, microchips, Japanese beer, airframes, and automobiles (see [2-6] for examples). The findings are generally consistent: for any given firm there is often a uniform and unique rate of learning for each individual production process and, under certain conditions described below, for total product manufacturing cost.

However, because rates of learning vary across a given industry and between industries, it is difficult to forecast the manufacturing costs for a specific firm in an industry, especially in the absence of detailed and proprietary cost data. However, while the variation in observed rates of manufacturing cost improvement is distinct, it is also of relatively modest extent. This 'manageable' level of uncertainty allows the average industry-wide rate of cost improvement to be modeled with a probabilistic experience curve framework that provides for significant variation among firms.

2.1. Experience and Learning The experience curve describes the cost path of a manufactured product, beginning with the first and continuing to the 'nth' unit produced. This is a related concept to the 'learning curve,' but the learning curve describes only the improvement in the efficiency of the labor component of total manufacturing cost, whereas the experience curve applies to the entire value added (i.e., all costs other than materials costs). The concept of the experience curve helps to explain why new technologies and products maintain or increase their performance-to-cost ratios over the course of time. The progress of a firm or industry

along an experience curve for a new technology represents the steady decline in its inflation-corrected unit cost of manufacture. These cost reductions are due to four primary factors: scale economies, technological improvements in production processes, improvements in product design, and improved production worker and organizational efficiency.

While many different functional forms for the experience curve are possible and have been investigated, the most commonly used expression is the simple log-linear form shown in equation 1.

$$C_n = C_1 * V_n^{(\log \partial / \log 2)} \quad (1)$$

Where:

C_n = Cost of value added to nth unit

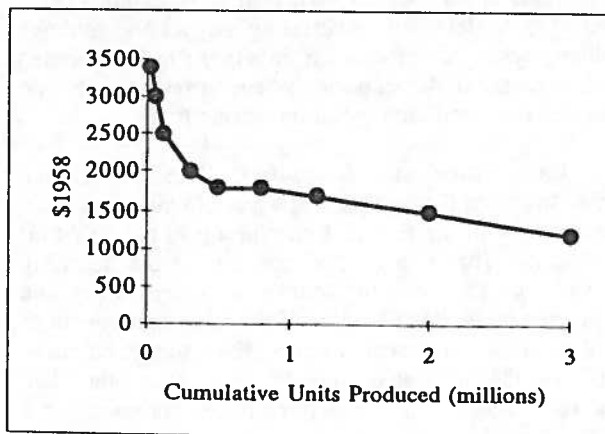
C_1 = Cost of value added to 1st unit

V_n = Cumulative production at nth unit

∂ = Experience curve slope

This relationship predicts that the constant dollar cost of adding value to a product falls by a constant percentage with each doubling of accumulated manufacturing experience. For example, an 80% experience curve would predict that the constant dollar cost of a product will fall by 20% with each doubling of cumulative production volume. Hence, cost reductions are relatively dramatic during the early stages of manufacture, as scale economies are captured and the production process is perfected, and then drop off as doublings in volume take longer to achieve.

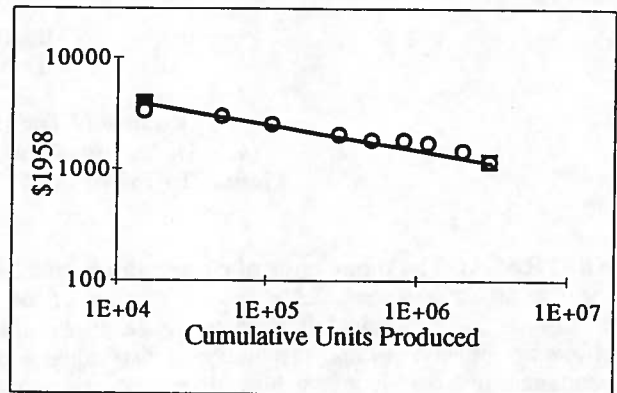
2.2. The Model-T Experience Curve One classic example where the data fit a simple log-linear experience curve model well is in the early history of the automobile industry. Figure 1 depicts the decline in the price of the Model T Ford from 1909 to 1918. During this period, the price fell from over \$3,000 (in \$1958) to under \$1,000 [7].



Source: [7]

Figure 1 Price Path of Model-T Ford (1909-1918)

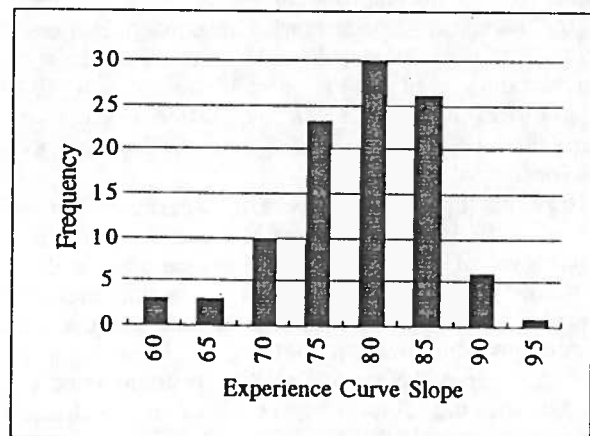
Figure 2 depicts the same data on a log-log scale, showing a good fit to the straight line of a log-linear experience curve with an 85% slope.



Source: [7]

Figure 2 Log-log Plot of Price Path of Model-T Ford

2.3. Experience Curve Slope Variation Due to important variations within and between industries, care must be taken in applying and interpreting experience curves. According to one study of about 100 curves, slopes do vary significantly across industries, as Figure 3 illustrates, but they are typically between 70 and 90% (implying cost reductions of 30 to 10% with each doubling of accumulated output). While in some cases a curve of a certain slope seems to describe the cost path for most firms in an industry -- a 70% curve for dynamic RAM chips is one example -- experience curve slopes more often vary within an industry [4].



Source: [4]

Figure 3 Variation in Experience Curve Slope

Many explanations are possible for these variations in experience curve slope. Variation between industries might be explained by such factors as the degree of product complexity, market structure, and industry maturity. Variation among individual firms in the same industry can occur for many reasons, including relative levels of vertical integration, corporate work ethics,

research and development expenditures, access to technical information, and so on. While considerable efforts has been directed toward understanding these variations, this remains an important area for further research.

Through the duration of a product's passage through one of its development stages (e.g. introduction, takeoff and growth, maturity, etc.), however, industry-wide aggregates of experience curve slopes appear to be relatively stable [5]. Confounding the data somewhat are the difficulties in applying experience curve analyses. For instance, the use of product price data as a proxy for actual manufacturing cost, due to the proprietary nature of cost data, introduces considerable inaccuracy since the relationship between manufacturing cost and retail price may not be stable. An additional complication with many studies is the difficulty in controlling for variations in product performance, durability, and quality over time. Experience curve analyses are most convincing, and probably have the most predictive power, where data are available for these variables.

In summary, experience curves are a function of complex processes and are not automatic or easily predicted. The use of a probabilistic type of analysis is required in order to handle the significant level of uncertainty involved.

3. COSTS OF BPM EV DRIVE SYSTEM

Consider the example of a 30-40 kW brushless permanent magnet (BPM) motor-controller system for a compact EV. Small numbers of these systems are currently in prototype to low volume production by a few U.S. and Japanese companies. While more attention is currently being focused on AC induction systems, BPM systems offer some advantages: higher efficiencies (due to lower rotor and excitation losses), better torque control, and lower weights and volumes than their asynchronous AC counterparts. Additionally, they are able to run at lower system voltages (typically about 180V versus 300V or so for AC systems) with similar levels of performance. These benefits are weighed against higher materials costs (primarily for the rare earth magnets used), and somewhat higher tooling costs in production [8]. In any case, we use the example of a BPM system to illustrate the use of experience curves and to provide some sense of the likely cost reductions for electric powertrains.

Today's BPM systems are hand-built prototypes and cost approximately \$13,000 to manufacture (author estimate, derived from current retail prices). As production increases, one would expect sharp drops in unit costs as fixed costs are spread over an increasing number of units, workers become more familiar with their operations and thus increasingly productive, astute engineers and managers identify ways in which to streamline and debug production processes, and new equipment is devised and built to satisfy the unique needs of producing the product.

Here we use a Monte Carlo experience curve framework to quantify the likely cost reductions of the

BPM EV drive system. The Monte Carlo simulations use random number generators to compute large numbers of input variables from probability distributions. In this case, critical and uncertain experience curve slope and materials cost variation parameters are characterized in this way. This technique allows uncertainty to be carried through the analysis, rather than masked through the choice of discrete parameters or indirectly addressed through the use of traditional sensitivity analysis.

In this analysis we consider two components, the motor and the motor controller, to illustrate how different assumptions for each component can be applied and allowed to interact within the experience curve framework. In principle, any number of components can be individually modeled and then aggregated into an overall experience curve for a complete product, such as a complete vehicle. In the Model T example, above, the curve presented is for the complete vehicle, but it can be imagined that behind that aggregate curve are many smaller curves for individual vehicle components.

Examining each component individually is a more empirically sound approach to creating an aggregate curve, but defining individual curves can still be problematic. It is not known, for instance, how much actual experience curve slopes vary within and between industries, nor how much learning and experience is shared between firms within (and perhaps even between) industries. The following example is based on reasonable assumptions that are supported by the present state of knowledge. There is room for refinement, as additional information becomes available on the actual costs associated with the BPM drive system in volume production and as a better understanding is obtained of the cost dynamics within different industries.

3.1. Materials Costs In applying an experience curve analysis, the first step is to obtain a good estimate of the materials cost of the product. This is particularly important where materials costs are a significant portion of the total cost, or where they are volatile; in either case they require consideration independent of the effects of the experience curve. It may be useful to examine inflation-corrected price trends for specific materials when the volatile portion of the materials cost of the product is driven predominantly by one or a few materials, as in the case of lead for a lead acid battery.

One must interpret price trends carefully when making forecasts, however, because of the volatility of many resource prices and because prices of non-renewable resources are not necessarily reliable indicators of resource scarcity. It is exceedingly difficult to determine the scarcity of a resource based on its inflation-corrected price, because other factors besides scarcity, such as market structure, interest rates, and regulation levels, all affect economic indicators. Furthermore, the assumption that we are moving linearly down the Ricardian 'ladder' of resource quality, from highest to lowest quality, is not always correct [9].

Based on these considerations, economist R.B. Norgaard concludes that economic indicators will only be

able to reflect scarcity under the impossible conditions that resource allocators are perfectly informed of the actual level of scarcity and of all future demand conditions [9]. We must once again humbly acknowledge the complexity, uncertainty, and 'unknowability' involved, and this leads us to incorporate another probabilistic variable: the percentile annual change in materials cost over time.

For this analysis, the current materials cost for the motor has been taken from an analysis of a Unique Mobility, Inc. BPM motor by Cuenca (1995) at the Argonne National Laboratory. The cost breakdown, by motor component, is presented in Table 1.

Table 1 Materials Costs for 32 kW BPM Motor

Component	Cost (\$1995)
Stator core	68
Stator winding	22
Housing	50
Rotor	26
Magnets	120
Attachment band	6
Shaft	3
Miscellaneous	30
Total	325

Source: [10]

An exact cost for the materials needed to manufacture the controller is not readily available, but it can be approximated by noting that controller costs are largely driven by the costs of insulated gate bipolar transistors (IGBTs), currently sold at prices of \$75-100. The controller for a 30-40kW motor would require 4 or 5 such devices, and adding the costs of a microprocessor and other components leads us to an approximate controller materials cost of \$700. We must remember that the correct cost of materials to consider is the expenditures made by the OEM -- the final producer or assembler of the product. Thus, the materials costs for the controller include the cost to the OEM of finished IGBTs, and not the costs of raw silicon and copper wire.

As a second probabilistic variable, in order to allow materials costs to vary over time, we have introduced an annual variation in each component's materials cost. In accounting for the variation in the materials cost for the BPM motor, we note that a significant portion (about 37%) of the materials cost is the cost of lightweight and powerful rare earth magnet material. The use of these materials (typically of the samarium-cobalt or neodymium iron boron variety) has been enabled by relatively recent breakthroughs in magnet materials, and the current high cost might therefore be expected to drop somewhat. The other components are primarily common metals, which have shown a slow decline in inflation corrected price over the last 100 years [11], but which may or may not continue along the historical trend. In light of these factors, we choose a relatively conservative estimate of minus-one percent (-1%) for an

average annual change in the cost of the motor materials, with a standard deviation of 2.

For the motor controller, we again note that BPM controller costs are largely driven by IGBT costs. The cost of these devices is following its own experience curve, and there are other complex issues involved such as the potential for technological breakthroughs in the materials and engineering needed to control the motor. These 'breakthrough' types of impacts are generally more likely for complex electronic components than they are for simple manufactured ones. As one example, at a certain level of production volume, it becomes economical to design an application-specific integrated circuit to replace the assemblage of individual transistors and other components that had previously been the most economical solution. This substitution allows all future units to experience lower materials costs, and it synergistically reduces the weight and cooling load of the entire controller unit.

Thus, there are 'break points' in materials costs where certain technologies become economical. Already, Toshiba America Electronic Components has reported the development of a new, high-power IGBT design with ratings as high as 2500V and 1000A [12]. In the future, the use of one of these new 'press-pack' IGBTs may replace the current costly practice of stringing together several lower power IGBTs in parallel. Although not all potential breakthroughs are realized, the possibility of significant future materials cost savings does exist. Given the opportunities for achieving materials cost reductions in the controller unit, we choose a mean annual cost variation of minus three percent (-3%), with a standard deviation of 2.

In order to account for these annual fluctuations in materials cost within the experience curve framework, which itself is measured in units of cumulative production and not calendar year, we need to assume a rough market penetration scenario so that we know how many years elapse between successive levels of accumulated manufacturing experience. Due to the logarithmic nature of the experience curve relationship, increasingly more years of production are required to achieve each successive level of cumulative production. For example, under the production assumptions used here, reaching cumulative production volume levels of ten thousand, one hundred thousand, one million, and ten million BPM systems requires two, four, nine, and twenty years, respectively, from an initial production level of 2,000 units. It is important to note, however, that the experience curve framework can be fitted to any projection of future production, and it can be fine tuned as production actually occurs.

3.2. Experience Curve Assumptions In order to apply the experience curve framework, it is necessary to assess the cumulative production levels for the motor and controller, and the ratio in which they are expected to be produced in the future. Establishing the current cumulative production level upon which to base an analysis can be accomplished through various means,

such as analyzing industrial census reports or interviewing industry experts. The sensitivity of the experience curve analysis to this parameter diminishes with higher levels of accumulated production, so assessing it carefully is particularly important in cases where near-term costs are of interest.

For this example, we have assumed that approximately 4,000 BPM motors and 2,000 motor controllers have been produced to date, in the 30-40 kW size range. These assumptions are based partly on serial numbers of a BPM motor and controller system recently purchased by UC Davis, and the knowledge that only a few companies worldwide are producing BPM drivetrains suitable for use in EVs. Furthermore, we assume that one of every two BPM motors that are to be produced in the 30-40 kW size range will be used in EV applications, and that the future production ratio of motors to controllers is thus 2:1.

Next, the experience curve exponent itself must be specified for each component. Rather than choosing a single value for this critical parameter, a Monte Carlo method has been employed whereby a mean and standard deviation are chosen for the slope, which is assumed to have a normal distribution among firms in the industry. Random samples are then drawn from this distribution. For this analysis, the motor mean slope and standard deviation were assumed to be 80% and 1.5, and the controller mean slope and standard deviation were assumed to be 75% and 1.7. For each component, 1,000 random samples were chosen from the probability distribution, costs were calculated at each of several future cumulative production levels, and the values were then combined into 1,000 composite cost figures for each cumulative production level. Table 2 summarizes the parameters chosen for this example.

Table 2 Parameters Used for Monte Carlo Simulation

Parameter	Motor	Controller
Mean curve slope	80%	75%
Std. deviation curve slope	1.5	1.7
Time 0 cumul. prod. (units)	4,000	2,000
Production factor	2x	1x
Mean ann. mats. cost var.	-1%	-3%
Std. dev. mats. cost var.	2.0	2.0

3.2. Results of Monte Carlo Simulation

The results of the Monte Carlo experience curve simulation can be depicted in both graphical and tabular form. Table 3 presents the results in terms of mean and standard deviation of motor/controller system cost for each of several future cumulative production levels. These results show that BPM system costs have the potential to drop significantly, perhaps even to as little as \$1200 with a high level of accumulated production

volume. The results also show that the level of uncertainty in costs diminishes over time as well.

Table 3 BPM Drive System Cost Results

System Cum. Prod. Level	Mean of Cost (\$1995)	Std. Deviation of Cost
2,000	12,960	n.a.
10,000	7,416	1,451
100,000	3,651	772
1,000,000	2,043	427
10,000,000	1,175	365

The graphical depiction of the cost results is perhaps more useful because it allows one to see the evolution of the probabilistic spread in costs as production accumulates. Figures 4 and 5 depict this evolution. Note in Figure 4 that the range of costs within one standard deviation of the mean narrows as higher levels of cumulative production are reached. Similarly, in Figure 5 the frequencies of cost estimates near the mean cost value increase with each successive production level.

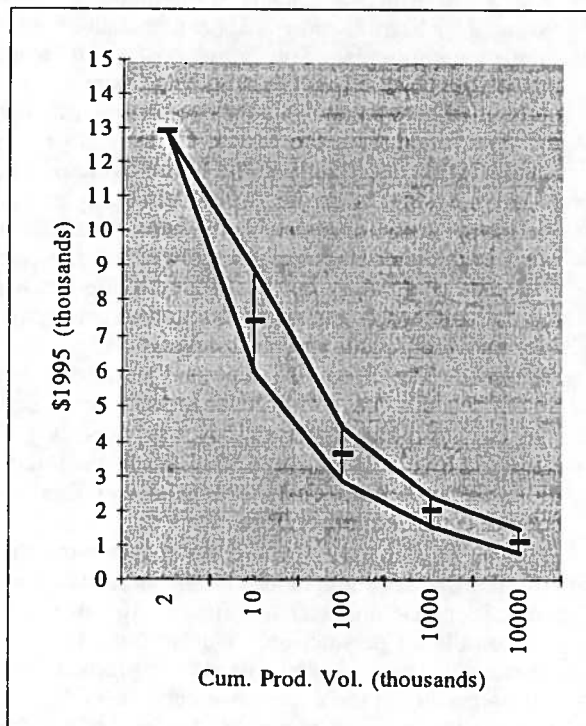


Figure 4 Probabilistic Experience Curve for a 30-40 kW BPM EV Drive System

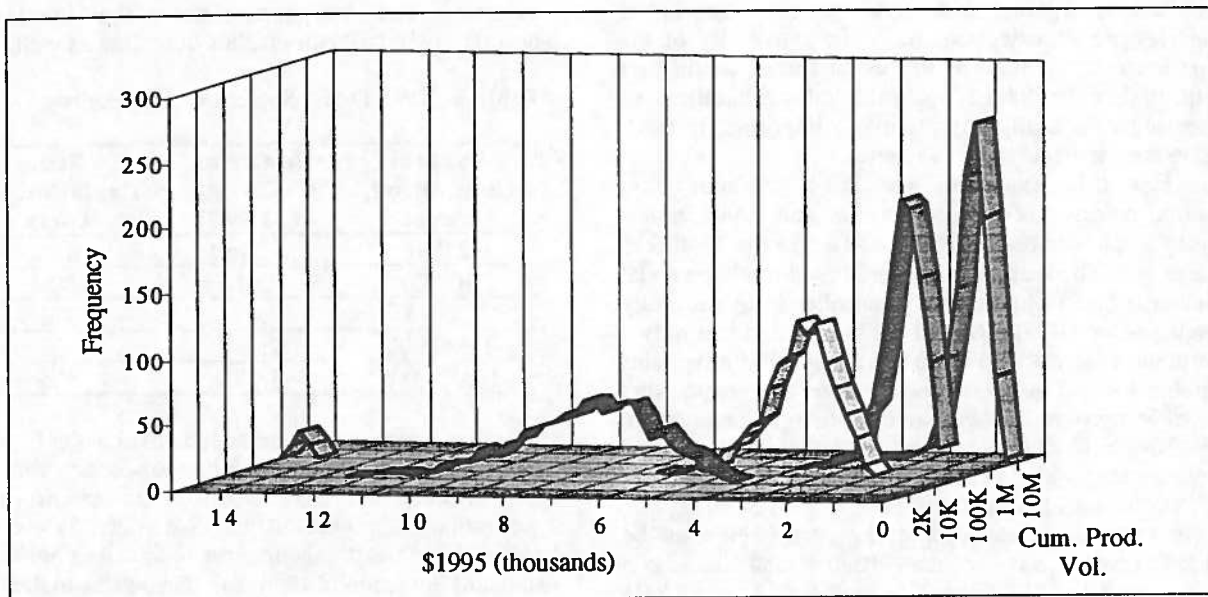


Figure 5 Probabilistic Cost Forecast for a 30-40 kW BPM EV Drive System

4. CONCLUSIONS

Costs will drop dramatically as production scales up and companies become more adept at manufacturing EVs and their components. But some costs will drop more rapidly and with more certainty than others.

We presented here an analysis for one particular drive system. We found with the Monte Carlo experience curve analysis that uncertainty in the future cost path for a BPM drive system is greatest relatively early in the 'take-off and growth' phase and then diminishes somewhat in the later stages of the growth phase. The range in cost is greatest before production becomes 'learned-out' and when annual production volumes are variable, and then costs tend to converge toward the materials cost. The effect of the annual materials cost variation offsets this cost convergence to some degree, as more years elapse and materials costs slowly diverge from initial levels, but since the assumed mean variations in materials costs are relatively slight, convergence is the dominant effect.

While at first it may seem counter-intuitive that drivetrain costs are more certain farther in the future, consider that this scenario runs to 10 million units of accumulated production. Unless the BPM EV drive system becomes widely used, the product would not progress down the experience curve very fast. Only if production ramped up rapidly to a level of 500,000 units per year would 10 million units be produced in twenty years. This level of annual production, and the passage of so much time, would virtually assure that the system be manufactured at low cost. However, it should be noted that it may be difficult to predict when each successive level of cumulative production volume will be achieved, due to uncertainties in the market response to EVs, the number of vehicles that automakers will actually produce, and the degree to which BPM systems share the market with AC induction systems.

In the near term, volumes of production are relatively uncertain, and therefore costs will be uncertain as well. The cost difference between producing a batch of 1,000 or 100,000 systems today would be great due to differences in economies of scale, the level of factory automation, and so on. The experience curve framework illustrated here can thus depict a range of cost variation, but because of uncertain production volumes, and the probabilistic style of this analysis, it cannot precisely forecast a discrete cost at any particular point.

Because costs to a particular firm for developing and commercializing a new product are related to the particular expertise, resources, and organization of that firm, and to their business plan, one cannot easily use experience curves to forecast firm-specific costs of new technologies and products. But experience curves do have great value for strategic planning and policy analysis. Experience curves are an appropriate and powerful tool for forecasting industry-wide cost reductions as a function of time, cumulative industry output, and other aggregate variables. Company planners can use experience curves to explore likely and possible cost futures for different technologies, and likely industry cost functions for those technologies. Policy analysts can use experience curves to craft appropriate R&D strategies and effective policies to nurture potentially attractive technologies. At UC Davis, we are developing detailed cost models for a range of electric-drive technologies (from pure battery-powered electric vehicles to fuel cell hybrids). The output from these efforts will be sophisticated forecasts of future electric vehicle costs and a set of forecasting tools that can be refined as more experience and information is acquired.

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