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# An Infant Mortality and Long-Term Failure Rate Model for Electronic Equipment

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This paper describes the reliability model used by system designers at AT&T Bell Laboratories to predict component and equipment reliability. A decreasing-failure-rate Weibull model describes the high incidence of early-life failures, or infant mortality. This is combined with the constant-failure-rate (exponential) model traditionally and widely used for the long term. Formal modeling of both early-life and long-term reliability is needed to manage the development and manufacture of reliable products. The effects of temperature and electrical stress on failure rate are taken into account. A model for the effect of integrated circuit dynamic burn-in on reliability is also described.

## I. INTRODUCTION

*Reliability* describes the ability of a system to continue to perform its required function to the satisfaction of the user. Predicting the reliability of a new electronic system is an important part of the system design process. If the design will not meet reliability objectives, it must be improved by using more reliable components, adding system redundancy (tolerance to component failures), or performing burn-in or other screening.

The ability to satisfy customers is the most critical factor for a viable product. But reliability has other economic impacts as well. Repair costs, both during a warranty period and beyond, depend on

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the reliability. Reliability also affects the numbers of spares needed in the field to accommodate expected repair needs.

System reliability depends on the reliability of its components in their application environment. Unfortunately, it is impossible to predict the operating life for any individual electronic component. It is, however, possible to treat large populations of such components statistically with acceptable results. For example, the number of failures among a large population of components and each component's probability of survival or failure can be estimated. The statistical behavior of the components then determines the statistical behavior of the entire system. In this way the reliability of an electronic system can be estimated.

This paper describes the techniques and models currently used by system designers at AT&T Bell Laboratories to predict the failure probabilities of electronic components. There are other widely used reliability prediction models. Most are based on a simple constant-failure-rate model. One such widely used method is described in Ref. 1, MIL-HDBK-217D. For many purposes, these models are inadequate. Early-life reliability predictions provide information needed to balance requirements, design, screening, and field support activities for commercial products. By not reflecting the relatively high failure rates associated with early equipment life, the constant-failure-rate models do not provide the information needed to manage these early-life reliability issues.

The model described here is more realistic. It has elements in common with the conceptual "bathtub curve" reliability model. Under this model, a relatively large number of defects can be expected early in equipment life. This is referred to as "infant mortality". The likelihood of failure then falls dramatically to a low, constant level called long-term reliability. This low failure rate is the behavior expected of mature products. Eventually, components can degrade and the incidence of failure increases during "wear-out". The model presented here reflects both infant mortality and long-term behavior. Integrated circuit reliability dominates the reliability of modern electronic equipment. Because properly designed and manufactured silicon integrated circuits do not experience "wear-out" behavior, it is not modeled.

To go along with the model, we also have tabulated, elsewhere, reliability estimates for a wide variety of components. These estimates are based on AT&T Bell Laboratories data whenever possible. Otherwise, estimates are obtained from MIL-HDBK-217D, the *de facto* industry standard.

As we already mentioned, predictions of reliability are useful in estimating its impact on both customer satisfaction and economic viability. Both the early-life and long-term aspects of reliability are important and need to be addressed. The need to address long-term reliability is well known. In addition, formal modeling of early-life reliability provides information essential to managing the design, manufacture, reliability testing, and screening programs needed to assure that initial product reliability will satisfy customers.

## II. INFANT MORTALITY (SHORT-TERM RELIABILITY)

Infant mortality is characterized by an initially high, but rapidly decreasing, failure rate. The early failures come from a small fraction of the components considered to be weak. These weak units contain defects (usually manufacturing defects) that are not immediately fatal but that will cause failure in a relatively short time. Examples of these defects are poor internal electrical connections, the presence of contaminants, and insulating layers that are too thin.

Failures due to infant mortality can appear in two different ways. In one, failures occur during operation after some time. These are called "device operating failures" or DOFs. The failures are time dependent. The infant mortality part of the reliability model describes their occurrence.

In addition to the DOFs, initial failures are found at various first tests, including first circuit pack tests, first system test, or when the system is first tested after shipment to the field. These failures are called "dead on arrivals" or DOAs. They cannot be related to operating time. A component can test as satisfactory, be assembled into equipment, and then fail to work. No operation has occurred. Instead, these failures may be thought of as event dependent rather than time dependent. Somehow, handling during equipment manufacture has induced failure of the weak component. DOAs are not reflected in the reliability model. Although their existence is well recognized, we do not know how to quantitatively predict their occurrence.

During infant mortality, components exhibit a "high incidence of failure", high relative to later life (the long term). This should be kept in perspective. Only a very small fraction of components actually fail (typically much less than one percent). See the discussion in Section VII on calculating numbers of failures for more details.

## III. LONG-TERM RELIABILITY

Infant mortality failures are mostly caused by defects. Even in the long term, some failures continue to appear due to manufacturing defects; however, other failures occur due to more fundamental component properties. The important aspect, though, is that the failure rate is low and relatively constant in the long term. This is the behavior observed in large populations of mature components. Failures occur at a fairly constant rate within the entire population; therefore, it can be treated as a homogeneous population of components having constant failure rates.

## IV. RELIABILITY DEFINITIONS

Before looking at the specific reliability model, we should review some basic reliability definitions. Reliability models are based on the probabilities of survival or failure of a component or system. These probabilities can be described by one of several common functions.[2] Assume that a component starts to operate at time $t = 0$. Then $F(t)$ represents the probability that the component fails at or before time $t$. This is called a *cumulative distribution function* and it has the properties

$$\begin{aligned} &F(t) = 0 && \text{for} \quad t < 0, \\ &0 \le F(t) \le F(t') && \text{for} \quad 0 \le t \le t', \\ &F(t) \to 1 && \text{for} \quad t \to \infty. \end{aligned}$$

The *reliability function,* $R(t)$, gives the probability of surviving past time $t$. It is related to $F(t)$:

$$R(t) = 1 - F(t).$$

This function is the source of the usual definition of reliability as "the probability of surviving". The derivative of $F(t)$ is a *probability density function* represented by $f(t)$:

$$f(t) = \frac{d}{dt} F(t)$$

or

$$F(t) = \int_0^t f(x)dx.$$

In practice, the instantaneous failure rate or hazard rate $\lambda(t)$ is often more useful than the functions just mentioned. From this point on, *failure rate* will mean instantaneous failure rate:

$$\lambda(t) = \frac{f(t)}{R(t)} = -\frac{d}{dt} \ln[R(t)],$$

which implies that

$$R(t) = e^{-\int_0^t \lambda(x)dx}.$$

The failure rate $\lambda(t)$ of a unit has the following interpretation: If the unit has survived until $t$, the probability of failing in a small time interval $\Delta t$ at $t$ is $\Delta t\ \lambda(t)$.

## V. COMPONENT FAILURE RATE MODEL

The reliability model described here applies to individual components. We use the failure rate function to describe the reliability model, since it is the most convenient.

The basic reliability model consists of two parts, shown by the heavy lines in Fig. 1. During the infant mortality period, the failure rate is described by a two-parameter Weibull model. The Weibull failure rate[3] can be expressed as

$$\lambda(t) = \lambda_1 t^{-\alpha}.$$

This distribution appears as a straight line when plotted on logarithmic scales, as in Fig. 1. The slope of the line is $-\alpha$ and the intercept at $t = 1$ hours is $\lambda_1$. The failure rate is initially high but decreases rapidly.

Beyond 10,000 hours the model assumes that the failure rate is constant. The exponential model, which implies a constant failure rate, is used. The long-term failure rate is simply

$$\lambda(t) = \lambda_L.$$

Defining the Weibull-to-exponential switchover point to be at ex-

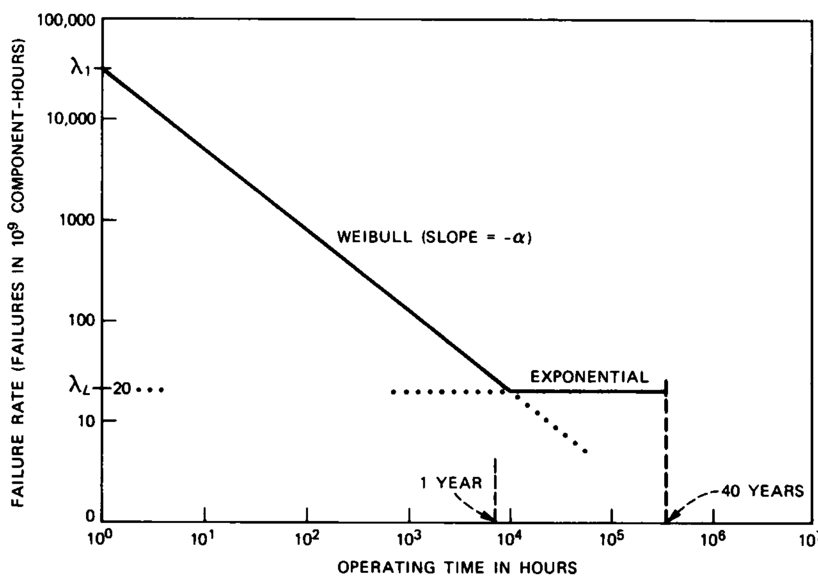


Fig. 1—A component failure rate model (shown by solid lines) combining a Weibull model and an exponential distribution. The failure rates shown here are typical, but are not intended to correspond to any particular component.

actly 10,000 hours is arbitrary but reasonable. Weibull behavior has been observed to persist for at least a year (8760 hours). At that point, the failure rate is changing very slowly. Therefore, any time somewhat greater than one year could have been chosen as the switchover point with little impact on the modeled failure rates; 10,000 hours was a conveniently round number.

There are two distinct sources of information on component reliability: direct monitoring of performance in the factory or field, and accelerated life tests. Factory or field data give a real measure of component reliability in the short term (a year or so), and some data are also available for the long term. Accelerated life tests provide information about reliability expected in the very long term (tens to hundreds of years).

Reliability studies seldom continue for more than two or three years. Therefore, primarily infant mortality is observed. Plotting the logarithm of the observed failure rate versus the logarithm of operating time usually gives a straight line. The straight line means that a Weibull distribution describes the failure rate behavior well, as we see in Fig. 2. We use the Weibull model to describe infant mortality because of such data.

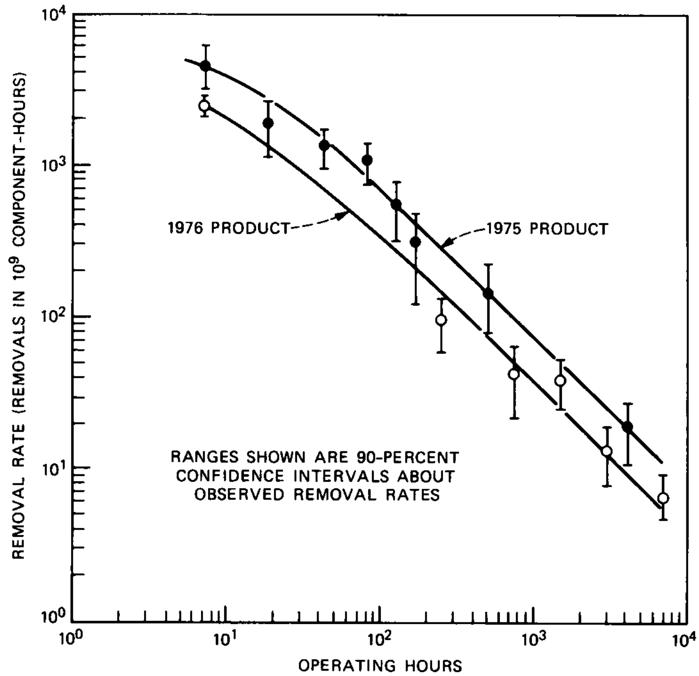


Fig. 2—Infant mortality removal rate of beam-lead sealed-junction $T^2L$ integrated circuits (small-scale integration/medium-scale integration) (see Ref. 4).

As just mentioned, we can directly measure the time dependence of infant mortality failures. However, measuring the lifetime distribution of the main population in the long term is impractical using normal operating conditions, since so few components fail. Therefore, we use accelerated test conditions to estimate the lifetime distribution and, hence, the failure rate, at normal use conditions. The test results imply that only a very small fraction of semiconductor components will fail at normal use conditions within a forty-year service life. This is a very important result. It means that wear-out *will not occur* during the service life. (In fact, wearout of semiconductor components should never occur.) Figure 3 illustrates this point. For semiconductors, a lognormal model describes the main lifetime distribution in accelerated tests.[5] Two such lognormal failure rate curves, extrapolated to normal use, are shown in Fig. 3. These examples represent values in the range usually observed.

Accelerated testing does not define the long-term failure rate very precisely during the service life. Accelerated life conditions are far removed from normal use conditions; therefore, a long extrapolation is required to estimate real field performance. This is inherently a tricky business. Furthermore, in accelerated life tests, the sample size is generally small. In such cases the tests cannot accurately show the distribution of the first few percent of the failures. However, only the lowest few percent of the population failure times will occur within

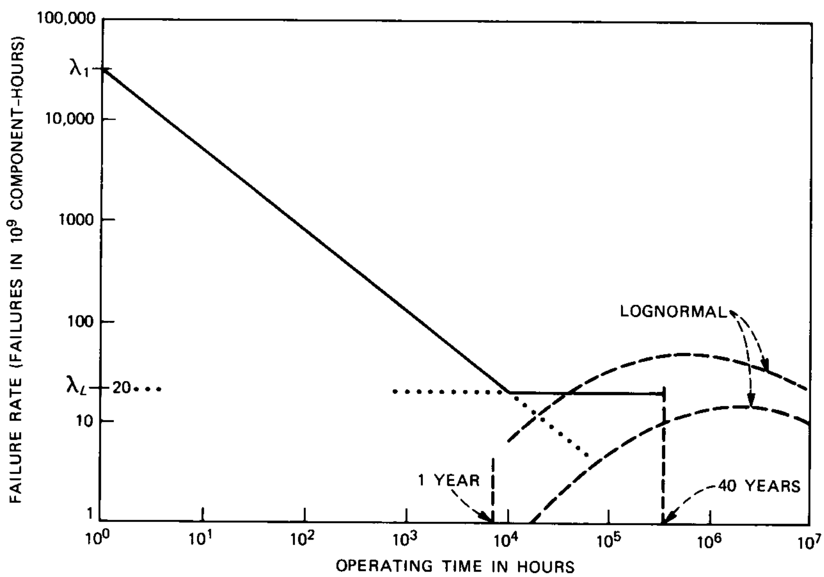


Fig. 3—The two lognormal curves (dashed lines) show possible relationships between accelerated-stress results and the basic failure rate model.

the service life. Therefore, accelerated testing does not accurately predict the failure rate distribution during the service life. For the lognormal examples shown in Fig. 3, only two percent of the components will have failed before the maximum failure rate is reached (in Fig. 1, at forty to four hundred years).

Since neither direct observations nor accelerated life testing defines the time dependence of the long-term failure rate, how then do we justify using the constant-failure-rate exponential model? We have used the exponential model largely by default, since it is almost universally used to model long-term failure rates as, for example, in MIL-HDBK-217D. The model is a reasonable compromise between the decreasing failure rate of the Weibull model and the increasing failure rate of the lognormal curve.

Field tracking does not define the failure rate during the very long term, but it can give failure rates at the end of infant mortality and the beginning of the long term. From those we can estimate the long-term failure rates. Accelerated life testing results are used in addition to tracking data. From these results we predict the total fraction of the population estimated to fail within the service life, which must be consistent with the failure rate estimates. If it is not, the estimates must be reevaluated.

### 5.1 Sources of component failure rates

If field tracking or accelerated testing data are available, the procedure just described is used to estimate the long-term failure rate. Where we do not have any relevant data, we use MIL-HDBK-217D numbers. With few exceptions, our estimates for semiconductor components come from AT&T Bell Laboratories data and those for nonsemiconductors come from MIL-HDBK-217D.

The infant mortality data that exist are solely from semiconductor components. These data form the basis for our estimates of the infant mortality parameters for all semiconductor components.

We do not have good infant mortality data on nonsemiconductor components. We do, however, believe that infant mortality exists for these components. Because we do not have good data, we chose a value of $\alpha = 0.6$ at the lower end of the range observed in equipment (between 0.6 and 0.9). Furthermore, we assume the infant mortality failure rate at 10,000 hours equals the long-term failure rate. These two assumptions, taken together, describe the existence of infant mortality, to a modest extent, in nonsemiconductor components.

### 5.2 Effect of temperature

Up to this point, we have only described the failure rate for a component as a function of time. In reality, a component's operating environment will also affect the failure rate. The component's operating temperature is one such environmental factor. It can have a strong effect on the failure rate.

We base the component failure rate estimates on an assumed 40°C "typical" ambient temperature, since this is the temperature at which most of the available field tracking data are taken. Ambient temperature refers to the temperature in the immediate vicinity of the component. In most cases the failure rate estimates can be used directly. In cases where the temperature departs significantly from the typical value, its effect must be taken into account.

The effect of temperature is usually modeled through its effect on the rate of aging of a component. At a higher temperature, failures will generally occur sooner and, therefore, at a greater rate. The difference in rates of component aging at two different temperatures is described by an acceleration factor. If $T_2$ is a higher temperature than $T_1$, then the Arrhenius relationship gives the following acceleration factor:

$$A(T_2, T_1) = e^{\frac{E_a}{k_B}\left(\frac{1}{T_1} - \frac{1}{T_2}\right)},$$

where $k_B$ is the Boltzmann constant and $E_a$ is the "activation energy". $T_1$ and $T_2$ are in units of degrees Kelvin. This Arrhenius relationship is well understood for chemical reactions. However, its use in the current context is based purely on empirical evidence. Therefore, the constant $E_a$ does not really have physical meaning as an activation energy. Rather, it should be considered as an empirical curve-fitting constant.

With the exponential model, a factor of $A(T_2, T_1)$ increase in the rate of aging leads to a factor of $A(T_2, T_1)$ increase in the constant failure rate, that is:

$$\lambda_{T_2} = A(T_2, T_1)\lambda_{T_1}.$$

Under the Weibull model for infant mortality, the effect of temperature on the failure rate is not as simple. A factor of $A(T_2, T_1)$ increase in the rate of aging leads (after some careful algebra) to a factor of $A(T_2, T_1)^{1-\alpha}$ increase in the failure rate:

$$\lambda_{T_2}(t) = A(T_2, T_1)^{1-\alpha}\lambda_{T_1}(t).$$

It should be noted that the activation energy, and hence the acceleration factor, in the long term is not necessarily the same as during infant mortality. It depends on whether the expected cause of failures (failure mechanism) is the same. Table I lists the activation energies used.

Table I—Activation energies for selected components

| Component | $E_a$ (eV) | Reference |
|---|---|---|
| Infant Mortality | | |
| All components | 0.4 | 4 |
| Long Term | | |
| Discrete semiconductor | 0.4 | Unpublished work |
| Bipolar integrated circuits | 0.4 | Unpublished work |
| Metal-Oxide Semiconductor (MOS) integrated circuits | 0.5 | Unpublished work |
| Ceramic capacitors | 1.0 | 6 |
| Plastic capacitors—metallized and foil | 0.12 | 6 |
| Film resistors—metal or carbon | 0.08 | 6 |
| Carbon resistors | 0.34 | 6 |

### *5.3 Effect of electrical stress*

The level of electrical stress at which a component operates can also affect the failure rate. The higher the level of electrical stress, the more quickly we expect a component to fail. The effect of electrical stress, as for temperature, is modeled with an acceleration factor. This gives the difference in rate of aging at different values of applied electrical stress. The relationship we use to describe $S$, the acceleration factor, is

$$S(p_2, p_1) = e^{m(p_2 - p_1)},$$

where $p_2$ and $p_1$ are stress levels. These stress levels are given as a percentage of the maximum specified level. The electrical parameters that constitute electrical stress are different for different types of components (see Table II).

The stress constants (m) are based on information in MIL-HDBK-217D for long-term operation. There is no effect of electrical stress on integrated circuits, since the applied voltage is specified and assumed to be constant. Due to lack of information, no effects of electrical stress on failure rates during infant mortality are modeled.

The level of applied electrical stress assumed for typical operation is 25 percent. If actual levels of applied electrical stress significantly differ from 25 percent, then the acceleration must be taken into account. As with temperature acceleration, the electrical stress acceleration factor simply multiplies the constant long-term failure rate, as follows:

$$\lambda_{p_2} = S(p_2, p_1)\lambda_{p_1}.$$

Figure 4 shows how the combined effects of elevated operating temperature and high electrical stress can affect a component's failure rate. Both temperature acceleration ($A_{LT}$) and acceleration due to electrical stress ($S$) can affect the long-term failure rate. Only temperature acceleration ($A_{IM}$) affects the failure rate during infant mortality.

Table II—Electrical stress dependence ($S$) of selected components

| Component | Electrical Stress Parameter | Range of m Values |
|---|---|---|
| Integrated circuits | Not applicable | — |
| Resistors | Power | 0.006–0.024 |
| Capacitors | Voltage | 0.024–0.150 |
| Switches | Current | 0.013 |

Note that these acceleration factors change the time at which the long-term failure rate is reached in the model.

### *5.4 Effect of dynamic burn-in screening*

One widely used method to reduce the impact of infant mortality on equipment is the "screening" method. This refers to some activity performed on components or equipment to screen or "weed out" infant mortality failures *before customer use.* Components or equipment are stressed in some way and then tested. Any failures are removed or repaired. By inducing these failures to occur prior to use, customers should experience fewer equipment failures. Some commonly used screens are thermal cycling, high-voltage stress, or simply electrical operation (burn-in).

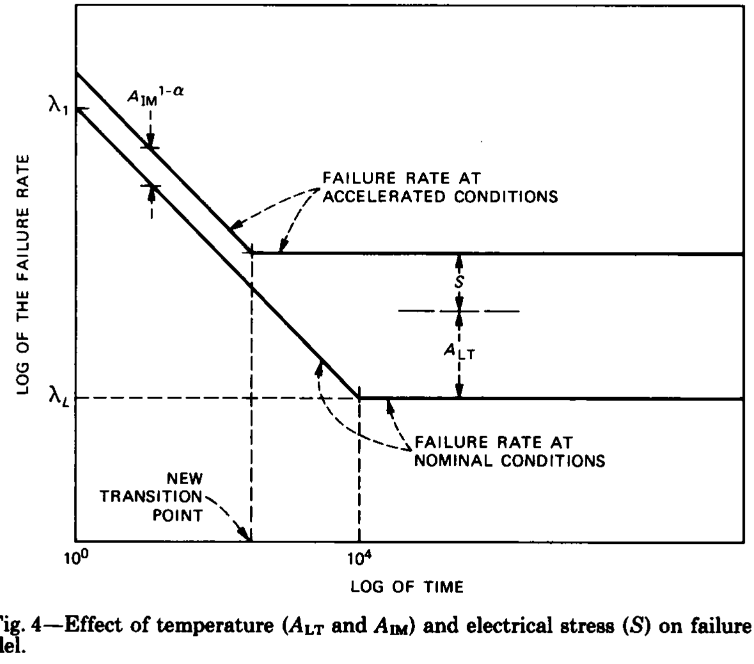


Fig. 4—Effect of temperature ($A_{LT}$ and $A_{IM}$) and electrical stress ($S$) on failure rate model.

A variety of screens are believed to be effective in some cases. However, we have formally modeled the effects of only dynamic burn-in. This refers to the electrical operation of components or systems in a manner simulating eventual use. It consists of powering up and dynamically exercising the component or system for a period of time. This is distinguished from static burn-in in which power is applied but no dynamic exercise takes place. The burn-in may or may not occur at an elevated temperature.

We model only dynamic burn-in because we do not have a sufficiently good understanding of the quantitative effects of other screens. Even the understanding of the effects of dynamic burn-in is poor. Mathematically, our burn-in model follows naturally from the basic failure rate model. However, there is little direct evidence to substantiate the model.

One assumption provides the basis for the dynamic burn-in model. We assume that the failure rate of a component depends on the length of time of previous operation, *wherever that operation occurred.* As is clear from our model in Fig. 1, the more operating time a component has accumulated within the infant mortality period, the lower will be its failure rate. Therefore, a manufacturer can reduce the failure rate a customer will experience by operating components or equipment for a period of time before shipment.

Calculating the effect of dynamic burn-in is a matter of calculating the effective operating time to which the burn-in is equivalent. The effective operating time, $t_{eff}$, corresponds to operation at the nominal 40°C. Then, if $t$ represents the amount of operating time after the burn-in, the failure rate at 40°C is

$$\lambda(t) = \lambda_1(t + t_{eff})^{-\alpha}.$$

Operation after burn-in might occur at a temperature higher than 40°C. In that case, the above failure rate is modified by the temperature acceleration factor already discussed.

Figure 5 illustrates the modeled effect of dynamic burn-in. The straight dashed line shows the basic infant mortality failure rate. The solid curve gives the failure rate after a burn-in equivalent in time to $t_{eff}$. Note that this curve is a simple replotting of the dashed line but starting at age $t_{eff}$ rather than at zero age.

To calculate $t_{eff}$, we again make use of the temperature acceleration factor, $A_{IM}$, introduced earlier. If burn-in occurs at a temperature above 40°C for $x$ hours, then the effective burn-in time is $t_{eff} = A_{IM}x$. ($A_{IM}$ is the acceleration factor, for the burn-in temperature, relative to 40°C.)

Burn-in can be performed at any of several stages. Components can be burned in. Burn-in can also occur at the circuit pack or at the

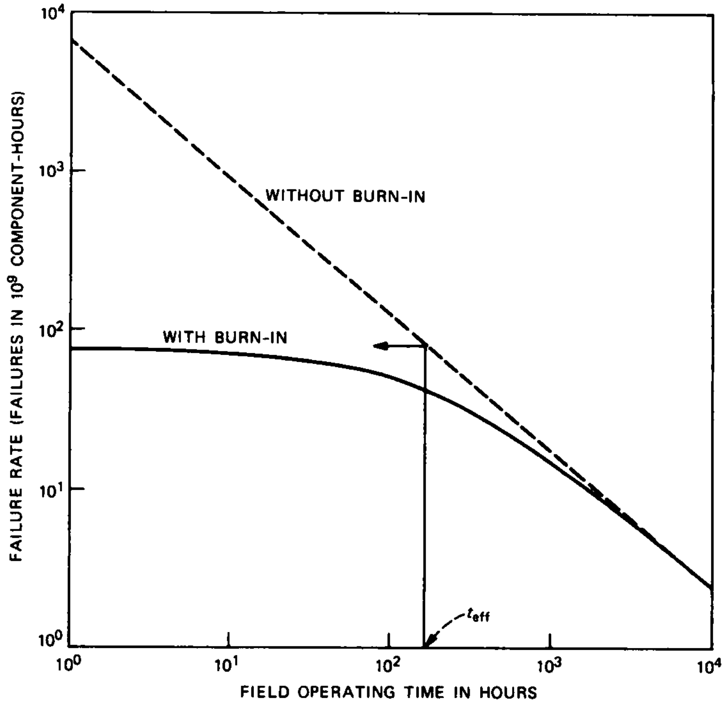


**Fig. 5—Effect of burn-in on early system failure rate.**

system level. Moreover, equipment can be burned in at more than one of these stages. Under the model, the effect of burn-in is cumulative. With more than one burn-in, the effective burn-in times at each stage are added to give the total effective burn-in time which is

$$(t_{eff})_{total} = \sum_{i}^{\text{all stages}} (t_{eff})_i.$$

Caution should be exercised in using this additive assumption of burn-in treatments. In some instances the initial failure rate of a population of devices during a second burn-in was larger than the final failure rate during the first burn-in. This "setback" may have been due to the testing of the devices and insertion of the devices into circuit boards, which was done between the two burn-in treatments. This additional handling may damage some devices (e.g., by electrostatic discharge) causing them to fail sooner than they would have otherwise.

## VI. FAILURE RATES FOR EQUIPMENT

Up to this point, we have described the failure rate models applied to individual components. It is a simple matter to combine the com-

Table III—Environmental application factors

| Environment | $E$ |
|---|---|
| Permanent structures, environmentally controlled | 1.0 |
| Ground shelters, not temperature controlled | 1.1 (Ref. 7) |
| Manholes, poles | 1.5 (assumed) |
| Vehicular-mounted equipment | 8.0 (Ref. 7) |

ponent failure rates to estimate the failure rates of equipment. Basically, component failure rates are added together to give equipment failure rates. There is, however, one final modification we make to the summed failure rates. This modification accounts for a failure rate effect, which we do not understand well enough to apply at the component level. Rather, we apply it at the equipment level.

The modification involves an environmental application factor, $E$. It reflects environmental factors other than temperature that affect the equipment failure rates. Values of $E$ are listed in Table III. These cover the usual environments for AT&T telecommunications equipment. They are based on information in Ref. 7.

With the inclusion of the equipment-level application factor, equations giving equipment failure rates can be written. For infant mortality the equipment failure rate is

$$\lambda_{\text{total}}(t) = E \sum_{i}^{\text{all components}} (A_{\text{IM}})_i^{1-\alpha}(\lambda_1)_i[t + (t_{\text{eff}})_i]^{-\alpha_i}.$$

The long-term failure rate is

$$\lambda_{\text{total}} = E \sum_{i}^{\text{all components}} (A_{\text{LT}})_i S_i (\lambda_L)_i.$$

## VII. PREDICTING THE NUMBER OF INFANT MORTALITY FAILURES IN A TIME INTERVAL

Being able to predict the numbers of failures during the infant mortality period is important for a number of reasons. The estimates are useful for anticipating customer reaction. They can be used to understand warranty repair costs and to plan repair strategies. If any of these factors appear undesirable or unacceptable, the design, screening, or requirements of the products can be reevaluated. If this is done at an early enough stage, changes can be made when the impact on cost is low. Predictions also provide standards against which component or equipment performance can be measured. Once production begins, the results of ongoing reliability testing can be compared to the standards to show where to concentrate ongoing efforts to make improvements.

One calculation that is particularly useful is predicting the number of failures out of some population during a stated time interval. The fraction of units failing between $t_1$ and $t_2$ is

$$\text{fraction fail} = \int_{t_1}^{t_2} \lambda(t)dt,$$

where $\lambda(t)$ is the unit's time-dependent failure rate. This approach is strictly correct when all failures in a population are repaired. In addition, it is correct if they are replaced with units of the same age. However, it is also a good approximation even if failing units are replaced by units of different age or not at all, if the fraction failing is small (less than a few percent).

The following example illustrates the strong effect of infant mortality. Typical failure rate parameters for integrated circuits are $\lambda_L$ = 10 FITs, $\alpha = 0.8$, and $\lambda_1$ = 16,000 FITs. (One FIT equals one failure per $10^9$ component-hours.) In the long term, we would expect about $10^{-8}$ failures per component-hour, or $7.2 \times 10^{-6}$ failures per component-month. In a system made up of 10,000 such components, we would expect 0.072 failures per system during one month. In the infant mortality period, the situation is drastically different. In the *first* month, we would expect

$$\text{fraction fail} = (1.6 \times 10^{-5}) \int_0^{720} t^{-0.8}dt,$$

or roughly 0.0003 failures per component. This gives three failures per system in the first month. The number of failures expected during the first month is roughly forty times higher than expected in one month in the long term. Clearly, such an effect, if not anticipated, could lead to nasty surprises.

## VIII. COMPARISON WITH MIL-HDBK-217D

Many of the concepts embodied in our failure rate model are also used in MIL-HDBK-217D, the *de facto* industry standard for failure rate prediction. There are, however, some important differences between the two models as well. As we already mentioned, the largest difference is in our formal inclusion of a model for infant mortality. This enhancement overcomes the major shortcoming of the MIL-HDBK-217D methodology, especially as applied to commercial products.

A second difference lies in the magnitudes of long-term failure rate estimates for integrated circuits. Our numbers are based on predivestiture Bell System experience. They are generally lower than those in MIL-HDBK-217D. Our data show that the MIL-HDBK-217D failure rates for integrated circuits are unrealistically high, especially those for Large-Scale Integration (LSI) components. A final difference is in our dynamic burn-in model, which predicts an effect of burn-in on the infant mortality but not on long-term failure rates. MIL-HDBK-217D assumes that burn-in impacts long-term failure rates.

## IX. SUMMARY

We have described the basic component reliability model used at AT&T Bell Laboratories to predict component and equipment reliability. It is a two-part model. A Weibull model describes infant mortality. An exponential model describes long-term behavior, beyond roughly the first year. The infant mortality part of the model is very important. It quantitatively describes the initially high, but rapidly decreasing, early-life failure rates. Recognizing such behavior is becoming critical as increasingly complex electronic systems are being sold to a variety of customers. Widely recognized methods of predicting reliability, such as MIL-HDBK-217D, do not model infant mortality effects.

Given the basic component reliability models and failure rate estimates, failure rates of equipment can be easily estimated. These equipment estimates, including infant mortality, are essential when planning for new, competitive product offerings and manufacturing them to have well-controlled reliability.

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