Towards a Predictive Model of Mobile Robot Reliability

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Abstract

Mobile robots are notoriously unreliable. In order to make significant improvements in mobile robot reliability, we need quantitative methods and precise language for measuring and discussing reliability. Such methods exist within the reliability engineering literature but have seen little use in the design of mobile robots. In this report we present an overview of reliability engineering methods which can be used to predict the probability of failure for mobile robots. We also present here a novel extension to the concept of mean time to failure that incorporates the effects of operating conditions on failure rate. Finally, we demonstrate how these techniques can be used in mobile robot mission design to predict the probability of completing mission tasks. Using these methods, a mission designer can make informed decisions trading reliability against other variables such as cost.

Keywords — *Mobile robots*, *field robotics*, *reliability*, *failure*.

Contents

1 Introduction

The current generation of mobile robots has poor reliability. Reference [1] summarizes historical failure data for small field robots and reveals that the robots were either broken or under repair approximately half of the time. According to some robotics researchers, reliability is the single largest obstacle to the success of mobile robots [2].

In order to design more reliable robots[1] and robot teams, we need analytical tools for predicting robot failure. In the robotics literature, however, there is little formal discussion of reliability and failure. Reference [1] finds that most of the literature on robot failures is concerned primarily with automated fault detection and recovery. An example is [3], where fault detection is used to discard faulty sensor readings among a group of redundant sensors. According to [1], "what is not found in the literature is analyses which explore how robots fail and the underlying reasons behind those failures."

References [1], [4], [5] and [6] begin to address this void by presenting and analyzing data on failures of field robots. Reference [1] provides an overview of robot failure rates at the system level (i.e., robot model X failed Y number of times in Z hours of operation) and also breaks down failures according to the subsystem which failed (actuators, control system, power, and communications). Reference [4] extends the work in [1] both by the inclusion of additional failure data of the same type and also by addition of new categories of failure—those which are due to human error. Reference [6] provides a detailed analysis of failures experienced by some of the robots used in searching the World Trade Center wreckage in 2001.

The failure data presented in these papers are valuable in that they provide a prioritization for analyzing the reliability of robot subsystems. For instance, 35% of the robot failures documented in [1] were due to failure of the actuators or related components. Another 26% were failures of the computers or software. The power subsystem caused 13%, communications caused 12% and sensing caused 10% of failures. This data indicates that for the robots in these papers, it may be wise to concentrate reliability imrpovement efforts on the actuator and computer/software subsystems.

This conclusion is also supported by [7], which presents a list of the most common failures observed in small field robots used by the U.S. military in Iraq. The relative frequencies of these failures are not given, but of the 18 common failures listed, 10 are in the actuator subsystems.

These papers help us to begin to identify the causes of mobile robot failure, which is the first step towards improving robot reliability. Once we have identified possible causes of failure, we would then like to develop a model which will allow us to predict the failure of components and robots. With such a model we can evaluate alternatives for reducing the impact of component and robot failure on mission success.

For example, it is often claimed that multirobot teams will be more reliable than single robots since the mission may still be completed even if one or more robots fail. The counterclaim is that for the same cost as developing a team of robots one could instead develop a single highly reliable robot that would have a

[1] We will use the term "robot" hereafter to mean "mobile robot."

very small chance of failure during the mission. Without methods for predicting robot reliability, we cannot evaluate these claims quantitatively.

In this report we present initial work towards such methods. In Section 2 we review terminology and techniques from the reliability engineering literature. In Section 3 we present a novel extension to the concept of mean time to failure that incorporates the effects of operating conditions on failure rates. In Section 4 we show how this model can be used to predict the probability of a robot completing a mission task.

2 Reliability Background

Reliability is the probability that a system will be operating properly at a given time. Another way of saying this is that reliability is the probability that no failures will occur before a given time. When evaluating the reliability of a system, we must first identify the ways in which the system may fail and then determine the probabilities of those failures occurring.

Many failures are the result of human error. These errors can be classified into three categories: errors of omission, errors of commission, and operational errors [8]. Errors of omission are related to design; i.e., the design specifications fail to define the device in a way that will allow it to function correctly. Errors of commission are related to implementation; i.e., the product fails to match the design specifications. Operational errors relate to improper use of the system, for instance, using it in an environment for which it was not designed.

What all of these errors have in common is that they can be eliminated, or at least dramatically reduced, through process improvement. Methods such as ISO 9000 Quality Management can be applied to reduce design and implementation errors, and knowledge from human factors and other disciplines can be applied to reduce operational errors.

For many devices, there are additional failures that are due to inherent properties of the materials and processes used by the device. For example, the grease in a bearing will eventually dry out and the bearing will fail due to lack of lubrication. No amount of process improvement can eliminate this physical reality.

What can be done is to design the bearing so that there is a very small chance of failure during the expected lifetime of the product. Alternatively, the product can be designed so that the bearing can be easily relubricated or replaced, and then a maintenance or replacement interval can be specified as part of the design. These alternatives presumably have different costs and most likely different probabilities of bearing failure. It is these tradeoffs among design options, probability of failure, and cost that are typically considered in the domain of reliability engineering, and it is these tradeoffs, as they apply to robots and robot teams, which we wish to consider in our work.

In the rest of Section 2 we provide an overview of fundamental definitions and models from the reliability engineering literature (taken largely from [9]). While some readers may be familiar with this background information, we have found that most robotics researchers have at best an informal understanding of reliability methods, so it should be useful to review this material here.

2.1 Terminology

Reliability is the probability that a system will be operating properly at a given time. Reliability and *failure* are related as

$$R(t) = 1 - F(t) \qquad (1)$$

where *R(t)* is the *reliability function* or the *survival function*, and *F(t)* is the *unreliability function*.

The most common measure of reliability provided by manufacturers is the *mean time to failure* (MTTF). MTTF is the expected value of the reliability:

$$MTTF = \int_0^\infty R(t)dt \ . \qquad (2)$$

The *hazard rate h(t)* is the instantaneous rate of failure at a given time. The reliability function and the hazard rate are related as

$$R(t) = \exp\left(-\int_0^t h(x)dx \right) . \qquad (3)$$

2.2 Reliability Model

Reliability models are descriptions of how the hazard rate changes over time. For many electronic and mechanical devices, when the hazard rate is plotted as a function of time, the resulting curve resembles Fig. 1 [9:109]. This characteristic shape is referred to as the *bathtub curve*.

The bathtub curve has three distinct regions. At the left side of the curve, the hazard rate decreases with time. This corresponds to the period during which items fail largely due to defects in materials or construction. There are many early failures, but as defective items drop out of the population, the remaining population has a lower hazard rate. This is referred to as the *burn-in* or *infant mortality* period.

In the middle section, there is a period of approximately constant hazard rate, where random failures dominate. This period is referred to as the *service life* or

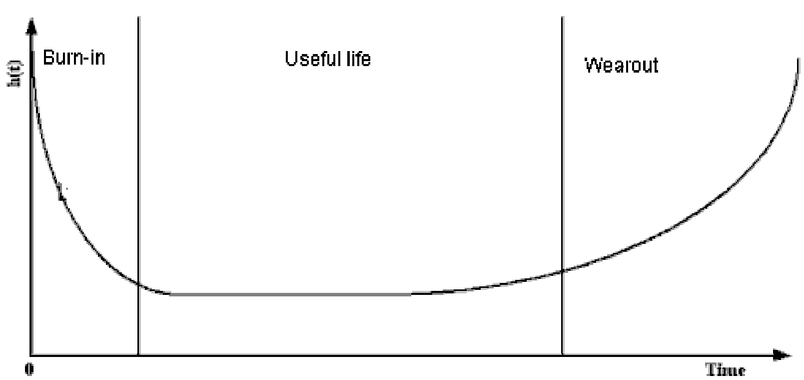

Figure 1 - Bathtub curve

useful life.

At the right side, the hazard rate increases with time. During this period, components have reached the end of their useful lives and begin to fail due to deterioration. This is referred to as the *wearout* phase.

2.3 Application to Mobile Robots

In our reliability model we consider robots to be made of multiple modules. We use *module* here to refer to some subsystem of interest. While we have a particular concept of module in mind for our research purposes, the reliability model proposed here is not tied to our specific module concept. The modules could, for instance, be functional divisions of the robot as in Fig. 2, or they could simply be all the individual components making up the robot.

In applying the bathtub model to robot modules, we assume that there will be a period of initial testing which allows burn-in failures to be dealt with before components are placed into service. We also assume that the service life of components will be specified by the manufacturers and observed in mission planning so that modules will be removed from service before wearout failures begin to dominate.

Given these two assumptions, the hazard rate of a robot module needs to be known only during the service life phase. This hazard rate is modeled as a constant and can therefore be defined by a single value. Since it is also important to know when this hazard rate is valid, a second value is needed to indicate when the end of the service life is reached. The reliability of a module can therefore be modeled with just two parameters—the (constant) hazard rate and the service life length.

2.4 Consequences of Constant Hazard Rate

A constant hazard rate is represented in the literature by λ. Substituting into (3) gives

$$R(t) = e^{-\lambda t} \quad . \tag{4}$$

Thus, the reliability of a device with a constant hazard rate is equal to one at the beginning of the service life and decays exponentially towards zero.

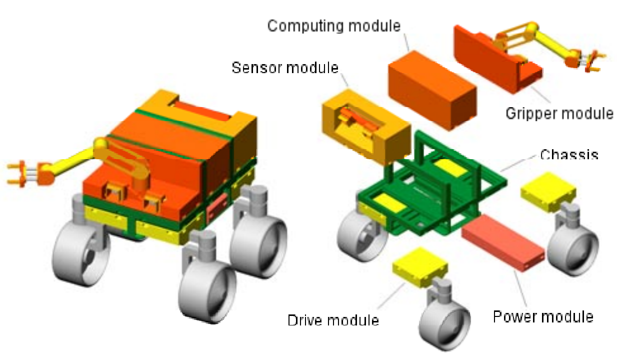

Figure 2 - Modular robot concept.

Substituting (4) into (2) yields the MTTF:

$$MTTF = \frac{1}{\lambda} \ . \tag{5}$$

The relationships in (4) and (5) allow us to calculate the probability of failure of a component from the manufacturer's published MTTF. It is important to remember that this MTTF applies only during the central, constant-hazard-rate portion of the bathtub curve. It is a common mistake to assume that MTTF measures how long an item will last [10]. For most components the MTTF is much greater than the service life, so the item will fail due to wearout long before the time corresponding to MTTF is reached. Reference [11] has this to say about the confusion:

> Note that there is no direct connection or correlation between service life and failure rate. It is possible to design a very reliable product with a short life. A typical example is a missile for example: it has to be very, very reliable (MTBF of several million hours), but its service life is only 0.06 hours (4 minutes)! 25 year old humans have an MTBF of about 800 years (λ about 0.1%/year) but not many have a comparable "service life." Just because something has a good MTBF, it does not necessarily have a long service life as well. [11:5]

It is also important to realize that the MTTF provided by a manufacturer represents the failure rate for the component under a single set of operating conditions. If, for instance, the device is operated at a different ambient temperature than the test conditions, then the published MTTF may no longer apply. We revisit this issue in Section 3.

2.5 Combining Reliabilities

The preceding information allows us to evaluate the reliability of a single module. We also need to be able to combine module reliabilities in order to evaluate the reliability of entire robots.

In the case of modules in series, the system is operational only when each module is operational. Therefore, the reliability of a system with N modules in series can be expressed as

$$R_S = \prod_{i=1}^{N} R_i \ . \tag{6}$$

When each module has a constant hazard rate, the system hazard rate is

$$\lambda_s = \sum_{i=1}^{N} \lambda_i \ . \tag{7}$$

For modules in parallel, where the failure of the system requires that all modules fail, the unreliability of a system with N parallel modules is

$$F_S = \prod_{i=1}^{N} F_i \ . \tag{8}$$

Substituting (1) into (8), the system reliability can be expressed as

$$R_S = 1 - \prod_{i=1}^{N} (1 - R_i) \tag{9}$$

The general form of the system hazard rate for parallel modules is unwieldy and will not be reproduced here. It can be found at [9:201]. For the special case where all of the parallel modules have identical constant hazard rates, the system reliability becomes

$$R_S = 1 - (1 - e^{-\lambda t})^N \tag{10}$$

and the system hazard rate is

$$\lambda_S = \lambda \cdot (1 + \frac{1}{2} + ... + \frac{1}{N})^{-1} \ . \tag{11}$$

3 Extension of MTTF for Operating Conditions

The methods described above enable us to model the reliability of components using MTTF data provided by a manufacturer. However, the MTTF given by the manufacturer represents the hazard rate only under some designated operating conditions. The reliabilities of many of the components in a mobile robot will change under different operating conditions. For instance, we expect that a robot operating in a desert would demonstrate different reliability than an identical robot operating in an office building.

In order to make reliability predictions over a wide range of operating conditions, we need a way to extrapolate MTTF at different operating conditions from the single-point MTTF provided by the manufacturer. Equations relating how operating conditions affect reliability are available for many components. These relationships are used, for instance, in accelerated-life testing, where devices are subjected to high stresses in order to induce failure, and the observed failure rates are then extrapolated back to normal operating conditions.

3.1 Effect of Temperature and Load on Mechanical Bearing

An example of a robot component whose reliability is affected by operating conditions is a mechanical bearing. Such bearings are often found in robot motors and joints. The failure rate of mechanical bearings is significantly affected by operating conditions such as temperature, rotational speed, and load. Here we show how the single-point MTTF for a mechanical bearing can be extrapolated over a range of temperature and load conditions.

Reliability of bearings is often expressed by the L_{10} life, which is the time at which 10% of the population has failed. For a mechanical bearing the L_{10} value is given by

$$L_{10} = \left(\frac{C}{P}\right)^d \cdot \left(\frac{10^6}{60n}\right) \tag{12}$$

where C is the rated bearing load, P is the actual bearing load, d reflects the type of bearing ($d=3$ for a ball bearing, $d=3.3$ for a roller bearing), and n is the rotational speed [12].

Holding the speed constant and using $d=3$, we find that the life is related to the applied load as

$$\frac{L_{10}}{L_{10,0}} = \left(\frac{P_0}{P}\right)^3 \tag{13}$$

where the subscript 0 indicates the manufacturer's reliability data.

To relate L_{10} life and hazard rate, we use (4) with R=90%, giving

$$\lambda = \frac{-\ln(0.9)}{L_{10}} \ . \tag{14}$$

Combining (13) with (14) gives the relationship between hazard rate and operating load:

$$\frac{\lambda}{\lambda_0} = \frac{MTTF_0}{MTTF} = \left(\frac{P}{P_0}\right)^3 \ . \tag{15}$$

Bearing life is also greatly affected by temperature since the grease in the bearing breaks down faster at higher temperatures. The approximate relationship used for the effect of temperature on bearing failure is that every 10°C rise in temperature doubles the failure rate [13], or

$$\frac{\lambda}{\lambda_0} = \frac{MTTF_0}{MTTF} = 2^{\left(\frac{T-T_0}{10}\right)} \ . \tag{16}$$

3.2 Single Module Reliability Characteristic

Assuming independence of these temperature and load factors, we can combine (15) and (16) to evaluate the MTTF over a range of temperatures and loads, as in (17) and Fig. 3. We refer to this multidimensional representation of MTTF as a *single module reliability characteristic* (SMRC).

$$\frac{\lambda}{\lambda_0} = \frac{MTTF_0}{MTTF} = \left(\frac{P}{P_0}\right)^3 \cdot 2^{\left(\frac{T-T_0}{10}\right)} \quad . \tag{17}$$

Fig. 3 shows that the MTTF varies greatly even over a fairly small range of temperatures and loads. This illustrates why the single-point MTTF provided by manufacturers is inadequate to describe the reliability of devices operating under significantly conditions from those under which the MTTF was calculated. Using (16), a device operating at 40 °C will have a hazard rate that is four times higher than at 20 °C. Using (15), an increase in bearing load of 25% will result in a doubling of the hazard rate.

We can also see in Fig. 3 that the same MTTF can be achieved under multiple different operating conditions. For instance, in the current example the MTTF ratio is 0.69 for both (P/P_0=0.8, $T-T_0$=15 ^oC) and (P/P_0=0.9, $T-T_0$=10 ^oC). The SMRC therefore illustrates some of the tradeoffs that can be made among operating conditions and reliability. If the robot mission specifies a minimum MTTF, then the SMRC defines an operating envelope constraining the operation of the robot to certain load–temperature combinations.

In order to make it easier for the mission designer to explore these tradeoffs, we have begun development of a computer program which takes as input the manufacturer's reliability data and the range of operating conditions, and produces a graph of the SMRC along with a graph of lines of constant MTTF in the temperature–load plane. This software currently incorporates the temperature

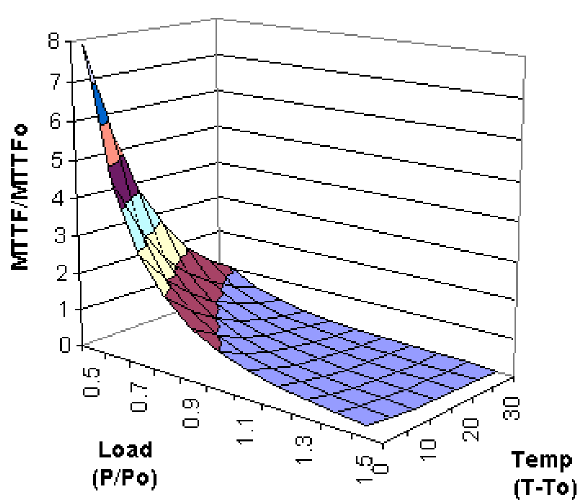

Figure 3 - Effect of operating conditions on bearing MTTF.

and load models of (15) and (16). We intend to expand it to encompass a variety of operational factors for different components. A screenshot of the software is presented in Fig. 4.

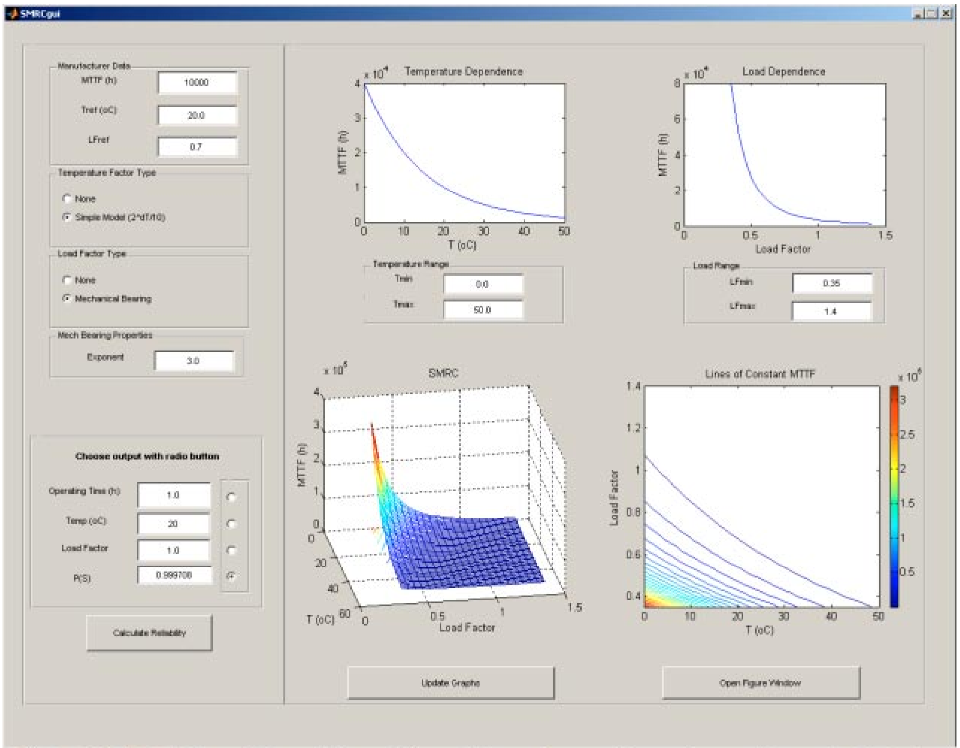

Figure 4 - Screenshot of SMRC GUI.

4 Application to Mission Design

We now apply the formulas described in the preceding sections to predict the probability that a robot will complete a mission task. Consider a planetary exploration robot that is tasked to extract core samples. The robot is composed of ten modules: power, attitude sensing, avionics, communications, manipulator, mast, and four mobility modules. The duration of the task is eight hours, and the usage of each module during the task is listed in Table 1.

Table 1 - Module usage during task.

Module	Usage (h)
Power	8
Attitude	8
Avionics	8
Communications	2
Manipulator	4
Mast	2
Mobility	6

The components making up each module are listed in Table 2 along with their respective failure rates. Table 2 also shows the overall module failure rates, which are calculated by adding the failure rates for each component, according to (7).

Table 2 - Failure rates for modules and their components

Module	Component	Quantity	Failure Rate (1/h)
Power	Battery	2	2.10E-007
	Battery Control Board	2	4.00E-007
	Mission clock	1	1.00E-007
	Power distribution unit	1	1.70E-006
	Power control unit	1	1.90E-007
	Shunt limiter	1	1.14E-005
	Electrical heater	2	3.00E-006
	Radioisotope heater	2	1.36E-005
	Thermal switch	2	9.50E-005
		Overall	2.38E-004
Attitude Sensing	IMU	1	9.10E-007
	Sun sensor	1	5.00E-006
	Temp sensor	2	1.10E-005
	Heater	2	3.00E-006
		Overall	3.39E-005
Avionics	Processor	1	8.60E-007
	Camera board	1	1.31E-005
	Motor control board	1	3.40E-005
	VME backplane	1	4.49E-006
	Temp sensor	4	1.10E-005
	Electrical heater	2	3.00E-006
	Radioisotope heater	2	1.36E-005
		Overall	1.30E-004
Communication	Antenna motor	2	6.40E-006
	Antenna	2	6.70E-006
	Transceiver	1	3.00E-005
	Temp sensor	2	1.10E-005
	Electrical heater	2	3.00E-006
		Overall	8.42E-005
Mobility	Drive motor	1	2.50E-006
	Drive gear train	1	1.90E-006
	Steering motor	1	6.40E-006
	Steering gear train	1	1.90E-006
	Encoder	2	1.50E-006
	Potentiometer	1	1.00E-005
	Temp sensor	2	1.10E-005
	Electrical heater	1	3.00E-006
		Overall	5.07E-005
Arm	Motor	5	6.40E-006
	Encoder	5	1.50E-006
	Potentiometer	5	1.00E-006
	Temp sensor	2	1.10E-005
	Electrical heater	2	3.00E-006
		Overall	7.25E-005
Mast	Motor	2	6.40E-006
	Encoder	2	1.50E-006
	Potentiometer	2	1.00E-006
	Temp sensor	2	1.10E-005
	Electrical heater	2	3.00E-006
		Overall	4.58E-005

4.1 Robot-Task Reliability

Using the overall module failure rates and equation (4) we can calculate the probability that each module will still be functioning at the end of the task. For the power module this gives

$$R = \exp\left(-8 \cdot 2.38x10^{-4}\right) = 99.810\% \ .$$

The reliabilities for all modules for this task are shown in Table 3.

Table 3 - Module reliabilities for task.

Module	Reliability (%)
Power	99.810
Attitude	99.946
Avionics	99.793
Communications	99.983
Manipulator	99.884
Mast	99.927
Mobility	99.919

Finally, we combine all of the module reliabilities by multiplying them (remembering that there are four mobility modules), giving an overall probability of task completion (POTC) of 99.022%.

4.2 Effect of Operating Conditions

Now consider that the operating conditions are different from those conditions under which the failure rates were specified. Perhaps the ambient temperature is 15 ^{o}C higher. We can apply (16) to determine the effect of the increased temperature. Here we assume that the rise in ambient temperature causes a 15 ^{o}C rise in component temperatures and that the temperature model in (16) applies to all of the components. Applying (16) to the power module gives

$$\lambda = \lambda_0 \cdot 2^{\left(\frac{T-T_0}{10}\right)} = \left(2.38x10^{-4}\right) \cdot 2^{\left(\frac{15}{10}\right)} = 6.73x10^{-4}$$

Applying (16) to the other modules and repeating the reliability calculations gives a POTC of 97.259%.

We also hypothesize a situation where the load on the motors is increased. Perhaps the terrain is steeper than expected, causing a doubling of the load on the mobility modules. Here we apply (15) to the drive motor and steering motor failure rates. For the drive motor

$$\lambda = \lambda_0 \cdot \left(\frac{P}{P_0}\right)^3 = \left(2.50x10^{-6}\right) \cdot (2)^3 = 2.00x10^{-5} \ .$$

Repeating for the steering motors, and then combining modules as before, gives a POTC of 98.628%.

The robot task reliabilities for these conditions, plus the additional condition where both temperature and load are increased, are summarized in Table 4. We see here that the whole is worse than the sum of its parts, as the reliability with the temperature increase is about 1.8% lower, with the increase in load is about 0.4% lower, and with both it is 2.9% lower.

Table 4 - Effect of operating condition on MTTF.

Conditions	POTC
Nominal	99.022%
Temperature +15 ^{o}C	97.259%
Motor load x2	98.628%
Both	96.169%

The meaning of small differences in POTC is not intuitive. A way to see the difference more clearly is to observe that under nominal conditions the robot can repeat this task four times with approximately the same reliability as performing the task once under the increased temperature and load (96.145% vs. 96.169%).

Finally, we can parameterize the component failure rates in terms of T and P in order to examine the overall effect of the operating conditions on the probability of task success. As before, we apply (16) to every component and (15) only to the drive and steering motors. The results are shown in Fig. 5.

5 Summary and Future Work

In this report we have presented initial work towards a predictive model of mobile robot reliability. We have introduced terminology and methods from the reliability engineering literature that can be used to predict the probability of failure for mobile robots. We have proposed an extension to the concept of mean time to failure that incorporates the effect of operating conditions on failure rate, and we have shown how these tools can be used to predict robot failure during a mission task.

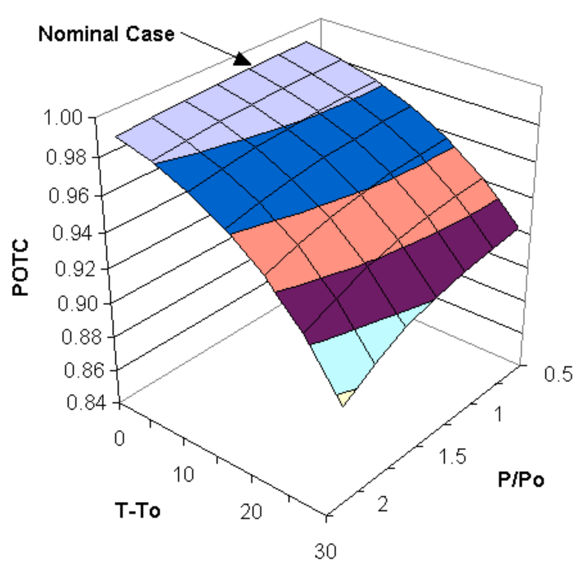

Figure 5 - Probability of task completion as function of operating conditions.

In future work we plan to apply the model presented here to evaluate the reliability of robot team missions in order to compare design alternatives. An example of the type of problem we would like to be able to solve is to compare the reliability of multirobot teams to individual robots. One argument that is often made in favor of multirobot teams is that they will be more robust than a single robot. While this seems intuitively to be true, there is the counterargument that for the price of developing and building a team of robots, one could instead build a single superior robot that will outperform the team of lesser robots. The tools presented in this report will allow for quantitative comparisons of the reliability of these alternatives.

We also plan to examine the relationship between cost and reliability. In order to make comparisons such as those described in the previous paragraph, we need to know how much more it costs to build higher-reliability robots.

Another area for future work is to examine more closely the assumption of constant hazard rate. While this assumption works well for many components, there may be some devices used in mobile robots which fail this assumption. For instance, many mechanical devices, including the bearing used as an example in this report, never experience a truly flat center portion of the bathtub curve, instead beginning to trend upward immediately after the burn-in period. There are reliability models available that can be used to describe such components more accurately, but they increase the complexity of the calculations. We need to examine whether the additional fidelity provided by more complicated models is necessary.

We also must assess the availability of reliability specifications for robot components. Manufacturers of some components, such as computer boards, usually provide specifications of MTTF along with conditions under which the MTTF applies. Other components, such as small motors, often come with no reliability specifications. If specifications are unavailable for a component, then the analysis in this report is not useful without some additional methodology that allows the estimation of component reliabilities. We need to explore whether enough information is available about robot components to perform reliability prediction without manufacturer input, using, for instance, the methods in [14].

Finally, we need to more closely examine the types of failure occurring with current robots and determine to what extent the techniques outlined in this paper can be applied. Most of the errors mentioned in the papers referenced in Section 1 are in fact not the type of random failures which can be modeled using these methods but are instead errors of design, construction, and usage, which should be reduced through process improvement. With the current state of the art in robotics, the methods in this paper are most applicable for the few robots which are already achieving high reliability, including NASA rovers, some military robots, and perhaps some commercial robots.

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