

A Statistical Analysis of Electrical Power Requirements in Vehicles

Ludwig Brabetz, Tobias Kerner, and Mohamed Ayeb
Universitaet Kassel

ABSTRACT

The increasing power and safety requirements of electrical systems present a challenge for future automotive electrical networks. However, the modeling of use-profiles and the overall power consumption of electrical systems proves to be difficult as the number of potential on/off combinations of the loads is tremendous. Furthermore, the operation of some loads is correlated or depends upon the operating conditions. Thus, simple worst-case calculations applied to this complexity often lead to an over-specification of components.

The proposed approach is based on the probabilities of loads being in the on-state and their respective interdependencies with each other and with boundary conditions such as time of day. Applying basic statistics and a new iterative algorithm, it allows the calculation of the probability of consumed total power for a given set of boundary conditions and of, very importantly, its expected continuous period. Such information is a sound base for the identification of critical power situations, the layout of components, and for investigations of the power balance. The paper presents the theory, method, database, results, and a first application example, followed by a discussion of future potentials.

CITATION: Brabetz, L., Kerner, T., and Ayeb, M., "A Statistical Analysis of Electrical Power Requirements in Vehicles," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(2):2015, doi:10.4271/2015-01-0243.

INTRODUCTION

Both the increasing power requirements and the integration of safety-critical electrical systems present a challenge for the development and validation of future automotive electrical networks [1][2][3]. In particular, the layout of alternators, storage devices, and converters, and also the robust and optimum design of the electrical distribution system are all based on a profound understanding of the electrical power consumption. For this reason, considerable effort has been made to develop models of electrical systems and loads as well as their respective use-profiles. Unfortunately, even for a mid-sized vehicle, the number of loads leads to a tremendous number of possible combinations of on- and off-states. Furthermore, the simultaneous operation of some loads is highly improbable or excluded, whereas the operation of other loads is positively correlated. In addition, in most cases the use of certain loads depends on the operating conditions. To overcome this complexity, worst-case scenarios are often assumed, which, however, frequently lead to an over-specification of components or to unrealistic validation results.

The proposed statistical approach is based on the probabilities of loads being in the on-state and their individual power consumptions. These probabilities are defined as a function of boundary conditions such as drive cycle, time of day, weather, temperature, number of passengers, and so on. In addition, probabilities are allocated to the instances of these boundary conditions, whereas their interdependencies are described by using correlation matrices. Thus, the correlations between functions and their respective loads are also

specified. Applying basic statistics and an iterative algorithm, the presented approach allows for the calculation of the probability of consumed power over a specific time period for a given set of boundary conditions. This information allows the identification of critical power situations, the evaluation of their relevance, and the analysis of their technical impact (e.g. triggering of fuses, voltage instability). Furthermore, it is shown that the results are a sound base for detailed investigations regarding both the power- and energy balances. In this paper, first the theory and method are described, then results for the power distribution under varying operating conditions are presented. Furthermore, the probability of a continuous period of a given power consumption is depicted, addressing the fact that a short pulse of high power may be much less critical than a long one. Finally, future potentials are discussed.

THEORY

The most basic approach is to describe every load v in the vehicle by its nominal power consumption P_v and its probability w_{vo} to be in the on-state. Hence, the average power per load is $w_{vo} P_v$ as shown in Fig.1 [4]. Whereas this information is a valuable input for the energy balance, it is not sufficient for the prediction of the momentary power consumption, which can vary considerably. For this reason, the following statistical approach is made with the objective of determining the probability $w(P_{tot})$ of the total power consumption of the vehicle P_{tot} (or a subcircuitry) to be in a given power interval.

If a_v describes the state of the load v , the total power consumption for a given on/off configuration is:

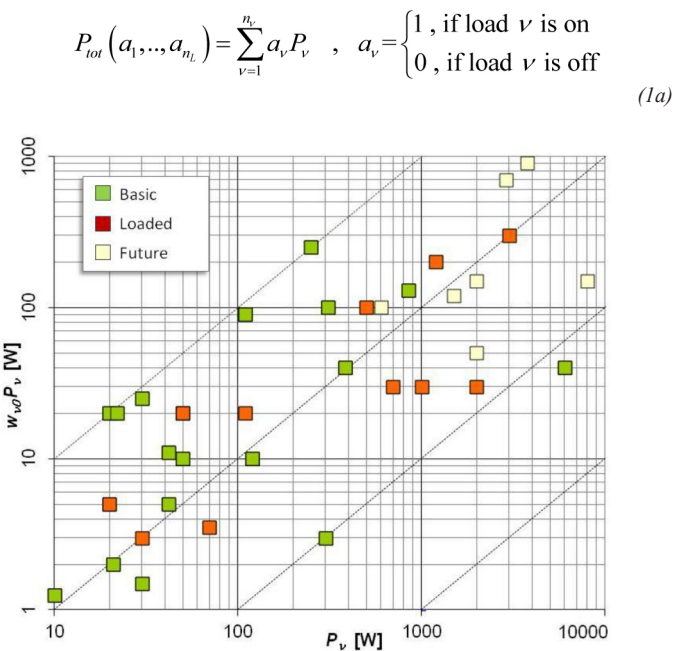


Figure 1. Nominal and average power consumption of loads [4]

The probability $w_{a1,...,an}$ for such a configuration is then

$$w_{a_1,...,a_n} = \prod_{v=1}^n w_{v0}^{a_v} (1 - w_{v0})^{(1-a_v)} \quad (1b)$$

which yields the probability $w(P_{tot})$ of the total power consumption of the vehicle P_{tot} being in $[P, P+\Delta P]$:

$$w(P) = \frac{1}{\Delta P} \sum_{\substack{a_1,...,a_n, \text{ if} \\ P \leq P_{tot}(a_1,...,a_n) < P+\Delta P}} w_{a_1,...,a_n} \quad (1c)$$

Table 1. Boundary conditions, their instances and probabilities

j	Boundary Condition	k_j	Instance	Probability p_{jk} [%]
1	Temperature	1	cold	30
		2	moderate	50
		3	warm	20
2	Light	1	dark, night	20
		2	dim	30
		3	bright	50
3	Weather	1	dry	50
		2	rain	35
		3	snow	15
4	Sight	1	clear	80
		2	fog	15
		3	dust	5
5	Drive Cycle	1	city	50
		2	road	20
		3	highway	30
6	Number of Passengers	1	n=1	60
		2	n=2	30
		3	n>2	10

At first glance, Eq. (1a,b,c) seems to be the sought-after solution, but unfortunately the probabilities w_v are not independent of each other. E.g., depending on the outside temperature, either the A/C or the seat heater system is likely to be in use. In most cases the correlations are more complex and not as obvious. Therefore, boundary conditions such as ambient temperature or weather (index j) and their instances, e.g. cold and warm (index k_j) are added:

In order to describe the impact of a boundary condition, e.g. temperature, on the probability of a load to be in the on-state, a weighting factor $\omega_{v,j,k}$ is introduced. For example, the temperature “warm” ($j=1, k_j=3$) strongly reduces the probability of the seat heater (here: $v=12$) to be on, hence $\omega_{12,1,3}$ is almost zero. By default, $\omega_{v,j,k}$ is “1” which corresponds to no correlation.

Thus, the probability of a load to be in the on-state becomes a function of a specific set of instances ($k_1...k_m$). For instance, the tuple (3,1,1,3,2) corresponds to the scenario “warm, dark, dry, clear, highway, two passengers”. One obtains

$$w_{v,k_1...k_m} = \prod_{j=1}^{n_j} \omega_{v,j,k_j} \quad (2a)$$

As a consequence, (1b) is to be replaced by the following equation,

$$w_{a_1,...,a_n} = \sum_{k_1...k_m} p_{k_1...k_m} \prod_{v=1}^n w_{v,k_1...k_m}^{a_v} (1 - w_{v,k_1...k_m})^{(1-a_v)} \quad (2b)$$

where $p_{k_1...k_m}$ is the probability of a specific set of instances. Hence the final task is the determination of $p_{k_1...k_m}$. For this reason, the probability p_{jk} of the instance j,k_j is used, e.g. $p_{1,3}=0.2$ means that 20% of the vehicle operating time is assumed to be in the temperature range “warm” (see Table 1). Thus, any operating scenario can be defined simply by varying these parameters. Normalization yields

$$\sum_k p_{j,k_j} = 1 \quad , \quad w_{v0} = \prod_{j=1}^{n_j} \sum_k \omega_{v,j,k_j} p_{j,k_j} \quad (3a)$$

Whereas most boundary conditions such as weather and drive cycle are independent of each other, some are correlated. For example, the instance “snow” (weather) enhances the probability for the instance “cold” (temperature). To take this fact into consideration, a factor K is defined as follows:

$$p_{k_a,k_b} = \begin{cases} \min(p_{a,k_a}, p_{b,k_b}) & K_{a,b} = 1: \text{ if } k_a \text{ then } k_b \text{ or if } k_b \text{ then } k_a \\ p_{a,k_a} p_{b,k_b} & K_{a,b} = 0: k_a \text{ and } k_b \text{ are not correlated} \\ 0 & K_{a,b} = -1: k_a \text{ and } k_b \text{ exclude each other} \end{cases} \quad (3b)$$

where p_{k_a,k_b} is the probability of the combination of the instances k_a and k_b , e.g. $p_{11,33}$ is the probability of “cold” and “snow”. For a more accurate description, K is converted into a continuous parameter by applying a polynomial fit to Eq. 3b:

$$p_{k_a,k_b} = p_{a,k_a} p_{b,k_b} (1 - K_{a,b}^2) + \frac{1}{2} \min(p_{a,k_a}, p_{b,k_b}) (K_{a,b} + K_{a,b}^2)$$

with $-1 \leq K \leq 1$. Table 2 shows the K factors which were assumed for the calculations in this paper. No value indicates no correlation, that is $K=0$.

Because not only two but also several boundary conditions can affect each other, e.g. temperature, weather, and light are not independent, a pragmatic solution is required for the calculation of $p_{kl,...,km}$ which considers multiple interdependencies without additional inputs.

Table 2. Assumed interdependencies K between instances

j				2			3			4		
	Boundary Condition		Light			Weather			Sight			
			k	1	2	3	1	2	3	1	2	3
		Instance	dark	dim	bright	dry	rain	snow	clear	fog	dust	
1	Temp.	1 cold	0,3		-0,3		-0,5	0,5			-0,2	
		2 moderate						-0,2				
		3 warm	-0,3		0,3			-1		-0,2	0,3	
2	Light	1 dark								0,1		
		2 dim								0,2		
		3 bright					-0,3	-0,3	0,5	-0,5		

For this reason, a pragmatic approach is used by applying an iterative algorithm. Starting with

$$p_{k_1,...,k_{n_j},0} = \prod_{j=1}^{n_j} p_{j,k_j} \quad (4a)$$

which corresponds to completely uncorrelated instances, one varies $p_{k_1,...,k_m}$ marginally and randomly to minimize the deviation ε from the given probabilities p_{jk} and $p_{ka,kb}$:

$$\varepsilon = \sum_{k_j} \left(p_{j,k_j} - \sum_{k_1,...,k_j,...,k_n} p_{k_1,...,k_n,i} \right)^2 + \sum_{k_a,k_b} \left(p_{k_a,k_b} - \sum_{k_1,...,k_a,...,k_b,...,k_n} p_{k_1,...,k_n,i} \right)^2 \quad (4b)$$

RESULTS

Table 3. Scenarios (use cases), “south” and “north” indicate simply a warmer or colder climate condition, while “best”, “avg” and “worst” represent extreme and mean operating conditions, respectively.

Scenario		p_{jk} [%]			
		best south	avg south	avg north	worst north
Temp.	cold	0	0	30	100
	moderate	100	20	50	0
	warm	0	80	20	0
Light	dark, night	0	30	20	100
	dim	0	20	30	0
	bright	100	50	50	0
Weath.	dry	100	70	50	0
	rain	0	30	35	50
	snow	0	0	15	50
Sight	clear	100	60	80	80
	fog	0	10	15	20
	dust	0	30	5	0
DriveC.	city	0	50	50	50
	road	100	40	20	20
	highway	0	10	30	30
# Pass	n=1	100	40	60	0
	n=2	0	30	30	0
	n>2	0	30	10	100

Table 4. Vehicle feature configurations, “# of loads” is the number of considered actuators and control units, “ P_{inst} ” is the installed power (power consumption, if all loads are in the “on” state), and “ P_{avg} ” is the calculated mean power as a function of the scenarios in Table 3.

Load configuration		best south	avg south	avg north	worst north
medium	# of loads	49			
	P_{inst} [W]	3570			
	P_{avg} [W]	708	965	928	1138
high	# of loads	64			
	P_{inst} [W]	10046			
	P_{avg} [W]	1128	1672	1529	1840
high + elA/C	# of loads	66			
	P_{inst} [W]	13046			
	P_{avg} [W]	1235	1806	2584	1843

The advantage of the method described above is, that as soon as P_v , $w_{v,0}$ and the parameters K in Table 2 are defined, any operating scenario can be investigated just by changing the probabilities in Table 1. As an example, Table 3 shows four scenarios which were used for the following calculations. Furthermore, any vehicle architecture can be investigated by simply adding or removing electrical loads. The presented results are based on feature configurations as listed in Table 4.

Figures 2 and 3 present the calculated power distribution $w(P)$ as a histogram for the first two feature configurations of Table 4 respectively, and for the four scenarios listed in Table 3. As stated in Eq. 1c, $w(P)\Delta P$ is the probability that the total power consumption of the vehicle P_{tot} is in the interval $[P, P+\Delta P)$. Within the same diagrams, the accumulated probability $p_{acc}(P)$ is shown (straight line and right coordinate). It describes the probability that the total power consumption P_{tot} is below P . As expected, $p_{acc}(P)$ converges at “1” for high values of P . Finally, the symbols indicate specific values of p_{acc} (from 0,9 to 0,999999) which are important for the risk assessment. The following observations can be made:

- There is a notable impact of the scenarios. However, the average scenarios, which describe best the real boundary conditions over lifetime for different climate areas, yield very similar power distributions (with regard to the total power consumption, the varied use of loads within the two scenarios seems to even out). Hence these distributions seem to be a sound data base for further investigations.
- There is a strong, but less than proportional, impact of the feature configuration. E.g., whereas the installed power is almost tripled by going from “medium” to “high” (see Table 4), the average power consumption is increased by only 60%. One reason is that most of the additional features are not required for the basic vehicle functions, so their frequency of use is comparatively low.

On the other hand, a considerable widening of the power distribution can be observed due to the additional features in the “high” configuration. Thus, as to be expected, power management becomes increasingly important in “loaded” vehicles.

- Compared to “medium”, the “high” feature configuration leads to non-neglectable probabilities $w(P)$ even at high power consumptions: For “medium”, 90% of all total power consumptions are below 1200 W, whereas for “high”, they