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Effects Function Analysis of ELF Magnetic Field Exposure in the Electric Utility Work Environment

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The incomplete understanding of the relation between power-frequency fields and biological responses raises problems in defining an appropriate metric for exposure assessment and epidemiological studies. Based on evidence from biological experiments, one can define alternative metrics or effects functions that embody the relationship between field exposure patterns and hypothetical health effects. In this paper, we explore the application of the ''effects function'' approach to occupational exposure data. Our analysis provides examples of exposure assessments based on a range of plausible effects functions. An EMDEX time series data set of ELF frequency (40–800 Hz) magnetic field exposure measurements for electric utility workers was analyzed with several statistical measures and effects functions: average field strength, combination of threshold and exposure duration, and field strength changes. Results were compared for eight job categories: electrician, substation operator, machinist, welder, plant operator, lineman/splicer, meter reader, and clerical. Average field strength yields a different ranking for these job categories than the ranks obtained using other biologically plausible effects functions. Whereas the group of electricians has the highest exposure by average field strength, the group of substation operators has the highest ranking for most of the other effects functions. Plant operators rank highest in the total number of field strength changes greater than 1 μT per hour. The clerical group remains at the lowest end for all of these effects functions. Our analysis suggests that, although average field strength could be used as a surrogate of field exposure for simply classifying exposure into ''low'' and ''high,'' this summary measure may be misleading in the relative ranking of job categories in which workers are in ''high'' fields. These results indicate the relevance of metrics other than average field strength in occupational exposure assessment and in the design and analysis of epidemiological studies. *Bioelectromagnetics 18:365–375, 1997.*

Key words: ELF; EMF; effects functions; exposure assessment; occupational exposure

INTRODUCTION

Epidemiological studies use job classifications of employees as a surrogate for exposure to power-frequency electric and magnetic fields [Savitz et al., 1994; Milham, 1985; Thériault et al., 1994; Floderus et al., 1995; Sahl et al., 1993]. In these studies, the occupational environment is surveyed for 60 Hz magnetic fields [Savitz et al., 1994; Sahl et al., 1993]. These measured fields are summarized and the resultant statistic is used to develop exposure scores. It has been assumed that the risk, if one exists, would be a linear function of average field strength (or cumulative field exposure). Biological experiments have suggested that biological effects of field exposure may depend on a variety of characteristics of field exposure, such as thresholds, frequency, exposure duration, field changes, and presence of DC fields. Nonlinear dose–response relationships should also be considered. In recent years, some attention has focused on characteristics of field exposure other than average field strength [Deadman et al., 1988; Matanoski, 1992; Matanoski et al., 1993; Bracken et al., 1995; Breysse et al., 1993, 1994; Sahl et al., 1993; Bowman et al., 1995]. However, most of this work examined mainly statistical measures characterizing field exposures and did not

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incorporate any indicator of biological evidence. Experimental evidence indicates that in addition to field strength, other field characteristics such as time variation of the field may also be relevant to producing a biological response. Elsewhere, we have suggested that ''effects functions'' may be more representative of the meaningful parameters of exposure [Morgan and Nair, 1992]. An ''effects function'' is defined as a functional relation between a certain field exposure pattern and levels of some hypothetical health effects [Morgan and Nair, 1992].

The objective of this study was to characterize the exposures to magnetic fields in one occupational environment by using effects functions. The time-weighted average magnetic field strength (or cumulative field strength) has been used as a measure of exposure most frequently in both occupational and epidemiologic studies. Even in the absence of certain knowledge of the function of field that determines the exposure metric, and of the dose–response relationship, it is meaningful to ask whether the commonly used average field strength is a surrogate for the effects functions at least in ranking the exposure of different job categories. We address two major questions: (1) How well does average magnetic field strength (or accumulated field exposure) serve as a measure to represent different categories of occupational field exposures, compared with time-dependent measures (effects functions) such as time spent above a certain field strength or the number of excursions above certain field strengths [Armstrong et al., 1990; Morgan and Nair 1992]? and (2) What characteristics of exposure might be used to distinguish, classify, and rank occupational field exposure?

Using field data collected in an electric utility work environment, effects functions can be simulated by computer programs to yield effects function values [Morgan et al., 1995]. Correlation coefficients between average field strength and other effects functions are compared to address the first question. Principal component analysis (PCA) is used to analyze the structure of the fields' time series data in terms of the effects functions, and traditional statistical measures such as geometric mean, standard deviation, and median as well as previously used measures such as fraction above a threshold [Jollife, 1986; Armstrong et al, 1990]. This analysis determines which of these variables are the best measure of data structure when all the variables are considered together. Results of PCA for different job classifications are compared to see how well effects functions and other measures discriminate among the field environment corresponding to different job titles and could therefore serve to differentiate among them.

The role of the PCA here is to reveal the interdependence of the metrics and to see which type of metrics (average fields, or various time-dependent measures, for example) contribute most to the data structure of the exposure. This analysis does not explain which of the effects functions are more biologically plausible as a ''true'' exposure metric for potential biological effects. If it is eventually shown that the biological effects depend on certain aspects of exposure, this analysis will help determine to what extent these aspects are present in these specific occupational data. Blair and Stewart have noted the advantage of alternative exposure measures in revealing whether a noted association between occupational exposure and health effect is in fact real [Blair and Stewart, 1992]

METHODS

Measurement Data

The data used in this study are two sets of power-frequency magnetic fields data collected by utility workers at the Southern California Edison Company in 1991 and 1992, respectively. Details of data collection are reported elsewhere [Sahl et al., 1994]. In general, workers in the study wore an EMDEX meter on their waist while working on their normally assigned full tasks. For this analysis, eight job categories were selected: electrician, substation operator, machinist, welder, plant operator, lineman/splicer, meter reader, and clerical worker. The first six categories are defined as craft workers. The total numbers of days were 458 for 1991 and 577 for 1992. Table 1 lists the sample sizes for each category.

To compare effects functions with other statistical measures that were analyzed on the 1991 data set [Sahl et al., 1994], we first did the analysis on 1991 and 1992 data sets separately. Then, the two data sets were lumped together as one data set of 1035 samples. We tested the two data sets for eight job categories separately to determine whether their statistical behavior indicated that they were drawn from the same population. Only meter readers would be viewed as heterogeneous (significance of 0.05 level, where $T = 2.496$, degree of freedom is 110, and probability is .014). Table 2 shows the results of the *t* test. The arithmetic mean for the group of machinists is 2.83 μT, which is different from the value of 1.42 previously reported [Sahl et al., 1994]. The main reason is that one sample of 37.8 μT is included in the current study, but excluded in the previous study. Even though this ''outlier'' is included, the *t* test result still shows the two sample means are not significantly different at the .05 level. Also, the sample sizes are slightly smaller for the ma-

TABLE 1. Sample Sizes of the Data Sets, Showing Number of Workers in Each Occupational Category for Data From Years 1991 and 1992

	Job title								
Year	Clerical	Meter readers	Plant operators	Substation operators	Electricians	Linemen/splicers	Machinists	Welders	Total
1991	55	53	53	15	55	171	26	19	458
1992	81	59	39	21	173	83	91	31	577
Combined	136	112	92	36	238	254	117	50	1035

TABLE 2. *t* Test for Sample Means of 1991 and 1992 Data Sets

	Job category							
	Clerical	Meter readers	Plant operators	Substation operators	Electricians	Lineman splicers	Machinists	Welders
Mean			1.01	1.82	3.35	1.19		
91	0.18	0.27					2.83	1.06
92	0.21	0.17	0.76	0.94	1.51	1.47	1.33	0.80
t value	−0.749	2.496	1.476	2.256	2.169	−0.675	1.483	0.893
Degree of freedom	134	112	90	34	236	252	115	48
Probability	0.455	0.014	0.144	0.031	0.031	0.500	0.141	0.376

jority of eight categories in the current study than in the previous work.

The 1992 data set has lower mean values for six of eight job categories, especially the categories of craft workers. When the 1991 data set was collected, the workers were able to see the readings from the screen of the EMDEX II meter. Some workers may have moved the meter from the normal position on the waist. When the 1992 data set was collected, it was impossible for the subjects to see the readings from the screen. This is one possible explanation for the systematic decrease in average field strength. Other possible reasons include sample variances due to the small sample sizes, which imply differences in job tasks, or in working environment.

Effects Functions and Statistical Measures

The biological basis for effects functions is discussed elsewhere [Zhang, 1993; Morgan and Nair, 1992]. In this study, we used three effects functions, as listed in Table 3, each with a range of parameters:

Effects Function 1 (E_1): Effect is proportional to the number of 5-min sequences per hour when 80% of field exposure is above a threshold. Threshold values chosen were 0.3, 0.5, and 1 μT, represented by $E_1(3)$, $E_1(5)$, and $E_1(10)$. Figure 1 illustrates the process of simulation of effects function $E_1(3)$. In Figure 1 (a), the envelop represents the actual field exposure history, and the vertical lines represent the time series sampled by the EMDEX meter, as EMDEX data. Figure 1 shows the steps of a simulation using an effects function for which the effect is measured by the number of occurrences where the field strength remains above a specified threshold value B_t for at least 80% of exposure duration t_1. Suppose t_1 is the time interval for five records after counting starts (i.e., 7.5 s when the EMDEX data are sampled every 1.5 s). A computer program then searches the time series for successive time intervals of five records within which at least four records lie above B_t, as shown in Figure 1 (b). This is done by looking at the first five records to see whether four of them lie above B_t, counting it as 1 if they do and 0 if they do not. If the count for 0 to 5 is 1, we next look at records 6 to 10. If the count for 0 to 5 is 0, we next look at records 2 to 6. This counting procedure is then repeated. The final result for the time series illustrated in Figure 1 (a) is 2.

Effects Function 2 (E_2): Effect is proportional to the counts per hour when the field strength changes are equal or greater than a threshold. Threshold values: 0.3, 0.5, and 1 μT, are represented as $E_2(3)$, $E_2(5)$, and $E_2(10)$. In addition, we also required that the baseline of field exposure is above a threshold (0.5 μT) for one example, represented as $E_2(3, 5)$.

Effects Function 3 (E_3): Effect is proportional to the number of 5-min sequences (counted with no overlap of time periods) per hour when 20% of field changes are equal to or greater than a threshold. Threshold values used were 0.3, 0.5, and 1 μT. These effects functions are represented as $E_3(3)$, $E_3(5)$, and $E_3(10)$.

TABLE 3. Summary of Effects Functions Used

	Definition	Parameters	Symbols
Effects function 1 (E_1)	Effect is proportional to the number of 5-min sequences per hour when 80% of field exposure is above a threshold, B_t	B_t = 0.3 μT B_t = 0.5 μT B_t = 1 μT	$E_1(3)$ $E_1(5)$ $E_1(10)$
Effects function 2 (E_2)	Effect is proportional to the counts per hour when the field strength changes are equal or greater than a threshold, ΔB_t & baseline of field exposure is ≥5.0 μT	ΔB_t = 0.3 μT ΔB_t = 0.5 μT ΔB_t = 1 μT ΔB_t = 1 μT	$E_2(3)$ $E_2(5)$ $E_2(10)$ $E_2(e, 5)$
Effects function 3 (E_3)	Effect is proportional to the number of 5-min sequences per hour when 20% of field changes are equal or greater than a threshold, ΔBt	ΔB_t = 0.3 μT ΔB_t = 0.5 μT ΔB_t = 1 μT	$E_3(3)$ $E_3(5)$ $E_3(10)$

Table 3 summarizes the three types of effects functions with different parameters, 10 in total. In addition, we used average field strength (arithmetic mean), standard deviation, and four other statistical measures, namely, the geometric mean, median, and fractions exceeding 0.5 and 1 μT, which were found to distinguish different job categories of utility workers better than other statistical measures [Sahl et al., 1994]. This strategy gives a total of 16 measures. With these measures, we conducted three types of analyses: the correlation of each measure with the arithmetic mean, a principal component analysis, and a Varimax Rotation of these data.

Methods of Analysis

We used methods from multivariate statistics to examine the structure of the exposure data. These multivariate techniques are used for analyses of statistical populations (such as ecological or biological populations) because the variables used to describe these populations are usually intercorrelated to varying degrees. In our case, several measures of exposure (variables)

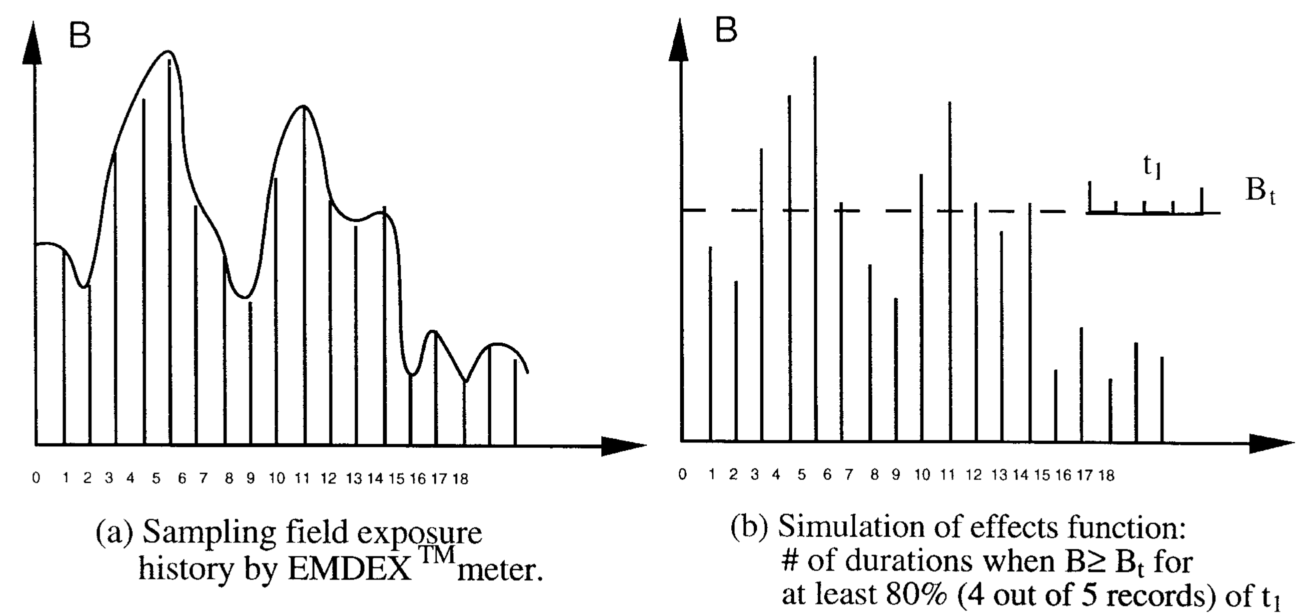

Fig. 1. Simulation of effects function 1. Effects function 1 is defined as a function proportional to the number of 5-min sequences per hour when 80% of field exposure data are above a threshold, B_t. (Table 3). The program searches the first five records to see whether four of these lie above B_5, counting it as 1 if it does and 0 if it does not. If the count for 0 to 5 is 1, we next look at records 6 to 10. If the count for 0 to 5 is 0, we next look at records 2 to 6. This counting procedure is then repeated. The result for this example is thus 2 for the value of $E_1(B_t)$

have been assessed for each object (group of workers). These variables are correlated. The multivariate techniques described below analyze this covariation to find how the measures (variables) are correlated, and which of the measures dominate in describing the exposure data. This analysis is then used to draw conclusions about the data and to answer the main questions of this work.

Correlation With Average Field Strength (Arithmetic Mean)

For each data set or subset, a correlation matrix was calculated. Correlation coefficients between average field strength and other statistical measures and effects function values indicate to what extent average field strength may be taken as a surrogate for these other measures of field exposure.

Principal Component Analysis of EMDEX Data

Principal component analysis (PCA) is a statistical method to summarize a multivariate data set as accurately as possible using a few components [Jollife, 1986]. PCA attempts to explain the variance-covariance structure of a data set through a few linear combinations of the original variables [Johnson and Wichern, 1988; Bryant and Atchley, 1975]. The objectives of PCA are (1) to reduce the dimensionality of the original data with minimum loss of information and (2) to interpret the data. In our case, the various statistical measures and effects function values (16 in all) of the exposure records may be considered the variables representing the exposure data. Although 16 components (linear combinations of the variables) are required to reproduce the total system variability, much of this variability can be accounted for by a smaller number of the principal components. There is almost as much information in these fewer components as there is in the 16 original components. Analysis of the principal components can also reveal relationships among the variables that are not evident before the analysis.

For our 16-variable data set, 16 components can be computed. If these components are listed in order of their contributions to the total variance, the first k components ($k < 16$) will explain the major part of the total variance. The coefficients for the original variables in this linear combination are called component loadings. These represent the correlation between the original variables and the specific principal component. PCA is generally used to reduce systems with tens or hundreds of variables. We use it here for a much smaller number (16) of variables. This does not reduce the value of PCA. It still yields useful information about which type of field variables contribute to the structure of the exposure data.

Varimax Rotation of the Principal Components

Varimax rotation is a procedure that assists with the interpretation of the contribution of the various exposure measures to the data structure. A varimax rotation rotates the principal components axes so that the variances are maximized. This is done by reducing the number of variables with nonzero coefficients or by increasing the values of the large coefficients as much as possible. Varimax rotation reveals the dominant contributions to the data structure [Stopher and Meyburg, 1979].

RESULTS

Ranks for Each Summary Statistic Across Job Categories

The relevant results are now summarized in terms of the ranking of the job categories according to statistical or effects function measures of exposure, the correlation among the measures, and the results of the principal component analysis.

The ranking of most exposure to least exposure is different depending on which measure is used to characterize exposure. A note about the computed effects function values is in order here. Unlike the arithmetic mean or other statistical measures of field strength, the effects functions are measured by counting characteristics of the field environment such as for example the ''number of times per hour the field strength changes by increments larger than 0.5 μT'' in the case of $E_2(5)$ (Table 3). Thus different job categories may be ranked on a specific effects function, but it is meaningless to compare numerical values of different effects functions.

Figures 2 and 3 show the ranking when mean field strength or a ''field change'' effects function is used as a measure of exposure, respectively. In Figures 2 and 3, box-plots show the ranges of effects function values between the 25th and 75th percentiles. The bars in the boxes represent the median effects function values. The horizontal line shows the 95th percentile. The asterisks show outliers. When all effects functions are considered, the notable results are as follows: (a) The two groups of non-craft workers, clerical and meter readers, have the lowest level of exposure in terms of statistical measures as well as effects functions. (b) The six groups of craft workers have higher levels of exposure than non-craft workers in terms of average field strength, but with wide ranges (Figure 2). The highest exposure levels are for substation operators, electricians, machinists, and linemen/splicers. (c) Among the six groups of craft workers, ranking by other statistical measures and effects function values

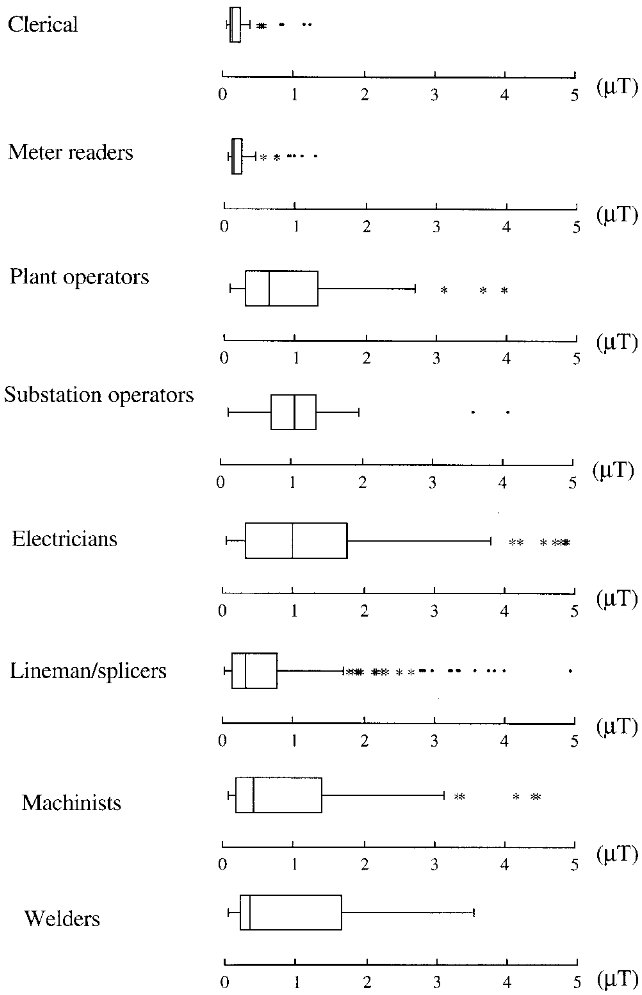

Fig. 2. Ranges of average field strength across job categories for the "combined" data set. The box plots show the range of effects function values between 25th and 75th percentiles. The bars *in the box* represent median values. The horizontal lines denote the 95th percentile. In this measure, plant operators rank in the low to middle range of craft workers.

are not in accordance with the ranking provided by average field strength. Table 4 summarizes the ranking of the six groups of craft workers according to the arithmetic mean and the nine effects functions for the combined data set. The ranking is done using the average value of each effects function for the occupational group. The table shows that for the majority of the effects function measures, the substation operator group ranks first, and the electrician group second. The lineman/splicer group ranks last in most cases. The third, fourth, and fifth rank may be occupied by machinists, welders, or plant operators depending on the effects function and parameter considered.

The plant operator group actually ranks first according to the effects functions $E_2(10)$ and $E_3(10)$ $E_2(10)$, proportional to counts per hour when field strength changes are equal to or greater than 1 μT; $E_3(10)$, proportional to number of 5-min sequences per hour when 20% of field changes are equal to or greater than 1 μT.

Even though this group is at the lower end of average field strength among the six groups of craft workers. This finding reflects the fact that even though the general field strength level is low for these workers most of the time, they are more frequently subjected to field strength excursions to values above 1 μT than any other type of workers considered. This analysis shows that the arithmetic mean would be a poor surro-

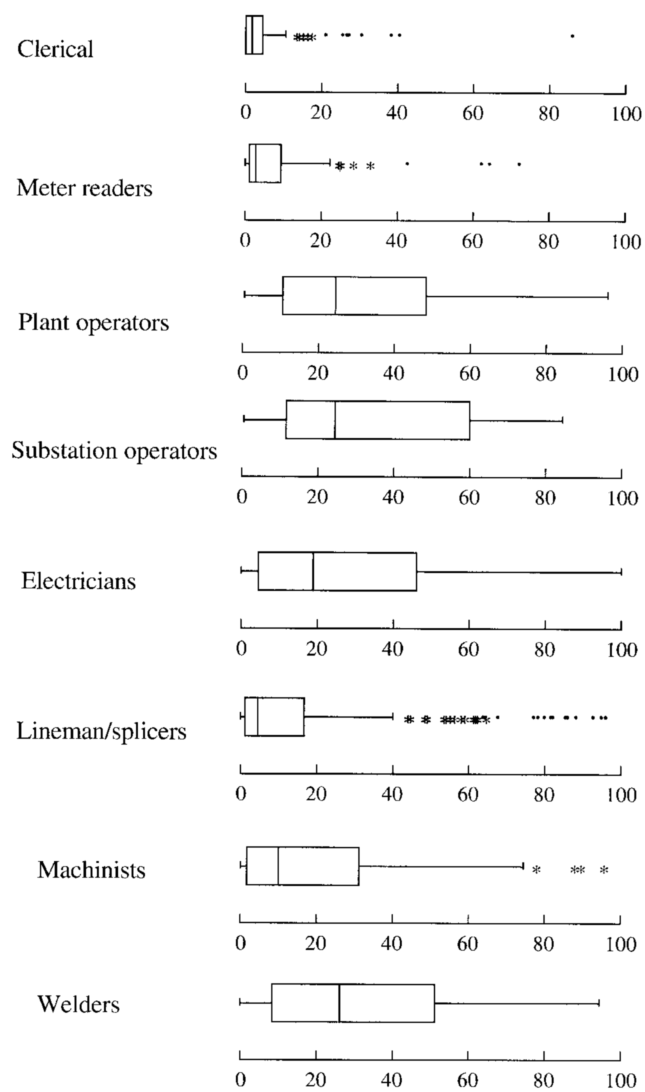

Fig. 3. Ranges of $E_2(10)$ measurements for the "combined" data set. $E_2(10)$ represents the effects function proportional to the counts per hour when the field strength change equals or exceeds 1 μT. In this measure, plant operators, substation operators, and welders have the highest median values of exposure.

TABLE 4. Rankings of the Six Groups of Craft Workers

	Job category					
Exposure metric	Substation operators	Electricians	Machinists	Plant operators	Welders	Linemen/splicers
Arithmetic mean	4	1	2	6	5	3
$E_1(3)$	1	2	3	4	5	6
$E_1(5)$	1	2	3	4	5	6
$E_1(10)$	1	2	3	6	5	4
$E_2(3)$	1	2	5	3	4	6
$E_2(5)$	1	3	5	2	4	6
$E_2(10)$	2	3	5	1	4	6
$E_3(3)$	1	2	4	5	3	6
$E_3(5)$	1	2	5	4	3	6
$E_3(10)$	4	2	6	1	3	5

*For the combined data set according to the arithmetic mean and the three effects functions with parameters set at 0.3, 0.5, and 1.0 μT. ''1'' stands for the highest value on the exposure metric considered, ''2'' for the second highest value, and so on.

TABLE 5. Correlation Matrix of Statistical Measures and Effects Functions for the Combined Data Set

	AM	GM	MED	SD	F0.5	F1.0	$E_1(3)$	$E_1(5)$	$E_1(10)$	$E_2(3)$	$E_2(5)$	$E_2(10)$	$E_2(35)$	$E_3(3)$	$E_3(5)$	$E_3(10)$
Ari. mean	1.00															
Geo. mean	0.27	1.00														
Median	0.27	0.72	1.00													
STDI.	0.81	0.14	0.10	1.00												
Fr. > 0.5 μT	0.26	0.70	0.49	0.16	1.00											
Fr. > 1.0 μT	0.27	0.73	.054	0.17	0.90	1.00										
$E_1(3)$	0.28	0.50	0.37	0.18	0.79	0.69	1.00									
$E_1(5)$	0.30	0.52	0.41	0.19	0.83	0.75	0.93	1.00								
$E_1(10)$	0.33	0.55	0.46	0.19	0.73	0.81	0.76	0.86	1.00							
$E_2(3)$	0.47	0.46	0.41	0.32	0.57	0.60	0.59	0.64	0.68	1.00						
$E_2(5)$	0.49	0.41	0.35	0.34	0.52	0.55	0.53	0.58	0.62	0.99	1.00					
$E_2(10)$	0.59	0.36	0.31	0.43	0.44	0.46	0.46	0.50	0.52	0.90	0.95	1.00				
$E_2(35)$	0.46	0.46	0.42	0.30	0.57	0.61	0.59	0.65	0.69	1.00	0.99	0.90	1.00			
$E_3(3)$	0.36	0.49	0.40	0.27	0.66	0.69	0.71	0.77	0.77	0.90	0.84	0.74	0.89	1.00		
$E_3(5)$	0.38	0.45	0.36	0.29	0.62	0.65	0.65	0.71	0.72	0.95	0.92	0.84	0.94	0.97	1.00	
$E_3(10)$	0.51	0.31	0.30	0.39	0.35	0.37	0.36	0.39	0.42	0.84	0.89	0.95	0.84	0.61	0.72	1.00

gate if one of the biologically valid exposure metric turns out to behave like one of the three types of effects functions discussed.

Correlations Among Measures

Table 5 is the Pearson correlation matrix for the combined data set. The matrices for data sets of 1991 and 1992 are similar to this one. This matrix shows that the arithmetic mean has a high correlation coefficient (0.81) with the standard deviation (SD), but generally low correlation coefficients (less than 0.5) with other statistical measures and effects functions.

The arithmetic mean has a weak correlation (<0.6) with E_1, E_2, and E_3 when the threshold field value is set at 0.1 or 0.3 μT and a slightly higher correlation with $E_2(10)$ and $E_3(10)$. This shows again that if field changes represent the biologically relevant metric of exposure, the arithmetic mean is not a good representative of exposure for this population of utility workers. The statistical measures (fraction > 0.5 μT) and (fraction > 1 μT) are highly correlated with the effects function $E_1(5)$ and $E_1(10)$ respectively. This correlation reflects the intrinsic property of this effects function which characterizes exposure mainly in terms of field strength and threshold. Effects function 2 and effects function 3 are also correlated. This is because strength changes are the inherent measures in these two effects functions, both of which count field changes but in different ways.

Principal Component Analysis

We used SYSTAT™ software package on Macintosh (SYSTAT Inc., Evanston, IL) for the Principal

TABLE 6. Principal Component Analysis: Component Loadings for Non-Craft Workers

Original variable	Component 1	Component 2	Component 3	Component 4
Arithmetic mean	0.836[a]	0.294	−0.290	0.221
Geometric mean	0.294	0.872[a]	0.243	−0.132
Median	0.235	0.875[a]	0.261	−0.013
Standard deviation	0.557	−0.137	−0.235	0.057
Fraction $> 0.5\ \mu T$	0.389	0.846[a]	0.129	−0.182
Fraction $> 1.0\ \mu T$	0.338	0.250	−0.315	−0.815[a]
$E_1(3)$	0.555	0.653	−0.024	0.315
$E_1(5)$	0.557	0.737	−0.027	0.218
$E_1(10)$	0.313	0.207	−0.823[a]	0.030
$E_2(3)$	0.924[a]	−0.325	0.070	0.016
$E_2(5)$	0.932[a]	−0.329	0.103	−0.017
$E_2(10)$	0.913[a]	−0.319	0.111	−0.073
$E_2(35)$	0.935[a]	−0.299	0.053	0.011
$E_3(3)$	0.899[a]	−0.323	0.046	0.053
$E_3(5)$	0.925[a]	−0.317	0.069	0.021
$E_3(10)$	0.550	−0.220	0.300	−0.260
Percent of total variance explained (total = 86.2)	47.1	25.5	7.4	6.2

[a]Denotes loadings greater than 0.7.

TABLE 7. Principal Component Analysis: Component Loadings for Craft Workers

Original variable	Component 1	Component 2	Component 3	Component 4
Arithmetic mean	0.323	0.108	0.855[a]	0.127
Geometric mean	0.195	0.346	0.074	0.450[a]
Median	0.185	0.215	0.060	0.925[a]
Standard deviation	0.191	0.056	0.956[a]	−0.014
Fraction $> 0.5\ \mu T$	0.253	0.745[a]	0.063	0.198
Fraction $> 1.0\ \mu T$	0.294	0.604[a]	0.060	0.248
$E_1(3)$	0.288	0.927[a]	0.079	0.103
$E_1(5)$	0.324	0.907[a]	0.080	0.125
$E_1(10)$	0.375	0.689[a]	0.079	0.189
$E_2(3)$	0.894[a]	0.326	0.136	0.144
$E_2(5)$	0.934[a]	0.258	0.153	0.089
$E_2(10)$	0.914[a]	0.178	0.268	0.075
$E_2(3, 5)$	0.895[a]	0.330	0.112	0.149
$E_3(3)$	0.694[a]	0.522	0.081	0.116
$E_3(5)$	0.805[a]	0.428	0.094	0.075
$E_3(10)$	0.907[a]	0.073	0.223	0.104
Percent of total variance expained (total = 82.4)	37.2	25.2	11.7	8.3

[a]Denotes loadings greater than 0.7.

Component Analysis and for varimax rotation. The results are shown in Tables 6, 7, and 8. Component loadings with values greater than .7 may be considered as contributing significantly to the structure of the data set. Four components capture 86.2% of the variance for non-craft workers and 82.4% of the variance for craft workers. These four components are used below to discuss the data structure rather than the 16 variables, which represent all the measures we used.

Tables 6 and 7 show the original component loadings for non-craft workers and for craft workers, respectively. These loadings yield a comparison between arithmetic mean and other measures. The arithmetic mean for non-craft workers (Table 6) shows a relatively high loading 0.84, comparable to those for E_2 and E_3 (0.9–0.94) which are the effects functions for field changes. This indicates that the arithmetic mean contributes as much as the field change effects functions to the field environment of non-craft workers. $E_3(10)$, however, has a loading of only 0.55. This reflects the

TABLE 8. Component Loadings after Varimax Rotation for Combined Data Set (1991 and 1992) for Craft Workers

Original variable	Component 1	Component 2	Component 3	Component 4
Arithmetic mean	0.503	0.444	−0.658	0.162
Geometric mean	0.609	−0.431	−0.334	−0.441
Median	0.519	−0.322	−0.337	−0.585
Standard deviation	0.335	0.480	−0.691	0.303
Fraction > 0.5 μT	0.758	−0.506	−0.118	0.065
Fraction > 1.0 μT	0.772	−0.482	−0.127	−0.033
$E_1(3)$	0.749	−0.397	0.026	0.365
$E_1(5)$	0.805[a]	−0.398	0.031	0.347
$E_1(10)$	0.814[a]	−0.345	0.013	0.198
$E_2(3)$	0.932[a]	0.261	0.187	−0.080
$E_2(5)$	0.900[a]	0.356	0.192	−0.094
$E_2(10)$	0.835[a]	0.481	0.072	−0.101
$E_2(3, 5)$	0.931[a]	0.247	0.204	−0.092
$E_3(3)$	0.916[a]	−0.014	0.204	0.098
$E_3(5)$	0.925[a]	0.133	0.239	0.042
$E_3(10)$	0.745	0.530	0.089	−0.200
Percent of total variance explained (total = 90.0)	59.6	15.2	8.7	6.5

[a]Denotes loadings greater than 0.7.

absence of excursions to values above 1 μT (the threshold field for $E_3(10)$) in the exposure data set of non-craft workers. This also indicates that while the arithmetic mean is representative of the exposure pattern of non-craft workers, field changes also contribute to the structure of their exposure data.

Table 7 shows the component loadings for the craft worker data set. For this group, arithmetic mean and other conventional statistical measures all have loadings less than 0.35 in the first component. The higher loadings of the effects functions E_2 and E_3 indicate that for craft workers, field changes provide a description of the data set that is more significant than that by the arithmetic mean, or standard deviation which is also shown by the weak correlation discussed in the previous section. This implies that if changes in field strength (rather than the value of field strength itself) are the basis for biological effects, then the arithmetic mean is a poor representative for the exposure metric in epidemiological or dose-response studies for populations whose exposure pattern is similar to that of our craft workers.

Table 7 shows also that for craft workers the field change effect functions E_2 and E_3 dominate component 1, the threshold and exposure duration measures dominate component 2, and the value of field strength and its variation dominate component 3. Seventy-four percent of the total variance is described by these components.

A varimax rotation of the data in Table 7 (craft-workers) yields the results in Table 8. Component 1 accounts for almost 60% of the total variance. This component has high (>0.8) contributions from E_1, E_2, and E_3, which reflect field changes. This finding confirms that field changes are important contributors to the structure of the data set representing craft workers.

DISCUSSION

We have used effects functions and statistical measures to characterize the magnetic field exposures of eight groups of workers from an electric utility work environment. The two non-craft job categories—clerical staff and meter readers—have generally low exposures, as well as a smaller range of exposure, on all measures we tested. We found that the arithmetic mean can be used to distinguish non-craft workers from craft workers. However, the average field strength does not have high correlation coefficients with other statistical measures or with effects functions. This means that the arithmetic mean is not sufficient to characterize exposures of craft workers unless the relevant biological effects turn out to be dependent on value of field strength alone, and not on field changes. These findings therefore do not support the suggestion made by Armstrong and co-authors that the arithmetic mean may be a reasonable surrogate for occupational field exposure assessment [Armstrong et al., 1990]. Although their data supported their suggestion, the larger sample size and more measurements in this study would suggest that the arithmetic mean is not sufficiently representative.

Some general observations about the representation of exposure by the various effects functions are as follows: (a) The principal component analysis shows that the exposures may be classified in terms of three primary components: one that represents ''field change,'' one that may be viewed as a ''threshold and exposure duration'' component, and, the third, a ''magnitude'' component. We attempted a clustering analysis based on the statistical and effects function measurements. But we did not get any indication that under certain effects functions, job categories may be clustered. There are two possible reasons: (1) we have not found ''the'' measure for clustering, and (2) ''the'' measure does not exist due to the complicated exposure conditions across job titles and tasks. (b) Effects functions for field changes (E_2 and E_3) contribute most to the total variance of data sets, even for non-craft workers. Although the EMDEX data with a sampling interval of 1.5 s do not include rapid transients (field strength changes rising and falling in much shorter time intervals) in the electric utility work environment, they capture some of the overall field changes. Some biological experiments have suggested the importance of field changes for biological effects [Wilson et al., 1989; Lerchl et al., 1991]. (c) Effects functions based on threshold and duration of field strength above the threshold (E_1) also explain a substantial portion of the variance. Although the E_1 effects functions are correlated with the statistical measure ''fraction greater than a threshold,'' the effects function measures have higher loadings than the statistical measures in the principal component analysis. So, they are not replaceable by the statistical measures. This means that if rapid field changes are biologically important, this effects function is more relevant for epidemiological studies of this population than the ''fraction above threshold'' measure. (d) Specific effects functions with different field parameters are generally correlated with one another, as is to be expected. However, this does not mean that only one or two field parameters are adequate for a complete representation of exposure. This is exemplified by the case of the plant operators group. This group has the lowest exposure ranking for craft workers on the basis of the arithmetic mean and other statistical measures as well as for several effects function measures. But this group ranks first among all groups for the effects function E_2 and E_3 (which count field strength changes) when the threshold is set at 1 μT although it ranks lower for the threshold values 0.3 and 0.5 μT. This illustrates the need for a parametric analysis in epidemiological studies using effects functions for exposure characterization.

CONCLUSION

The questions posed at the start of the paper were (1) whether the average magnetic field strength as a measure of exposure would rank the different occupational categories of utility workers in the same order as other measures such as effects functions, and (2) what characteristics of the field environments might distinguish the occupational categories of utility workers. The work described gives some answers to these questions. Results were compared for eight job categories: electrician, substation operator, machinist, welder, plant operator, lineman/splicer, meter reader, and clerical. Average field strength, the exposure metric normally used, yields a different ranking for these job categories than the ranking obtained using other biologically plausible effects functions. Whereas the group of electricians has the highest exposure by average field strength, the group of substation operators ranks first for most other effects functions. Plant operators rank highest in exposure when the effects function is taken as the total number of field strength changes greater than 1 μT per hour. The clerical group remains at the lowest end for all of these effects functions. This finding suggests that average field strength—the currently used metric—can be used as a surrogate of field exposure only for simply classifying exposure into ''low'' or ''high'' (or between non-craft and craft workers in this utility). It may not be valid (or may be misleading) for ranking of job categories of craft workers or those in which workers are in ''high'' fields.

The principal component analysis shows that exposures relevant to the craft work categories represented here may be classified in terms of three primary characteristics: one that represents ''field change,'' one that may be viewed as a ''threshold and exposure duration'' component; and the third, a ''magnitude'' component. These results indicate the relevance of measures other than field strength in occupational exposure assessment. This work is based only on two data sets, both from the same utility. Therefore, the results may not be generally applicable to all utilities. Similar analysis applied to data from a number of utilities is needed to see whether our conclusions may be generalized to similar job categories in all utilities.

The results of this study and the ranking of job categories according to different effects functions do not imply that one metric is more important that another in terms of health effects. In this sense, the PCA does not place one metric as more relevant to health endpoints or as more biologically plausible than another. For this, one would need to have the corresponding health data. Then the effects function PCA could be combined with health data to see if one metric correlates better with specific health endpoints. This result could then be used for design and analysis of epidemiological studies. The present analysis only helps sort out the interdependence between various exposure metrics.

This study provides potentially useful results for improving occupational exposure assessment and the design and analysis of epidemiological studies. We have provided examples for the use of effects functions for occupational magnetic field exposure in comparison with traditional statistical measures. Since there are many job categories among electric utility workers, it is important to explore measures that can distinguish the magnetic field exposure experienced by workers of different job categories, and further, have a basis in exposure parameters consistent with biological evidence.

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REFERENCES

Armstrong BG, Deadman JE, Thériault G (1990): Comparison of indices of ambient exposure to 60-Hz electric and magnetic fields. Bioelectromagnetics 11:337–347.

Blair A, Stewart PA (1992): Do quantitative exposure assessments improve risk estimation in occupational studies of cancer? Am J Ind Med 21:53–63.

Bowman JD, Thomas DC, London SJ, Peters JM (1995): Hypothesis: The risk of childhood leukemia is related to combinations of power-frequency and static magnetic fields. Bioelectromagnetics 16:48–59.

Bracken TD, Rankin RF, Senior RS, Alldredge JR, Sussman SS (1995): Magnetic field exposure among utility workers. Bioelectromagnetics 16:216–226.

Breysse PN, Lees PSI, McDiarmid MA, Curbow B (1993): ELF magnetic field exposures in an office environment. Am J Ind Med 25:177–185.

Breysse PN, Gray R, and Ad Hoc Working Group (1994): Video display terminal (VDT) exposure assessment. Appl Occup Environ Hyg 9:671–677.

Bryant EH, Atchley WR (1975): ''Multivariate Statistical Methods: Within-Groups Covariation.'' Stroudsburg, PA: Dowden, Hutchinson & Ross, Inc.

Deadman JE, Camus M, Armstrong BG, Héroux P, Cyr D, Plante M, Thériault G (1988): Occupational and residential 60-Hz electromagnetic fields and high-frequency electric transients: Exposure assessment using a new dosimeter. Am Ind Hyg Assoc J 49:409–419.

Floderus B, Persson T, Stealund C, Wennberg A, Öst Å, Knave B (1995): Occupational exposure to electromagnetic fields in relation to leukemia and brain tumors: A case-control study in Sweden. Cancer Causes and Control 4:465–476.

Johnson RA, Wichern DW (1988): ''Applied Multivariate Statistical Analysis.'' Englewood Cliffs, NJ: Prentice Hall.

Jollife IT (1986): ''Principal Component Analysis.'' New York: Springer-Verlag Inc., pp 125–128.

Lerchl A, Hanaka KO, Reiter RJ (1991): Pineal gland magnetosensitivity to static magnetic fields is a consequence of induced electric currents (eddy currents). J Pineal Res 10:108–116.

Matanoski GM (1992): Leukemia in telephone linemen. Final report prepared for Electric Power Research Institute (EPRI TR-101813). Palo Alto: Electric Power Research Institute.

Matanoski GM, Elliott EA, Breysse PN, Lynberg MC (1993): Leukemia in telephone linemen. Am J Epidemiol 137:609–619.

Milham S (1985): Mortality in workers exposed to electromagnetic fields. Environmental Health Perspectives 62:297–300.

Morgan M, Nair I, Zhang J (1995): A method for assessing alternative effects functions that uses simulation with EMDEX data. Bioelectromagnetics 16:172–177.

Morgan MG, Nair I (1992): Alternative functional relationships between ELF field exposure and possible health effects: Report on an expert workshop. Bioelectromagnetics 13:335–350.

Sahl JD, Kelsh MA, Smith RW, Aseltine DA (1994): Exposure to 60 Hz magnetic fields in the electric utility working environment. Bioelectromagnetics 15:21–32.

Sahl JD, Kelsh MA, Greenland S (1993): Cohort and nested case-control studies of hematopoietic cancers and brain cancer among electric utility workers. Epidemiology 4:104–114.

Savitz DA, Ohya T, Loomis DP, Senior RS, Bracken TD, Howard RL (1994): Correlations among indices of electric and magnetic field exposure in electric utility workers. Bioelectromagnetics 15:193–204.

Stopher PR, Meyburg AH (1979): ''Survey sampling and multivariate analysis for social scientists and engineers.'' Lexington, MA: Lexington Books.

Thériault G, Goldberg M, Miller AB, Armstrong B, Guenel P, Deadman J, Imberman E, To T, Chevalier A, Cyr D, Wall C (1994): Cancer risks associated with occupational exposure to magnetic fields among electric utility workers in Ontario and Quebec, Canada, and France 1970–1989. Am J Epidemiol 139:550–572.

Wilson BW, Stevens RG, Anderson LE (1989): Neuroendocrine mediated effects of electromagnetic field exposure, possible role for the pineal gland. Life Sci 45:1319–1332.

Zhang J (1993): Parametric approach to quantitative assessment of EMF risks. PhD Thesis, Carnegie Mellon University. Pittsburgh, PA.