

freedom to provide adequate sensitivity, in which case the investigator may wish to change the experiment (e.g., by choosing more levels of some factors or more observations per treatment combination, or by changing from random to fixed levels of some factors).

### ★6.4 EMS RULES

Sections 6.2 and 6.3 showed the importance of the EMS column in determining what tests of significance are to be run after the analysis is completed. Because of the importance of the EMS column in these and more complex models, it is often useful to have a simple method of determining these values from the model for the given experiment. A set of rules can be stated for the *balanced case* that will determine the EMS column very rapidly, without recourse to their derivation. The rules will be illustrated on the two-factor mixed model of Section 6.3. To determine the EMS column for any model:

1. Write the variable terms in the model as row headings in a two-way table.

$A_i$
$B_j$
$AB_{ij}$
$\epsilon_{k(ij)}$

2. Write the subscripts in the model as column headings; over each superscript write *F* if the factor levels are fixed, *R* if random. Also write the number of observations each subscript is to cover.

	$a$	$b$	$n$
	$F$	$R$	$R$
	$i$	$j$	$k$
$A_i$			
$B_j$			
$AB_{ij}$			
$\epsilon_{k(ij)}$			

3. For each row (each term in the model) copy the number of observations under each subscript, provided the subscript does not appear in the row heading.

	$a$	$b$	$n$
	$F$	$R$	$R$
	$i$	$j$	$k$
$A_i$		$b$	$n$
$B_j$	$a$		$n$
$AB_{ij}$			$n$
$\epsilon_{k(ij)}$			

4. For any parenthetical subscripts in the model, place a 1 under the subscripts given in parentheses.

	<i>a</i> <i>F</i> <i>i</i>	<i>b</i> <i>R</i> <i>j</i>	<i>n</i> <i>R</i> <i>k</i>
$A_i$		<i>b</i>	<i>n</i>
$B_j$	<i>a</i>		<i>n</i>
$AB_{ij}$			<i>n</i>
$\varepsilon_{k(ij)}$	1	1	

5. Fill each remaining cell with a 0 or a 1, depending on whether the subscript represents a fixed *F* or a random *R* factor.

	<i>a</i> <i>F</i> <i>i</i>	<i>b</i> <i>R</i> <i>j</i>	<i>n</i> <i>R</i> <i>k</i>
$A_i$	0	<i>b</i>	<i>n</i>
$B_j$	<i>a</i>	1	<i>n</i>
$AB_{ij}$	0	1	<i>n</i>
$\varepsilon_{k(ij)}$	1	1	1

6. To find the expected mean square for any term in the model:
- Cover the entries in the column (or columns) that contain nonparenthetical subscript letters in this term in the model (e.g., for  $A_i$ , cover column *i*; for  $\varepsilon_{k(ij)}$ , cover column *k*).
  - Multiply the remaining numbers in each row. Each of these products is the coefficient for its corresponding term in the model, provided the subscript on the term is also a subscript on the term whose expected mean square is being determined. The sum of these coefficients multiplied by the variance of their corresponding terms ( $\phi_\tau$  or  $\sigma_\tau^2$ ) is the EMS of the term being considered (e.g., for  $A_i$ , cover column *i*). For our example, the products of the remaining coefficients are *bn*, *n*, *n*, and 1, but the first *n* is not used, as there is no *i* in its term ( $B_j$ ). The resulting EMS is then  $bn\phi_A + n\sigma_{AB}^2 + 1 \cdot \sigma_\varepsilon^2$ . For all terms, these rules give the following partial ANOVA table.

	<i>a</i> <i>F</i> <i>i</i>	<i>b</i> <i>R</i> <i>j</i>	<i>n</i> <i>R</i> <i>k</i>	EMS
$A_i$	0	<i>b</i>	<i>n</i>	$\sigma_\varepsilon^2 + n\sigma_{AB}^2 + nb\phi_A$
$B_j$	<i>a</i>	1	<i>n</i>	$\sigma_\varepsilon^2 + na\sigma_B^2$
$AB_{ij}$	0	1	<i>n</i>	$\sigma_\varepsilon^2 + n\sigma_{AB}^2$
$\varepsilon_{k(ij)}$	1	1	1	$\sigma_\varepsilon^2$

These results are seen to be in agreement with the EMS values for the mixed model in Section 6.3. Here  $\phi_A$  is, of course, a fixed type of variance: