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SPLIT-PLOT × SPLIT-BLOCK ANALYSIS WITH CONTROL A TREATMENTS

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Summary

A new class of split-plot × split-block (SPSB) designs for at least three factor experiments is introduced in the paper. The SPSB designs are the most widely used in agriculture research, especially for field trials. Basic farming practices, e.g. crop cultivars, herbicide applications, fertilization methods or tillage type are compared using demonstration strips on a farm field. In the paper we consider a situation when the mentioned above SPSB designs are augmented by a new group of A treatments (control treatments) that are to be replicated less than the test A treatments. The problem of the arrangement of such treatments in the experiment often appears. It is connected with the structure of experimental units and/or with a limited experimental material of some factor. A numerical example is presented to illustrate the method of the constructing the design and its analysis under mixed linear model.

Key words and phrases: augmented block design, control treatments, efficiency balance, split-plot × split-block design, test treatments

Classification AMS 1993: 62K10, 62K15

1. Introduction

Many split-plot × split-block (SPSB) experiments used in agriculture, biochemistry or plant protection are designed to study new crop plant cultivars or

chemical agents etc. (e.g. LeClerg et al., 1962; Mucha, 1975; Wadas et al., 2004, 2005). A problem of comparison of the new treatments with those earlier described is usually very important in these experiments. Frequently limited amount of the experimental material does not allow to use a complete design. Such experiments may then be laid down in an incomplete (non-orthogonal) design. Preferably, its efficiency with respect to the interesting treatment comparisons (contrasts) is full. One of strategies for such situations is planning SPSB experiment designs augmented to accommodate a set of new treatments of one factor that are to be replicated less than others.

Augmented SPSB designs can be generated by designs from a class of *augmented block designs* known from the literature also as s*upplemented* or more generally *reinforced block designs*, introduced for one-factor experiments (cf. Pearce, 1960; Federer, 1961; Corsten, 1962; Caliński, 1971; Caliński and Ceranka, 1974; Singh and Dey, 1979; Puri et al., 1977; Ceranka and Krzyszkowska, 1994). Generally, two sets of treatments exist in all the above designs. Usually one set is referred to us the set of test (basic) treatments and the other - the set of control (supplementary) treatments. The major aim of such experiments is the comparison of both the sets of treatments and treatment comparisons within sets. The augmented designs were used in split-block and split-plot arrangements (c.f. Mejza I., 1998; Kachlicka and Mejza, 1998, 2002a, 2002b, 2003; Federer, 2005; Federer and Arguillas, 2006; Federer and King, 2007). They were introduced also in generating incomplete SPSB designs by Ambroży et al., (2004).

The ideas in the mentioned papers were used to construct a class of augmented split-plot × split-block experiment designs. It should be noticed that the resulting designs belong to a class of incomplete SPSB designs with orthogonal block structure (*OBS*). They are also generally balanced (cf. Houtman and Speed, 1983; Mejza S., 1992). A modelling and analysis of data obtained from such experiments were presented by Ambroży and Mejza (2003, 2004*b*, 2006). There are given, among other things, general statistical properties with reference to an estimation of the orthogonal contrasts among main effects of the factors and interaction contrasts.

2. Assumptions and notations

Consider an $(s \times t \times w)$ - experiment in which the first factor, say A, has s levels $A_1, A_2, \ldots, A_s$, the second factor, say B, has t levels $B_1, B_2, \ldots, B_t$ and the

third factor, say C, has w levels $C_1, C_2, \ldots, C_w$. Let v (= stw) be the number of all treatment combinations.

We assume that a desirable three factor experimental design structure consists of b blocks which can be grouped in R superblocks where each superblock contains b/R blocks. It should be underlined that number of superblocks and the number of blocks inside each superblock is strictly connected with an applied here constructing method of that design (see paragraph 3). The blocks then should have a row–column structure (perpendicular strips) with k_1 ($\leq s$) rows and t columns of the first order, shortly, columns I. So there are $k_1 t$ ($\leq st$) intersection plots of the first order within each block, below called whole plots. Then each column I has to be split into w columns of the second order, shortly, columns II. So there are $k_1 tw$ ($\leq stw$) intersection plots of the second order within each block, below called small plots. Here the rows correspond to the levels of the factor A, termed also as row treatments or A treatments, the columns I correspond to the levels of the factor B, called also column I treatments or B treatments, and the columns II are to accommodate the levels of the factor C termed as column II treatments or C treatments.

Since the units have to be randomized before they enter the experiment, a randomization model with six main strata is here suitable. In the experiment we perform the four-step randomization [blocks $\rightarrow$ rows and (columns I $\rightarrow$ columns II)]. It leads to a mixed linear model with fixed treatment effects and random block, row and column effects. This model is of the form as in Ambroży and Mejza (2003, 2006) and it has the following properties:

$$\mathrm{E}(\mathbf{y}) = \boldsymbol{\Delta}'\boldsymbol{\tau}, \quad \mathrm{Cov}(\mathbf{y}) = \mathbf{V}(\gamma) = \sum_{f=1}^{6} \mathbf{D}'_f \boldsymbol{\xi}_f + \sigma^2 \mathbf{I}_n,$$

where $\boldsymbol{\Delta}'$ is a known design matrix for v treatment combinations, and $\boldsymbol{\tau}$ ($v \times 1$) is the vector of fixed effects of treatment combinations, $\mathbf{D}'_f$ are design matrices for blocks (f = 1), rows within blocks (f = 2), columns I within blocks (f = 3), columns II within columns I (f = 4), whole plots within blocks (f = 5) and subplots within whole plots (f = 6), and $\boldsymbol{\xi}_f$, f = 1,…, 6, and $\mathbf{e}$ ($n \times 1$) are random effect vectors of blocks, rows, columns I, columns II, whole plots, subplots and technical errors, respectively.

According to the orthogonal block structure (*OBS*) of the considered SPSB designs, the dispersion matrix $\mathbf{V}(\gamma)$ can be expressed by $\mathbf{V}(\gamma) = \sum_{f=0}^{6} \gamma_f \mathbf{P}_f$,

where $\gamma_f \geq 0$ and the $\{\mathbf{P}_f\}$ are a family of known pairwise orthogonal projectors adding up to the identity matrix (cf. Houtman and Speed, 1983). The range space $\Re\{\mathbf{P}_f\}$ of $\mathbf{P}_f$, $f = 0,1,\ldots, 6$ is termed the f-th stratum of the model and the $\{\gamma_f\}$ are unknown stratum variances. It can be shown (Ambroży and Mejza, 2003, 2006) that in the incomplete SPSB design the $\mathbf{P}_f$ matrices generate six main strata: the inter-block stratum (1), the inter-row (within the block) stratum (2), the inter-column I (within the block) stratum (3), the inter-column II (within the column I) stratum (4), the inter-whole plot (within the block) stratum (5) and the inter-subplot (within the whole plot) stratum (6).

This model can be analyzed using the methods developed for multistratum experiments (cf. Nelder, 1965a, 1965b). Some details connected with ANOVA and particular analyses based on theory of orthogonal contrasts are presented in Ambroży and Mejza (2003, 2006).

3. Construction method of the augmented SPSB designs and an example

In this paper we consider one case of a construction of the augmented SPSB design using traditional method based on Kronecker product of matrices. The method consists in applying an augmented block design to the row treatments (A treatments) taking the remaining factors as in a complete (orthogonal) SPSB design. We assume that the row treatments (A treatments) consist of two groups with v_1 test (basic) A treatments and v_2 additional (control) A treatments, so $v^* = v_1 + v_2$.

The generating factor A is allocated in the augmented block design d^* with the following incidence matrix (see, Kachlicka and Mejza, 2000):

$$\mathbf{N}_{d^*} = \begin{bmatrix} \tilde{\mathbf{N}}_1 \\ \mathbf{I}_R \otimes \mathbf{1}_q \mathbf{1}'_{b_1/R} \end{bmatrix}.$$

In this case $\tilde{\mathbf{N}}_1$ denotes the incidence matrix of a randomized complete block (RCB) design. It is assumed that its b_1 blocks each with $\tilde{k}_1$ units can be grouped into R superblocks of the same size (b_1/R blocks). The superblocks are then supplemented by q (different in each superblock) additional treatments, i.e.

$v_2 = Rq$. So, the number of units inside each block in the design d^* is equal to $k^* = \tilde{k}_1 + q$. Thus, the distinct eigenvalues of the matrix $\mathbf{C}_{d^*}$ with respect to $\mathbf{r}_*^{\delta}$ and their multiplicities are following: $\varepsilon_0^* = 1$, $\rho_0^* = 1 + R(q-1) + (v_1 - 1) = v_1 + v_2 - R$, $\varepsilon_1^* = \frac{\tilde{k}_1}{k^*}$, $\rho_1^* = R - 1$, where $\mathbf{r}_*^{\delta}$ is a diagonal matrix with diagonal elements equal to the vector of a replication of A treatments, i.e. $\mathbf{r}^* = [b_1\mathbf{1}'_{v_1} \vdots (b_1 / R)\mathbf{1}'_{v_2}]'$. It can be shown that the first class of efficiency equal to ε_0^* (=1) is connected with the comparison 1) between the basic (test) group and the additional (control) group of the A treatments, 2) among additional (control) A treatments inside each superblock, 3) the basic (test) A treatments only and the second class of efficiency equal to ε_1^* refers to the comparisons among the additional (control) A treatments between the superblocks.

In this paper the construction of the augmented SPSB design is based on Kronecker product of matrices (cf. Ambroży et al., 2004; Ambroży and Mejza, 2003, 2004*a*, 2006). So the incidence matrix with respect to blocks is of the form:

$$\mathbf{N}_1 = \mathbf{N}_{d*} \otimes \mathbf{1}_t \otimes \mathbf{1}_w .$$

The described above supplementation of the design *d** causes the resulting augmented SPSB design is always connected and it has parameters:

$$v = v^* tw,\ b = b_1,\ k = k^* tw,\ \mathbf{r} = \mathbf{r}^* \otimes \mathbf{1}_t \otimes \mathbf{1}_w ,$$

where *v*, *b*, *k*, **r** denote the number treatment combinations, the number of blocks, the size of blocks and the vector of replication of the treatment combinations, respectively. Needed in the analysis information matrices for the treatment combinations (in general forms) can be find in the mentioned above papers. Using those matrices the statistical properties (general balance, stratum efficiencies, estimability of contrasts) can be easy checked.

Example. Consider a $(7 \times 2 \times 2)$ - experiment of type SPSB in which the A treatments are allocated on the rows (strips) according to the incidence matrix as follows:

$(\mathbf{N}^*)' = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 1 \end{bmatrix}$. Remaining factors, *B* and *C* are as in a complete (orthogonal) SPSB design. It means that not all (*st* = 14) treatment combinations of type $A \times B$ will appear on the whole plots inside each block what is going together with that not all treatment combinations of type $A \times B \times C$ (*stw* = 28) will appear on the subplots within whole plots in the SPSB design. It can be noticed that one group of the A treatments (say, test A treatments) is in a RCB design with parameters: $v_1 = 3$; $b_1 = 4$; $\tilde{k}_1 = 3$. We assume that the blocks of RCB design can be grouped into *R* superblocks. Each superblock of the RCB design is augmented with $q = 2$ different A treatments. So, in the experiment $v_2 = Rq = 4$ control A treatments will appear. The parameters of the augmented block design for the A treatments are following:

$$v^* = 7,\ b^* = 4,\ (\mathbf{r}^*)' = [4, 4, 4, 2, 2, 2, 2],\ \mathbf{k}^* = 5\mathbf{1}_4,\ \varepsilon_0^* = 1,\ \rho_0^* = 5,$$
$$\varepsilon_1^* = 0{,}6,\ \rho_1^* = 1.$$

So, the parameters of the augmented SPSB design are equal to:

$$v = 28,\ b = 4,\ k = 20,\ \mathbf{r} = [4, 4, 4, 2, 2, 2, 2]' \otimes \mathbf{1}_2 \otimes \mathbf{1}_2.$$

The sample layout (before randomization) of the augmented SPSB experiment in the Example is as fallowing

Block 1

	B_1		B_2	
	C_1	C_2	C_1	C_2
A_1				
A_2				
A_3				
A_4				
A_5				

Block 2

	B_1		B_2	
	C_1	C_2	C_1	C_2
A_1				
A_2				
A_3				
A_4				
A_5				

Block 3

	B_1		B_2	
	C_1	C_2	C_1	C_2
A_1				
A_2				
A_3				
A_6				
A_7				

Block 4

	B_1		B_2	
	C_1	C_2	C_1	C_2
A_1				
A_2				
A_3				
A_6				
A_7				

To design the experiment according to the plan given above we randomize from an experimental material (a field) four blocks of 20 subplots. The number

of the treatment combinations is equal to 28 therefore it exceeds the size of the blocks. The A treatments, B treatments and C treatments are randomly allocated to adequate perpendicular strips (rows, columns I, columns II) inside each block (see paragraph 2). The control treatments A_4 – A_7 well treatment combinations with them are replicated twice in the experiment. Statistical properties necessary in ANOVA of the augmented SPSB design from the example under mixed linear model are given in the table 1. They follow from algebraic properties of the stratum information matrices for the treatment combinations (cf. Ambroży and Mejza, 2003, 2004*b*, 2006). Eigenvalues of those matrices calculated with respect to the matrix $\mathbf{r}^{\delta}$ are interpreted as stratum efficiency factors and they are given in the table 1. It can be shown that the efficiency factors correspond to the following orthogonal contrasts $\mathbf{c}'\boldsymbol{\tau}$ among effects:

– of the A treatments (*A*), including:
  - of the test A treatments (A^T), (e.g. $\mathbf{c}' = \theta[1, -1, 0, 0, 0, 0, 0]\otimes\mathbf{1}_2' \otimes\mathbf{1}_2'$),
  - of the control A treatments within superblocks $(A^C)_1$, (e.g. $\mathbf{c}' = \theta[0, 0, 0, 1, -1, 0, 0]\otimes\mathbf{1}_2' \otimes\mathbf{1}_2'$),
  - of the control A treatments between superblocks $(A^C)_2$, ($\mathbf{c}' = \theta[0, 0, 0, 1, 1, -1, -1]\otimes\mathbf{1}_2' \otimes\mathbf{1}_2'$),
  - of both groups of the test and control A treatments (A^T *vs.* A^C), ($\mathbf{c}' = \theta[4, 4, 4, -3, -3, -3, -3]\otimes \mathbf{1}_2' \otimes\mathbf{1}_2'$),
– of the B treatments (*B*), ($\mathbf{c}' = \theta\,\mathbf{1}_7'\otimes[1, -1]\otimes\mathbf{1}_2'$),
– of the C treatments (*C*), ($\mathbf{c}' = \theta\,\mathbf{1}_7' \otimes\mathbf{1}_2'\otimes[1, -1]$),
– interaction of types: $A^T\times B$, $(A^C)_1\times B$, $(A^C)_2\times B$, $(A^T$ *vs.* $A^C)\times B$,
– interaction of types: $A^T\times C$, $(A^C)_1\times C$, $(A^C)_2\times C$, $(A^T$ *vs.* $A^C)\times C$,
– interaction of type: $B\times C$,
– interaction of types: $A^T\times B\times C$, $(A^C)_1\times B\times C$, $(A^C)_2\times B\times C$, $(A^T$ *vs.* $A^C)\times B\times C$.

All contrasts are normalized with respect to $\mathbf{r}^{-\delta}$, so in each case $\theta = 1/\sqrt{\mathbf{c}'\mathbf{r}^{-\delta}\mathbf{c}}$, where $\mathbf{r}^{-\delta}$ is a diagonal matrix with diagonal elements equal to reciprocals of numbers of replications of treatment combinations. Estimability of the contrasts in the strata was checked (see e.g. Ambroży and Mejza, 2006). All calculations were done by Excel and GenStat. In table 1 we present results, namely stratum efficiency factors of the design with respect to the contrasts. We can use them to calculate stratum sums of squares (*SS*) for "treatments" in ANOVA and in particular analyses (see e.g. Ambroży and Mejza, 2006).

It can be noticed that using the augmented SPSB experiment design from the Example all contrasts among A treatments are estimated in the stratum (2). So, the general hypothesis connected with the factor A can be tested in this

stratum. We only loss information about the contrasts among the control A treatments $(A^C)_2$ and interaction contrasts connected with them. Those contrasts are estimated in two strata, (1) and (2). The contrasts among effects of the test A treatments, the control A treatments within superblocks and between the test and control A treatments likewise other contrasts connected with main effects of the factors B, C, $B \times C$ interaction contrasts are estimated with full efficiency (=1) as in a complete SPSB design.

Table 1. Stratum efficiency factors corresponding to estimable orthogonal contrasts for the Example

Sources of variation	Degrees of freedom	Efficiency factors
	the inter-block stratum (1)	
control A treatments $(A^C)_2$	$\rho_1^* = 1$	$1-\varepsilon_1^* = 0.4$
Error (1)	$r(\mathbf{P}_1) - 1 = 2$	
	the inter-row (within the block) stratum (2)	
A	$s - 1 = 6$	
test A treatments (A^T)	$\rho_0^* - 3 = 2$	1
control A treatments $(A^C)_1$	$\rho_0^* - 3 = 2$	1
control A treatments $(A^C)_2$	$\rho_1^* = 1$	$\varepsilon_1^* = 0.6$
A^T *vs.* A^C	1	1
Error (2)	$r(\mathbf{P}_2) - 6 = 10$	
	the inter-column I (within the block) stratum (3)	
B	$t - 1 = 1$	1
$(A^C)_2 \times B$	$\rho_1^* (t - 1) = 1$	$1-\varepsilon_1^* = 0.4$
Error (3)	$r(\mathbf{P}_3) - 2 = 2$	
	the inter-column II (within the column I) stratum (4)	
C	$w - 1 = 1$	1
$B \times C$	$(t - 1)(w - 1) = 1$	1
$(A^C)_2 \times C$	$\rho_1^* (w - 1) = 1$	$1 - \varepsilon_1^* = 0.4$
$(A^C)_2 \times B \times C$	$\rho_1^* (t - 1)(w - 1) = 1$	$1 - \varepsilon_1^* = 0.4$
Error (4)	$r(\mathbf{P}_4) - 4 = 4$	
	the inter-whole plot (within the block) stratum (5)	
$A \times B$	$(s - 1)(t - 1) = 6$	1
$A^T \times B$	$(\rho_0^* - 3)(t - 1) = 2$	1
$(A^C)_1 \times B$	$(\rho_0^* - 3)(t - 1) = 2$	1
$(A^C)_2 \times B$	$\rho_1^* (t - 1) = 1$	$\varepsilon_1^* = 0.6$
$(A^T$ *vs.* $A^C) \times B$	$1 \cdot (t - 1) = 1$	1
Error (5)	$r(\mathbf{P}_5) - 6 = 10$	

	the inter-subplot (within the whole plot) stratum (6)	
$A \times C$	$(s - 1)(w - 1) = 6$	
$A^T \times C$	$(\rho_0^* - 3)(w - 1) = 2$	1
$(A^C)_1 \times C$	$(\rho_0^* - 3)(w - 1) = 2$	1
$(A^C)_2 \times C$	$\rho_1^* (w - 1) = 1$	$\varepsilon_1^* = 0.6$
$(A^T$ *vs.* $A^C) \times C$	$1 \cdot (w - 1) = 1$	1
$A \times B \times C$	$(s - 1)(t - 1)(w - 1) = 6$	
$A^T \times B \times C$	$(\rho_0^* - 3)(t - 1)(w - 1) = 2$	1
$(A^C)_1 \times B \times C$	$(\rho_0^* - 3)(t - 1)(w - 1) = 2$	1
$(A^C)_2 \times B \times C$	$\rho_1^* (t - 1)(w - 1) = 1$	$\varepsilon_1^* = 0.6$
$(A^T$ *vs.* $A^C) \times B \times C$	$1 \cdot (t - 1)(w - 1) = 1$	1
Error (6)	$r(\mathbf{P}_6) - 12 = 20$	

References

Ambroży K., Kachlicka D., Mejza I. (2004). Rozszerzone układy blokowe w konstrukcji układów mieszanych dla doświadczeń trójczynnikowych. *Colloquium Biometryczne* 34, 15–26 (in Polish).

Ambroży K., Mejza I. (2003). Some split-plot × split-block designs. *Colloquium Biometryczne* 33, 83–96.

Ambroży K., Mejza I. (2004*a*). Incomplete split-plot × split-block designs based on Kronecker type products. *Colloquium Biometryczne* 34, 27–38.

Ambroży K., Mejza I. (2004*b*). Split-plot × split-block type three factors designs. *Proc. of the 19th International Workshop on Statistical Modelling*, Florence, 291─295.

Ambroży K., Mejza I. (2006). *Doświadczenia trójczynnikowe z krzyżową i zagnieżdżoną strukturą poziomów czynników*. Wyd. Polskie Towarzystwo Biometryczne and PRODRUK, Poznań (in Polish).

Caliński T. (1971). On some desirable patterns in block designs. *Biometrics* 27, 275-292.

Caliński T., Ceranka B. (1974). Supplemented block designs. *Biom. J*., 16, 299-305.

Ceranka B., Krzyszkowska J. (1994). Reinforced block designs with two groups of treatments. *Biometrical Letters*, 31(1), 17-25.

Corsten L.C.A. (1962). Balanced block designs with two different numbers of replicates. *Biometrics*, 18, 499-519.

Federer W.T (1961). Augmented designs with one way elimination of heterogeneity. *Biometrics*, 17, 447-473.

Federer W.T. (2005). Augmented Split Block Experiment Design. *Agronomy Journal*, 97, 578-586.

Federer W. T., Arguillas F. O. (2006). Augmented Split-plot Experiment Design. *Journal of Crop Improvement.* 15 (1), 81-96.

Federer W. T., King F. (2007). *Variations on Split Plot and Split Block Experiment Designs*. Wiley.

Houtman A.M., Speed T.P. (1983). Balance in designed experiments with orthogonal block structure. *Ann. Statist*. 11, 1069-1085.

Kachlicka D., Mejza I. (1998). Supplemented block designs with split units. *Colloquium Biometryczne* 28, 77-90.

Kachlicka D., Mejza I. (2000). Właściwości statystyczne pewnych rozszerzonych zrównoważonych układów blokowych. *Rocz. AR. Pozn. Rolnictwo* 59, 61-72.

Kachlicka D., Mejza I. (2002a). Split-block designs with one factor in certain supplemented block designs. *Colloquium Biometryczne* 32, 39-50.

Kachlicka D., Mejza I. (2002b). Modelling and analysis of a resolvable split-plot design with supplemented whole plots. *FOLIA Facultatis Scientarium Naturalium Universitatis Masarykianae*, 83-90.

Kachlicka D., Mejza I. (2003). Two types of control treatments in incomplete split-block designs. *Colloquium Biometryczne* 33, 67–82.

LeClerg E.L., Leonard W.H., Clark A.G. (1962). *Field plot technique*. Burgess, Minneapolis.

Mejza I. (1998): Characterisation of certain split-block designs with a control. *Biom. J*. 40, 627-639.

Mejza S. (1992). On some aspects of general balance in designed experiments. *Statistica* 52, 263-278.

Mucha S. (1975). Reakcja odmian pszenicy jarej i ozimej na Antywylegacz. *Wiadomości Odmianoznawcze*, Rok II, Zeszyt 2/3, COBORU, Słupia Wielka.

Nelder, J. A. (1965a). The analysis of randomized experiments with orthogonal block structure. 1. Block structure and the null analysis of variance. *Proc. of the Royal Soc. of Lond. Ser. A*, 283, 147-162.

Nelder, J. A. (1965b). The analysis of randomized experiments with orthogonal block structure. 2. Treatment structure and general analysis of variance. *Proc. of the Royal Soc. of Lond. Ser. A*, 283, 163-178.

Pearce S.C. (1960). Supplemented balance. *Biometrika*, 47, 263-271.

Puri P.D., Nigam A.K., Narain P. (1977). Supplemented block designs. *Sankhya* 39, B, 189-195.

Singh M., Dey A. (1979). On analysis of some augmented block designs. *Biom. J*. 21, 87-92.

Wadas W., Jabłońska-Ceglarek R., Kosterna E. (2004). The effect of the cultivation method and nitrogen fertilization on the size and structure of the field of immature potato tubers. *Electronic Journal of Polish Agricultural Universities. Horticulture*, 7 (1), art-07.html.

Wadas W., Jabłońska-Ceglarek R., Kosterna E. (2005). The nitrates content in early potato tubers depending on growing conditions. *Electronic Journal of Polish Agricultural Universities. Horticulture*, 8 (1), art-26.html.

ANALIZA TYPU SPLIT-PLOT × SPLIT-BLOCK Z OBIEKTAMI KONTROLNYMI W OBRĘBIE CZYNNIKA A

Streszczenie

W pracy została przedstawiona nowa klasa układów split-plot × split-block (SPSB) dla doświadczeń z co najmniej trzema czynnikami. Układy SPSB są szeroko stosowane w badaniach rolniczych, szczególnie w polowych doświadczeniach. Podstawowe procedury związane z uprawą roli, takie jak plonowanie odmian, stosowanie herbicydów, metody nawożenia lub sposoby uprawy są porównywane właśnie stosując różnego rodzaju pasy na polu doświadczalnym. W pracy rozważamy taką sytuację, w której wspomniane wyżej układy SPSB zostają rozszerzone o nową grupę obiektów (kontrolnych) w obrębie czynnika A replikowanych mniejszą liczbę razy niż obiekty testowe tego czynnika. Pojawia się często problem rozmieszczenia takich obiektów w doświadczeniu. Związany jest on z dostępną strukturą jednostek doświadczalnych oraz (lub) z ograniczeniem materiału doświadczalnego jakiegoś czynnika. W pracy przedstawiono przykład numeryczny, który ilustruje prezentowaną metodę konstrukcji układu i określa sposób analizy danych przy modelu liniowym mieszanym.

Słowa kluczowe: rozszerzony układ blokowy, obiekty kontrolne, zrównoważenie pod względem efektywności, układ split-plot × split-block, obiekty testowe

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