Applied Mathematical Sciences, Vol. 9, 2015, no. 26, 1245 - 1263
HIKARI Ltd, www.m-hikari.com
http://dx.doi.org/10.12988/ams.2015.4121026

Wavelet-Based Confirmatory Factor Analysis: Monitoring of Damage Accumulation Factors

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Abstract

Under consideration is further development of the wavelet-based confirmatory factor analysis intended for monitoring of factors responsible for evolution of technical and other systems. According to the proposed approach, the samples of coefficients resulted from discrete wavelet transform of initial parameter time series under study and responsible for different observation periods are considered as values of observed variables in the subsequent confirmatory factor analysis to reveal time history of factor influences and estimate factor interaction. Identification of free factor model parameters is carried out by a novel direct (noniterative) procedure, which is an alternative to traditional local iterative optimization procedures based on the maximum likelihood criteria. A technique for estimating significance of factor model components is discussed. Application of the approach to the analysis of aircraft damage accumulation is given. Analysis of the variance components factor model representing influence of maneuvering load factors occurrences and climatic conditions of basing on aircraft damage accumulation rate revealed differences between national flying training schools to yield statistically significant effect on the process of aircraft damage accumulation under repeated loads.

Keywords: Condition monitoring, confirmatory factor analysis, wavelet analysis, variance components factor model, maximum likelihood method, goodness-of-fit measure, damage accumulation, service life time

1. Introduction

As a rule, available parameters measured for condition monitoring do not represent characteristics of a system under study in the mode that is suitable directly for understanding system status and formulating reliable conclusions sufficient for proper diagnostics. For multivariate measurements, which condition monitoring usually deals with, it is important to reveal some latent factors responsible for joint variability of observed measurable parameters, determine their nature and scope of influences, and use the obtained information to identify system condition.

It is desirable to replace the parameters those are easy to measure by the parameters those are easy to interpret and understand the system behavior, with minimal information losses being expected during this data mining. Functional relationships between revealed factors and observed parameters are also to be determined for further analysis. As a result of this study, a researcher should get the structure of causal connections between revealed factors and observed variables as well as immediate factor values to differentiate system status, if necessary.

To meet all the indicated requirements, empirical mathematical models and corresponding methods of multivariate statistical analysis were developed [2-4]. The most appropriate in the discussed situation are exploratory and confirmatory factor models and methods of their analysis. Both approaches are based on the analysis of sample covariance or correlation matrices of the observed parameters under study. The exploratory analysis assumes unknown number of uncorrelated factors with a priori undetermined interpretation[1], whereas the confirmatory one assumes the factors, their interpretation, causal connections with observed variables and correlation connections between latent factors to be known beforehand.

Since substantial hypotheses concerning the reasons of possible influences on the observed variables are usually available in practice, the latter approach is preferable. However, the traditional confirmatory factor analysis has its own intrinsic defects:

− It needs solution of the laborious local multivariate optimization problem to estimate the values of free model parameters that results in impossibility of the global minimum estimation and ambiguous solution
− Multivariate normality of observed variables is necessary to get convenient goodness-of-fit criterion for model identification.

[1] Factors are usually interpreted using variables, which they are connected with: to identify a factor it is necessary to assign it a name generalizing the meanings of relevant variables.

Besides, condition monitoring usually needs to take into account time dynamics of observed parameters, with their magnitudes for different time points being formally interpreted as different quantities to be analyzed. To comply with this demand, the simplex method of the confirmatory factor analysis was developed. However, it has serious inherent limitations, which frequently make its practical applications questionable, viz.: possibility of studying factor interaction for adjacent checkpoints only, impossibility of associating factors with time periods, acceptability for analysis of covariance and correlation matrices with simplex structure merely, etc.

To overcome aforesaid problems, a novel method combining capabilities of both wavelet transforms and trained confirmatory factor structures was developed. Its features and advantages, which were presented in papers [5, 7], are also given here in brief.

The main issue discussed in this paper is a practical application of the approach for studying influence of maneuvering load factors occurrences and climatic conditions of basing on aircraft damage accumulation rate.

2. Principal Stages of the Analysis

Principal stages of the suggested technology are presented in Figure 1. This technology combines capabilities of wavelet transforms and trained factor structures. According to the proposed approach, the samples of coefficients resulted from discrete wavelet transform of initial parameter time series under study and responsible for different observation periods are considered as values of observed variables in the subsequent confirmatory factor analysis to reveal time history of factor influences and estimates of factor interaction. Data representation created with the aid of wavelet transforms makes it possible to reveal differences in process characteristics for diverse scales. Identification of free factor model parameters (usually factor variances and covariances) is carried out by a new direct (noniterative) procedure based on the maximum likelihood method, which is an alternative to traditional local iterative solution of optimization problems.

Selection of discrete wavelet transform is determined by its capability to represent properly almost arbitrary time series, including frequently used in practice very short and singular ones, in contrast with the other approaches based on the Fourier transform, which are not acceptable for the time series representing dependencies of the given types. Wavelet coefficients which are responsible for different observation periods are considered as integral characteristics of the corresponding time intervals, which can be used for representation and analysis of relevant characteristics behavior during the time in question.

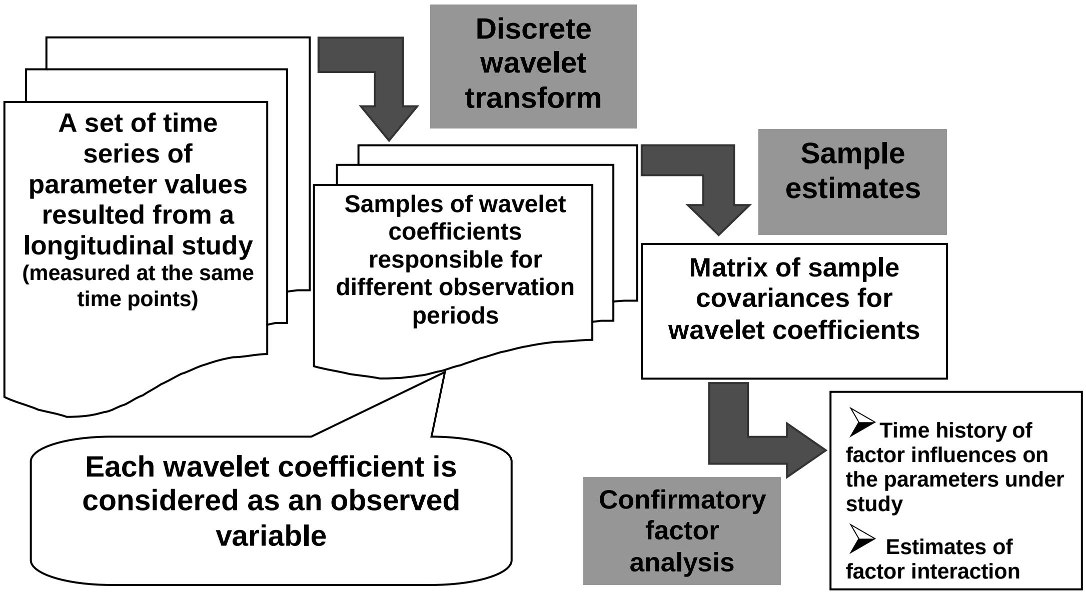

Figure 1. Principal stages of the analysis

2.1. Alternative Variant of the Confirmatory Factor Analysis

Proposed alternative variant of the confirmatory factor analysis allows finding the values of free model parameters by a direct (noniterative) method ensuring an unambiguous optimal solution.

Expressing observed variances and covariances via free factor variances and covariances with the aid of a factor model, in the alternative variant of the confirmatory factor analysis it is proposed:

– To compose overdetermined sets of equations

– To solve them by a direct (noniterative) method using a certain form of the maximum likelihood approach, which is different from the one used in the confirmatory factor analysis [5-7]

– To examine for the adequacy of the obtained equation sets to observations with the aid of statistical goodness-of-fit tests.

To avoid solving nonlinear equation sets as respects to correlation coefficients and factor loadings the variance components path model in which path coefficients (factor loadings) equal to unity is used.

Hereinafter, each observed variance and covariance is associated with an equation that expresses analytically their expected value via free variances and covariances of latent variables and equates it with the corresponding sample estimation. In particular, tracing rules of the path diagram[2] analysis may be used for that. Detour begins against a causal relationship, then it should be the change

[2] In path diagrams (see Figures 3-7 and 11-12 below), ovals (circles) correspond to latent factors, rectangles correspond to observed variables, unidirectional arrows correspond to causal relationships, double-headed arrows correspond to covariances, variances or correlations.

of a direction on covariance communications, and then movement along a causal relationship is the case. It is necessary to remember also, that covariance communication cannot be bypassed twice. As a result the set of the equations is obtained, in which number of the equations equals to the number of observed variances and covariances. If this number of equations exceeds the number of free model parameters, the overdetermined set of equations is the case that is necessary for the further decision. The method under consideration needs also multivariate normalcy of observed variables.

Let us represent the obtained overdetermined set of equations in matrix notation:

$$\mathbf{Ax=b},$$

where $\mathbf{A}$ - system nxm matrix, which coefficients are determined using the factor model (path diagram) under consideration; $\mathbf{b}$ - column nx1 vector of variance and covariance sample estimates, which are determined using observation results; $\mathbf{x}$ - column mx1 vector of unknown free model parameters of interest (viz.: variances and covariances for latent variables).

Let us consider the vector $\boldsymbol{\varepsilon}=\mathbf{Ax_*}-\mathbf{b}$ that represents the residual of pseudosolution $\mathbf{x_*}$ of the overdetermined system obtained by the least- squares method. Assuming in the general case that components of the residual vector are correlated let us express their nonsingular covariance matrix as $\boldsymbol{\sigma}^2\mathbf{V}$.

After substitutions vector $\mathbf{b}$ and matrix $\mathbf{A}$ can be expressed in the following way:

$$\mathbf{b}=\mathbf{V}^{½}\mathbf{b_0} \text{ and } \mathbf{A}= \mathbf{V}^{½}\mathbf{A_0},$$

where $\mathbf{V}=\mathbf{V}^{½}\mathbf{V}^{½}$[3]. Thus, let us turn to the set $\mathbf{A_0x}=\mathbf{b_0}$, for which the covariance matrix of the residual vector $\boldsymbol{\varepsilon_0}= \mathbf{V}^{-½}\boldsymbol{\varepsilon}$ looks like $\boldsymbol{\sigma}^2\mathbf{E}$ where $\mathbf{E}$ is identity matrix.

If

1) The equation set matrix is nonsingular ($rank\mathbf{A}=m$)
2) The residual vector $\boldsymbol{\varepsilon_0}$ has multivariate normal distribution
3) $\mathbf{x_*}=(\mathbf{A_0}^T\mathbf{A_0})^{-1}\mathbf{A_0}^T\mathbf{b_0}=(\mathbf{A}^T\mathbf{V}^{-1}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{V}^{-1}\mathbf{b}$ is pseudosolution calculated by the least-squares method,

then this pseudosolution is a maximum likelihood estimate and statistics

$$X^2=(\mathbf{b_0}-\mathbf{A_0}\,\mathbf{x_*})^T(\mathbf{b_0}-\mathbf{A_0}\,\mathbf{x_*})/\sigma^2=(\mathbf{b}-\mathbf{A}\,\mathbf{x_*})^T\mathbf{V}^{-1}(\mathbf{b}-\mathbf{A}\,\mathbf{x_*})/\sigma^2$$

has χ^2-distribution with n-m degrees of freedom.

Last statistics makes it possible to check the model validity. Under the assumptions indicated above, the presented statistics $\mathbf{X}^2$ makes it possible to test the hypothesis of representability of sample variances and covariances constituting the vector $\mathbf{b}$ with the aid of variances and covariances of latent variables contained

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[3] The only symmetric nonnegatively defined matrix $\mathbf{V}^{1/2}$, which is called the square root of $\mathbf{V}$, exists for every symmetric nonnegatively defined covariance matrix $\mathbf{V}$, so that $(\mathbf{V}^{1/2})^2=\mathbf{V}$.

in the model under study. Acceptance region is $\mathbf{X^2 \leq \chi^2_{n\text{-}m;\alpha}}$ where $\boldsymbol{\alpha}$ is criterion significance level.

In realization of the given approach the following simplifications conditioned by the decision features are useful:

1) Components of the residual vector ε are assumed to be uncorrelated;
2) Mean-square deviation values of different components of the vector ε are set equal to the same fixed proportion (percentage) of the corresponding components of the vector **b** (the hypothesis of proportionality);
3) The mentioned proportion (percentage) is selected to realize the equality $\mathbf{X^2 \leq \chi^2_{n\text{-}m;\alpha}}$ at the significance level $\boldsymbol{\alpha}$**=0.05**, after that the admissibility of this quantity is evaluated. (It is convenient to evaluate the level of this characteristics having determined its reasonable critical value, for example 0.1. Thus, a new criterion (critical percentage) appears instead of the significance level.

Advantages of the suggested technique are:
- The problem solution is not reduced to the local multivariate optimization
- The new way of a choice of adequate model where the percent of mistakes is estimated via the estimation of a residual vector
- Since this method is direct there is no multiplicity of solutions
- No need in search of global minima.

Taking into account that the direct method of solution allows studying laws of interrelations easily, connections between free parameters of the factor model may be investigated, namely: numerical estimations of certain parameters for the given combinations of other ones with the aid of a matrix formula could be calculated to reveal the dependencies of interest.

As in the traditional confirmatory factor analysis, the considered method also allows to make conclusions on statistical significance of different model components and judge about the importance of the model components under study using goodness-of-fit tests.

To do this one should compare X^2 statistics for two models: saturated model containing the component of interest and simplified model where this component is absent (equals to zero.) Let's denote hypothesis that the saturated model coincides with observation results as H_f. Significance level of the component of interest is revealed if there is no grounds to discard hypothesis H_f. At first one should estimate free parameters of the simplified model. The obtained value for X^2 statistics is compared with similar characteristics for the saturated model.

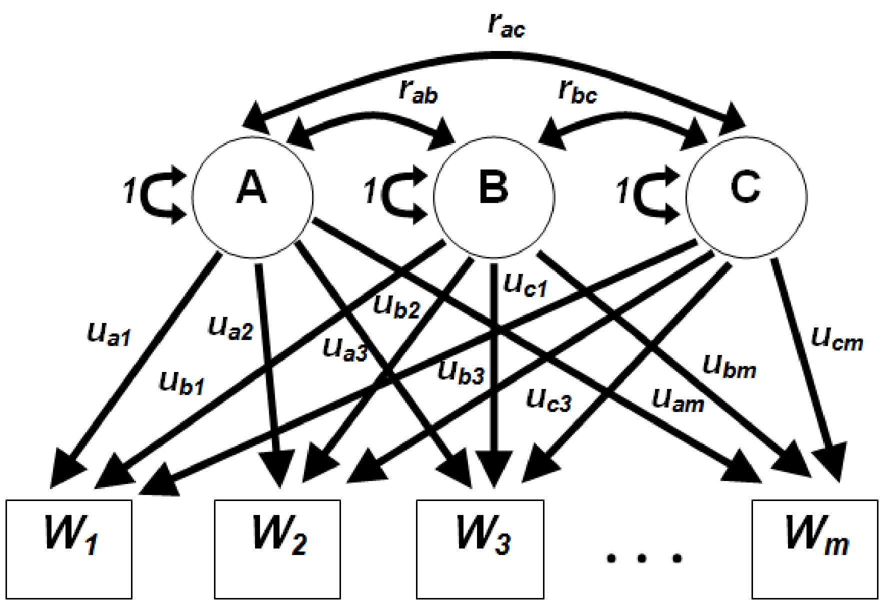
Since the difference in these statistics is asymptotically distributed as χ^2 with the number of degrees of freedom that is equal to the difference in degrees of freedom of saturated and simplified models, this difference is used to verify the zero hypothesis H_r that the simplified model coincides with the observation results against alternative hypothesis H_f.

If $\boldsymbol{H_r}$ hypothesis is not discarded at the given significance level then the component under study is treated as statistically insignificant and the conclusion is made that the available data do not evidence the influence of the studied model part on the observed characteristic under consideration. If $\boldsymbol{H_r}$ hypothesis is discarded (and $\boldsymbol{H_f}$ hypothesis is accepted), then one can talk about the influence of the studied component on the given characteristic.

Advantages of the wavelet-based confirmatory factor analysis in comparison with a traditional approach to longitudinal studies represented by the simplex method are given in paper [5].

3. Model Types

The ways of constructing new factor models for longitudinal studies instead of traditional simplex ones relying on the wavelet-based confirmatory factor analysis include development of path coefficients factor models and variance components factor models as well as and their modifications. Typical examples of these two model kinds are shown in Figures 2 and 3. Composition of wavelet coefficients to be analyzed in the capacity of observed variables depends on an application problem under consideration and may be varied.



F*igure 2*. *Path coefficients factor model represented by a path diagram.*

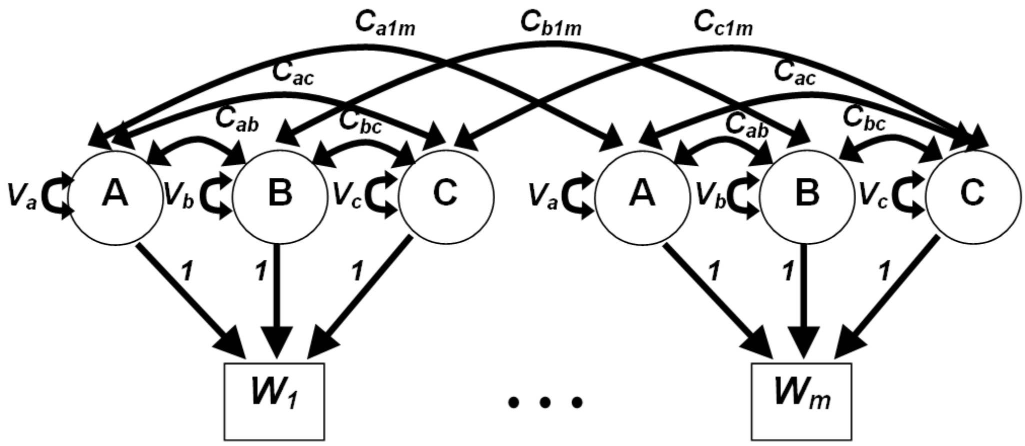


Figure 3. Variance components factor model represented by a path diagram.

In case of path coefficients factor models, expressions for covariances and variances of wavelet coefficients $\boldsymbol{W_i}$ are non-linear:

$$Cov(W_i,W_j)=\sum_k\sum_l r_{kl}u_{ki}u_{lj}\ ;$$

$$Var(W_i)=\sum_k\sum_l r_{kl}u_{ki}u_{li}\ ,$$

where $\boldsymbol{k}$ and $\boldsymbol{l}$ are factor numbers, $\boldsymbol{u_{**}}$ - path coefficients, $\boldsymbol{r_{**}}$ - correlations between factors. These non-linearities make it impossible to get simple direct unambiguous estimations of free model parameters of interest. As contrasted to this, in case of variance components factor models, similar expressions are linear:

$$Cov(W_i,W_j)=\sum_k C_{kij}\ ;$$

$$Var(W_i)=\sum_k V_k+\sum_k\sum_l C_{kl}\ ,$$

where $\boldsymbol{k}$ and $\boldsymbol{l}$ are factor numbers, $\boldsymbol{V_*}$ - variances, $\boldsymbol{C_{**}}$ and $\boldsymbol{C_{***}}$ - covariances between factors. This fact makes it possible to obtain direct estimations of free model parameters using the alternative variant of the confirmatory factor analysis described hereinbefore. Thus, it is the model type that may be used for solution of application problems in reality.

In practical situations, the basic variance components factor model generates a set of particular modifications representing problem peculiarities that are important for solution. For example, simultaneous analysis of different model groups can be useful for studying factor influences in case of several variants of observation conditions (see Figure 4).

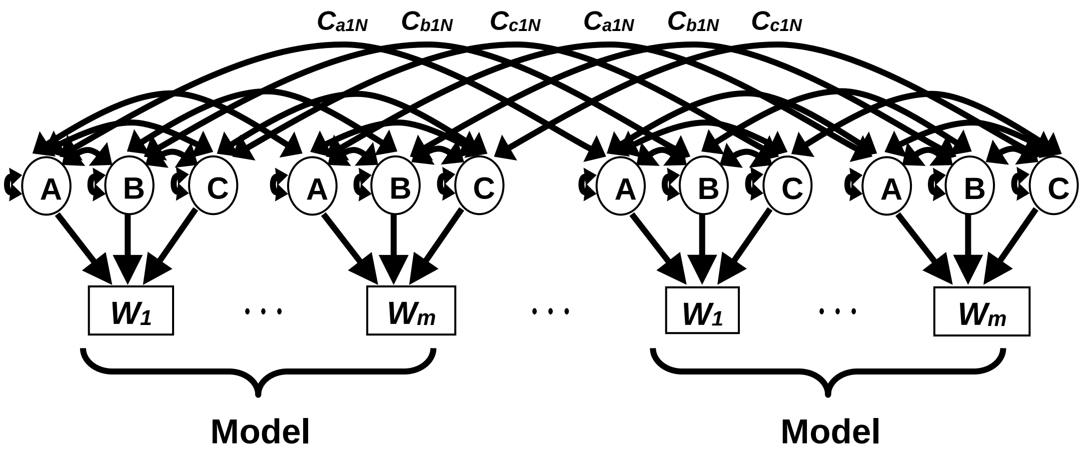


Figure 4. Studying factor influences in case of several variants of observation conditions: simultaneous analysis of model groups. $\mathbf{C}_{***}$ *are covariances between factors.*

Typical representation of the wavelet-based confirmatory factor analysis results destined for further interpretation includes:

– Factor variances and covariances estimated as free model parameters
– Estimated correlations between different factors relevant to the same time points
– Estimated correlations between the same factors relevant to different time points
– Statistical significance estimations for different model components.

Corresponding examples can be found in paper [1].
The given technique was software implemented on the base of the *LabVIEW* graphical programming environment (Figure 5).

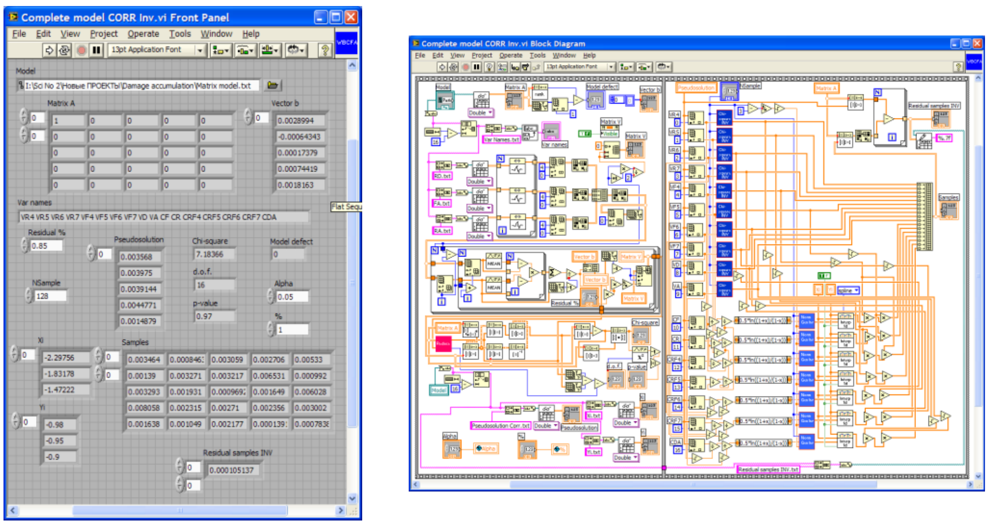


Figure 5. Model identification and calculating of factor model goodness-of-fit measure: LabVIEW software implementation.

4. Practical Application

4.1. Task Setup

Comparative analysis of operational loading for Russian maneuvering aircraft used in Luftwaffe (Federal Republic of Germany) and analogous operational characteristics following the Russian standard course of flying training are presented in this paper. Presented results were obtained with the aid of the wavelet-based confirmatory factor analysis combining capabilities of both wavelet transforms and trained confirmatory factor structures.

The mentioned aircraft were used in 1992-2004 in accordance with the Luftwaffe standard course of flying training. They also took part in training air combats with American fighters during war games. Besides the comparisons, the aim of the given analysis was to estimate significance of influences of two national flying training schools as well as influences of two national operational environments.

The term "loading" in use represents the characteristics generalizing all the variety of load successions acting on different airframe units (wings, fuselage, horizontal and vertical tails, etc) during operation. These characteristics can depict integrated repetition of accelerations at the center of gravity, repetition of loads acting on airframe units as well as damageability resulted from acceleration and load spectra per hour. The given quantities determine the rate of service life time consumption for an airframe.

The outcomes obtained are necessary to take into account corrections for the service life time consumption, which are conditioned by the Foreign operation peculiarities, and actions on support of flying stock safe operation by the technical state. These outcomes are also used to optimize timing of repair works and evaluate changes to be included in the activities that should be performed for detecting structure fatigue damages in due time.

4.2. Method of analysis and model for study

Features and advantages of the technology that has been applied for analysis, including comparison with the competitive methods, are presented in paper [5]. This technology combines capabilities of wavelet transforms and trained factor structures. According to the proposed approach, the samples of coefficients resulted from discrete wavelet transform of initial parameter time series under study and responsible for different observation periods are considered as values of observed variables in the subsequent confirmatory factor analysis to reveal time history of factor influences and estimates of factor interaction. Functional dependence representation created with the aid of wavelet transforms makes it possible to figure out differences in process characteristics for diverse scales. Identification of free factor model parameters (usually factor variances and covariances) is carried out by a new direct (noniterative) procedure based on the maximum likelihood method, which is an alternative to traditional local iterative solution of optimization problems.

Comparison of different sorts of factor structures yielded preference of variance components factor models. This fact was conditioned by linearity of their analytical representations, which is convenient for direct estimations of free parameters, and greater overdetermination reserve.

General form of selected models is shown in Figure 6. Factors **A** and **a** represent maneuvering load repetition for using aircraft by two different schools of flying training, correspondingly, whereas factors **B** and **b** represent climatic conditions of basing in two different countries. Initial dynamic series, which represent the rate of damage accumulation to be analyzed, are to be transformed into wavelet coefficients.

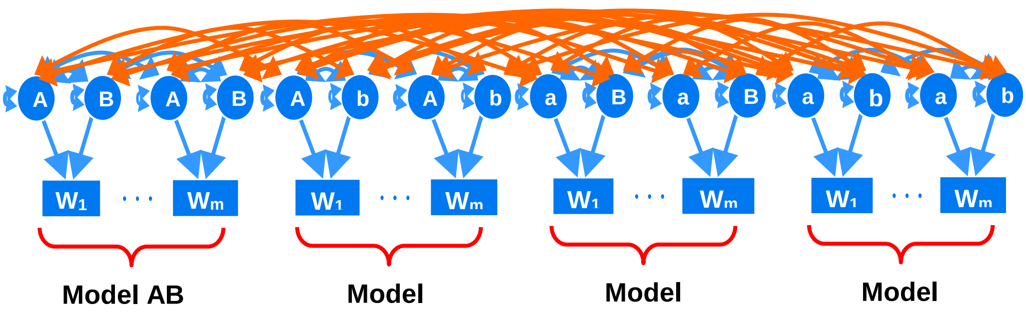


Figure 6. Path diagram representing general form of the models in use. Factors **A** *and* **a** *represent maneuvering load repetition for using aircraft by two different schools of flying training. Factors* **B** *and* **b** *represent climatic conditions of basing in two different countries.* W_* *are wavelet coefficients. Ovals (circles) correspond to latent factors, rectangles correspond to observed variables, double-headed arrows correspond to covariances and variances, unidirectional arrows correspond to causal relationships.*

Instantiation of this factor model for studying influence of maneuvering load occurrences and climatic conditions of basing on aircraft damage accumulation rate is given in Figure 7. It is destined for 8-point dynamic series realizations of the parameter under study, which represented rates of damage accumulation. Only four last wavelet coefficients (of eight) were used for analysis: this detail was conditioned by the application features. Influences of features of two national flying training schools (factors **R** and **F**) as well as influences of two national operational environments (factors **D** and **A**) are to be investigated with the aid of this model.

The algorithm of this model analysis was software implemented on the base of the *LabVIEW* graphical programming environment. The proper calculations that had been carried out revealed causal and temporal relationships between the latent factors in question and statistical significance of different model components.

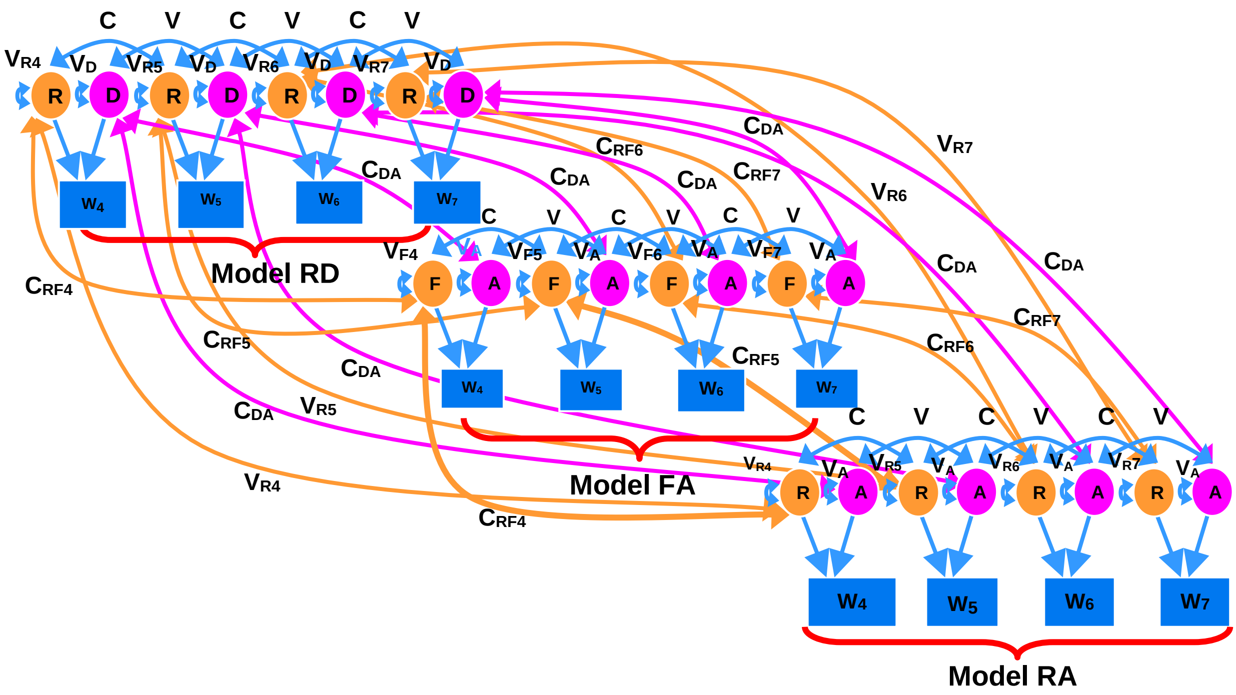


Figure 7. Model to study influence of maneuvering load occurrences and climatic conditions of basing on aircraft damage accumulation rate: influences of national features of pilotage technique are represented by factors **R** *and* **F**, *influences of national environment operation – by factors* **D** *and* **A**.

4.3. Data for study

G-loads and loads on horizontal and vertical tails were under investigation. Relational damage abilities resulted from these causes in case of the Foreign flying training school in abroad environment with regard to the same characteristic for the Russian training school in domestic environment for 23 observed aircraft are presented in Figure 8. Average relational damage abilities for the mentioned aircraft as functions of an operating year are shown in Figure 9.

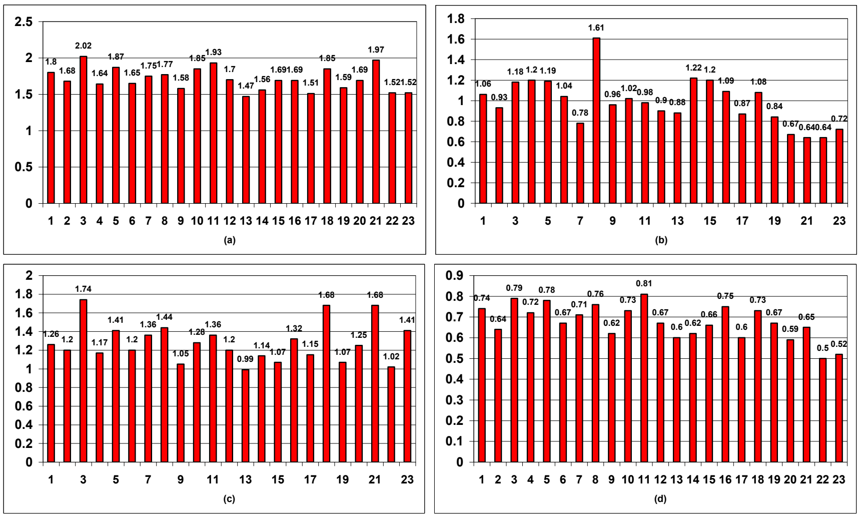


Figure 8. Relational damageability in case of the Foreign flying training school in abroad environment with regard to the same characteristic for the Russian training school in domestic environment for 23 observed aircraft: (a) resulted from g-load spectrum; (b) resulted from loads on horizontal tail; (c) resulted from positive loads on vertical tail; (d) resulted from negative loads on vertical tail.

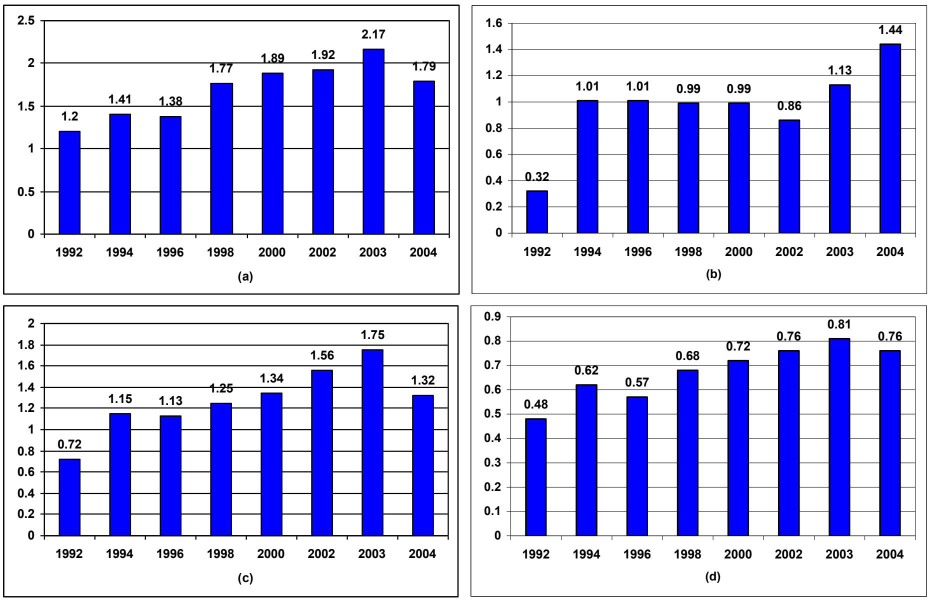


Figure 9. Average relational damageability in case of the Foreign flying training school in abroad environment with regard to the same characteristic for the Russian training school in domestic environment for 23 observed aircraft: (a) resulted from g-load spectrum; (b) resulted from loads on horizontal tail; (c) resulted from positive loads on vertical tail; (d) resulted from negative loads on vertical tail.

4.4. Calculation results

Three types of factor models were compared to estimate significance of influences of national flying training schools and national operational environments on the damageability resulted from different loads, viz.: saturated model containing both types of influences under study, models taking into account influences of national flying training schools only and models considering merely environment factors. Obtained comparison results are presented in Tables 1-4. The Daubechies D4 wavelet transform was used to reveal differences in process characteristics for the observation periods under study. Indicated goodness-of-fit measures distributed as χ^2 show how the expected covariance matrices derived from the given factor models, in which free parameters have been identified with the aid of the maximum likelihood method, conform to the sample covariance matrices of the observed variables.

Table 1. Goodness-of-fit measures for saturated and simplified factor models in case of damageability resulted from g-load spectra (critical percentage is 0.54).

Model	**Goodness-of-fit measure distributed as χ^2**	**Degrees of freedom**	***p*-value**	**Difference in χ^2 measures**	**Difference in degrees of freedom**	**p-value for difference in χ^2 measures**	**Significance of the excluded factor as compared with the saturated model**
Saturated model	23.8	16	0.09	-	-	-	-
Influences of national flying training schools merely (*optimum*)	29.9	19	0.05	6.1	3	0.11	Not significant
Influences of national operational environment merely	78.9	30	2.8E-6	55.1	14	8.3E-7	Significant

Table 2. Goodness-of-fit measures for saturated and simplified factor models in case of damageability resulted from loads on horizontal tails (critical percentage is 0.5).

Model	**Goodness-of-fit measure distributed as χ^2**	**Degrees of freedom**	***p*-value**	**Difference in χ^2 measures**	**Difference in degrees of freedom**	**p-value for difference in χ^2 measures**	**Significance of the excluded factor as compared with the saturated model**
Saturated model (*optimum*)	18.35	16	0.30	-	-	-	-
Influences of national flying training schools merely	29.88	19	0.05	11.53	3	0.01	Significant
Influences of national operational environment merely	95.57	30	9.2E-9	77.22	14	9.2E-11	Significant

Table 3. Goodness-of-fit measures for saturated and simplified factor models in case of damageability resulted from positive loads on vertical tails (critical percentage is 0.5).

Model	**Goodness-of-fit measure distributed as χ^2**	**Degrees of freedom**	***p*-value**	**Difference in χ^2 measures**	**Difference in degrees of freedom**	**p-value for difference in χ^2 measures**	**Significance of the excluded factor as compared with the saturated model**
Saturated model (***optimum***)	18.13	16	0.32	-	-	-	-
Influences of national flying training schools merely	29.7	19	0.05	11.57	3	0.01	Significant
Influences of national operational environment merely	90.34	30	5.8E-8	72.21	14	7.7E-10	Significant

Table 4. Goodness-of-fit measures for saturated and simplified factor models in case of damageability resulted from negative loads on vertical tails (critical percentage is 0.5).

Model	**Goodness-of-fit measure distributed as χ^2**	**Degrees of freedom**	***p*-value**	**Difference in χ^2 measures**	**Difference in degrees of freedom**	**p-value for difference in χ^2 measures**	**Significance of the excluded factor as compared with the saturated model**
Saturated model	24.34	16	0.08	-	-	-	-
Influences of national flying training schools merely (***optimum***)	30.51	19	0.05	6.17	3	0.1	Not significant
Influences of national operational environment merely	89.47	30	7.9E-8	65.13	14	1.4E-8	Significant

Variances and covariances represented by free parameters of the factor models under consideration, whose values were obtained by the maximum likelihood method, are given in Figure 10. These estimations yielded the correlations between factors **R** and **F** presented in Figure 11.

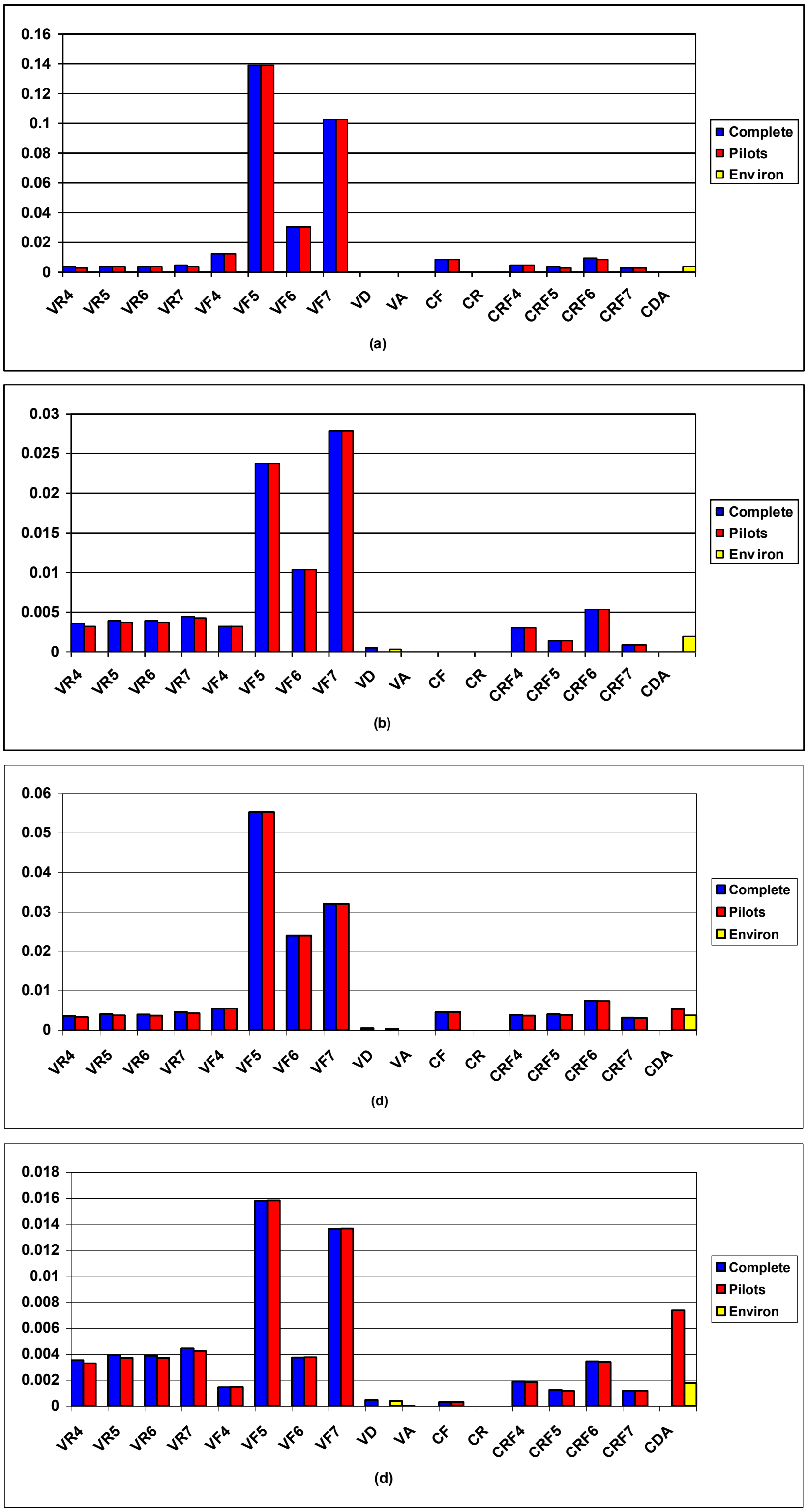


Figure 10. Estimated factor covariances: (a) resulted from g-load spectrum; (b) resulted from loads on horizontal tail; (c) resulted from positive loads on vertical tail; (d) resulted from negative loads on vertical tail.

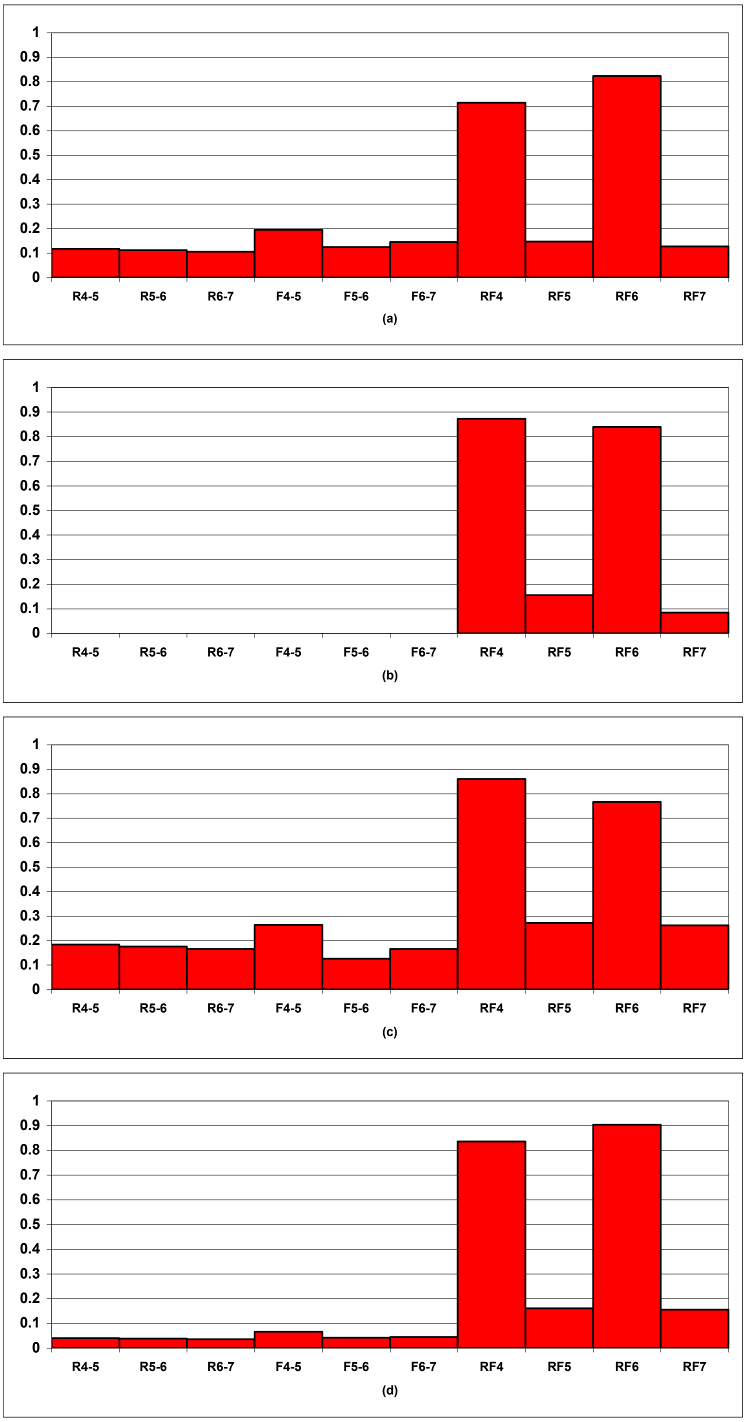


Figure 11. Estimated correlations between factors **R** *and* **F***: (a) resulted from g-load spectrum; (b) resulted from loads on horizontal tail; (c) resulted from positive loads on vertical tail; (d) resulted from negative loads on vertical tail.*

4.5. Results of data analysis

Goodness-of-fit tests for studying importance of model components made it possible to select an optimal factor model for each load type (see Tables 1-4) and come to the following conclusions:

– The factor representing features of national flying training schools is significant but the factor of national operational environment is not significant for damageability conditioned by g-loads and negative loads on a vertical tail
– The factors representing both features of national flying training schools and national operational environment are significant for damageability conditioned by loads on a horizontal tail and positive loads on a vertical tail

Analysis of the response to g-loads as well as to loads on horizontal and vertical tails yielded the following conclusions:

– Greater correlations (0.7-0.9) between Foreign and Russian operation conditions were in 1992-1994 and 2000-2002
– Lesser correlations (0.08-0.27) between Foreign and Russian operation conditions were in 1996-1998 and 2003-2004
– Low (0.1-0.26) and very-low (<0.06) correlations between the time-dependent factors representing features of national flying training schools took place for both Foreign and Russian pilots
– Variability of the factor representing features of a national flying training school was significantly greater in case of the Foreign school (F-statistic>2.7, df=22, p-value<0.015), with the exception of period 1992-1994 for loads on horizontal and vertical tails (F-statistic<1.5, df=22, p-value>0.17) and, in addition, of period 1999-2002 for negative loads on vertical tails (F-statistic=0.96, df=22, p-value=0.53).

5. Main Results and Conclusions

1. Proposed is a novel approach named the wavelet-based confirmatory factor analysis intended for monitoring of factors responsible for evolution of technical and other systems, which combines capabilities of wavelet transforms and trained factor structures. According to the given approach, the samples of coefficients resulted from discrete wavelet transform of initial parameter time series under study and responsible for different observation periods are considered as values of observed variables in the subsequent confirmatory factor analysis to reveal time history of factor influences and estimate parameters of factor interaction.
2. Identification of free factor model parameters is carried out by a new direct (noniterative) procedure based on the maximum likelihood method that is an alternative to traditional ambiguous local iterative solutions of multivariate optimization problems.
3. The proposed approach was software implemented and applied for studying influence of maneuvering load factors occurrences and climatic conditions

of basing on aircraft damage accumulation rate; analysis of system factors and testing of their significance revealed differences between national flying training schools to yield statistically significant effect on the process of aircraft damage accumulation under repeated loads.

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Received: December 27, 2014; Published: February 18, 2015