

## Update of Navarin walleye pollock stock assessment

Dmitry Vasilyev, Alexander Glubokov, Boris Kotenev  
VNIRO  
Moscow, Russia

Navarin pollock stock status was re-estimated using the following data:

- catch-at-age, weight-at-age, maturity-at-age (1984-2004);
- CPUE for 2 fleets (medium and large vessels) – as FSB relative indices;
- age-structured young fish surveys ((1) in summer and (2) in autumn) – as abundance-at-age indices;
- 0-group abundance estimates (from young fish surveys) - as SSB relative index.

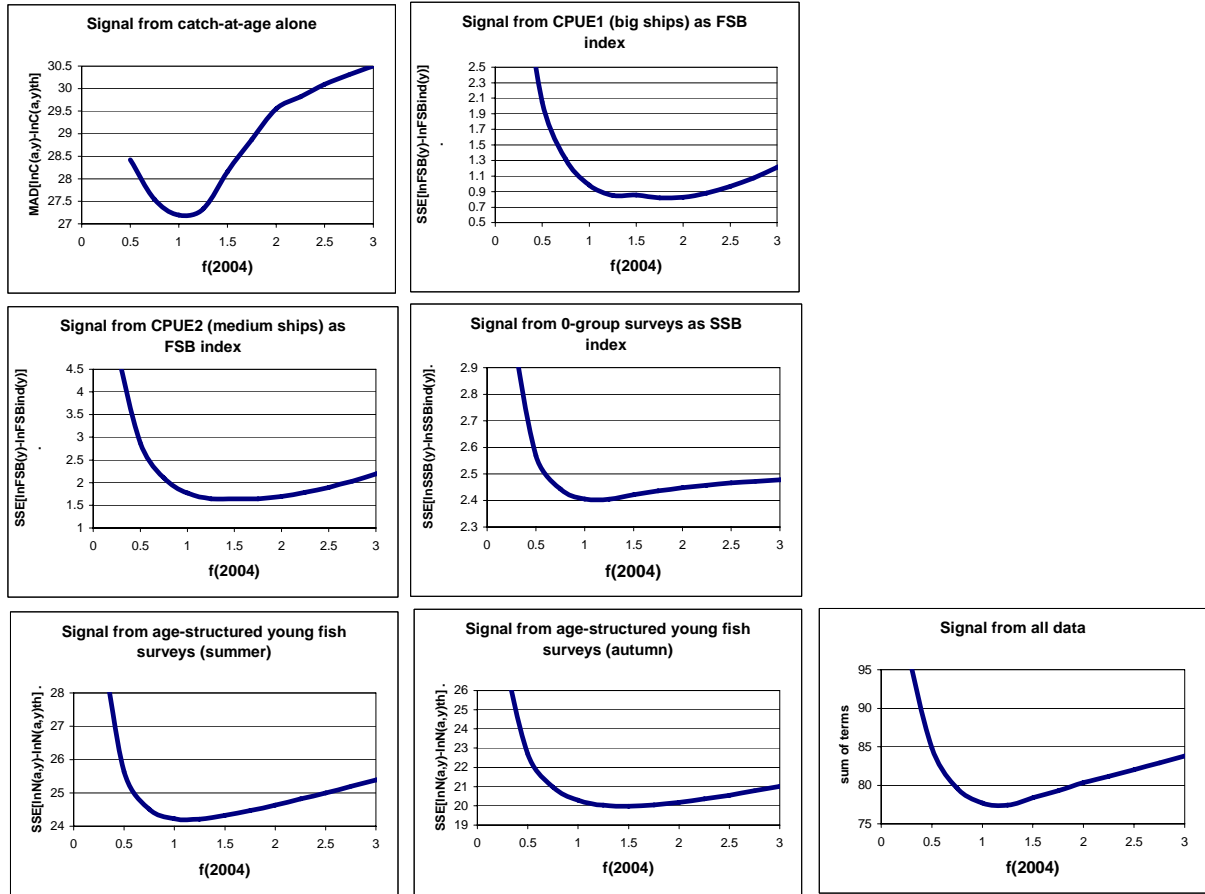
Stock assessment model was so called effort-controlled version of the ISVPA-group of separable cohort models (for details of the model see appendix and references to it). This version of the model attributes residuals in cohort part of the model to errors in catch-at-age data, assuming that selection pattern (patterns) is stable. This version is often more robust for noisy catch-at-age data. Additional robustness of cohort part of the model with respect to outliers in catch-at-age was attained 1) by minimization of median absolute deviation (MAD) of residuals in logarithmic catch-at-age as a measure of closeness of the model fit to catch-at-age data, and 2) condition of unbiased separable representation of fishing mortality coefficients. Change in selection pattern in 2001 was taken into consideration by estimation of two respective selection patterns.

In this assessment for the first time the estimates of abundance from young fish surveys were included. These data were incorporated into the model in two ways: (1) as age-structured abundance index and (2) 0-group abundance was used as relative index of SSB. Other sources of information were catch-at-age of commercial catches and CPUE time series of two fleets (medium and large vessels).

Profiles of components of the model loss function, as well as profile of the total loss function, are presented on figure 1 as a function of the effort factor value in the terminal year. Although level of noise in the survey data was found to be rather high, the results of application of the model revealed rather coherent signals about the stock size from all sources of information, including young fish surveys. It could be concluded that young fish surveys provide reasonable estimates of trends in abundance of young age groups, while survey-derived abundance estimates of age group 0+ may serve as a reasonable index of SSB in frames of age-structured stock assessment models.

Bootstrap-estimated uncertainty levels for model-derived estimates of fishing stock biomass (FSB) and total stock biomass (TSB) for age groups 2 and older (conditional parametric with respect to catch-at-age, non-conditional parametric with respect to auxiliary data; lognormal error distribution in catch-at-age, in FSB and SSB indices, and in age-structured abundance indices was assumed) are presented on figure 2.

Since it was hardly possible to assume any reliable stock-recruitment relationship having existing observations (see figure 3), yield-per-recruit analysis (figure 4) seems to be more reasonable source for biological reference points estimation in current informational situation.



Profiles of components of the ISVPA loss function with respect to effort factor in 2004

Figure.1

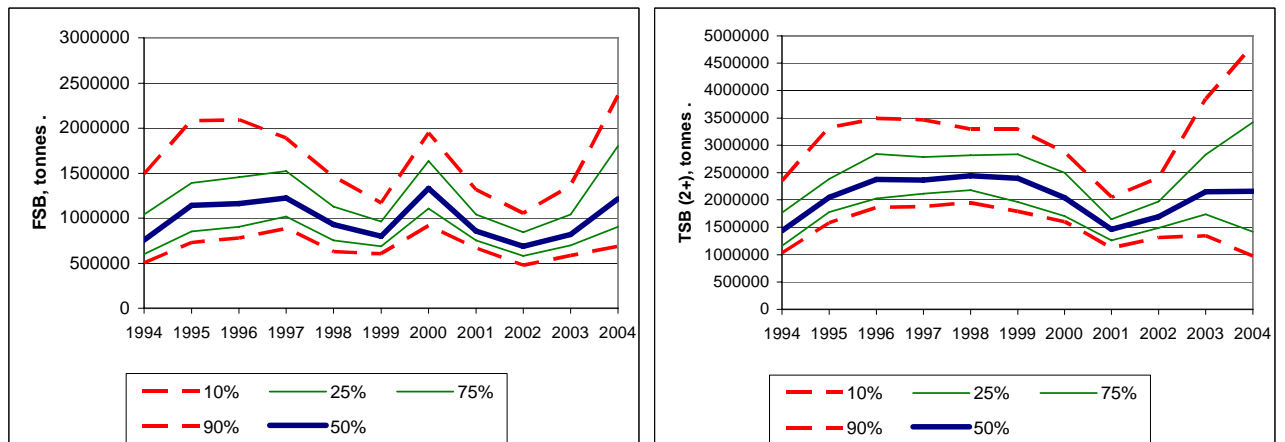


Figure.2. Percentiles of bootstrap distribution for FSB and TSB estimates.

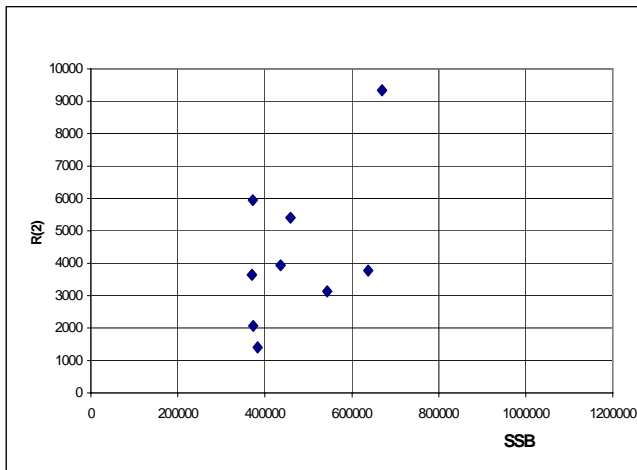
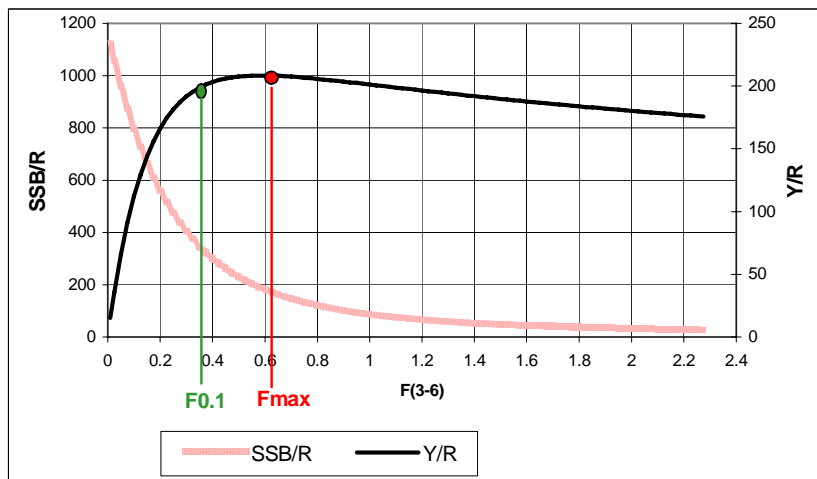


Figure 3. Estimates of recruitment vs. SSB.



YPR analysis

Figure 4.

**Appendix**

W.D. to ICES WGMHSA, 2004.

**DESCRIPTION OF THE ISVPA (version 2004.3)****D.A.Vasilyev** <dvasilyev@vniro.ru>

Brief description of the model is summarized in the table below:

Model	<b>ISVPA</b>
Version	<b>2004.3</b>
Model type	A separable model is applied to one or two periods, determined by the user. The separable model covers the whole assessment period
Selection	The selection at oldest age is equal to that of previous age; selections are normalized by their sum to 1. For the plus group the same mortality as for the oldest true age.
Estimated parameters	
Catchabilities	The catchabilities by ages and fleets can be estimated or assumed equal to 1. Catchabilities are derived analytically as exponents of the average logarithmic residuals between the catch-derived and the survey-derived estimates of abundance.
Plus group	The plus group is not modelled, but the abundance is derived from the catch assuming the same mortality as for the oldest true age.
SSB surveys	Considered as absolute or relative. If considered as relative, coefficient of proportionality is derived analytically as exponent of the average logarithmic residuals between the catch-derived and the survey estimates of SSB.
Surveys in year (terminal + 1)	Can be taken into account (in assumption that fishing pattern in the year (terminal+1) is equal to that of terminal year)
Objective function	<p>The objective function is a weighted sum of terms (weights may be given by user). For the catch-at-age part of the model, the respective term is:</p> <ul style="list-style-type: none"> <li>• sum of squared residuals in logarithmic catches, or</li> <li>• median of distribution of squared residuals in logarithmic catches MDN(M, fn), or</li> <li>• absolute median deviation AMD(M, fn).</li> </ul> <p>For SSB surveys it is sum of squared residuals between logarithms of SSB from cohort part and from surveys.</p> <p>For age- structured surveys it is SS, or MDN, or AMD for logarithms of N(a,y) or for logarithms of proportions-at-age, or for logarithms of weighted (by abundance) proportions-at-age.</p>
Variance estimates/ uncertainty	For estimation of uncertainty parametric conditional bootstrap with respect to catch-at-age, (assuming that errors in catch-at-age data are log-normally distributed, standard deviation is estimated in basic run), combined with adding noising to indexes (assuming that errors in indexes are log-normally distributed with specified values of standard deviation) is used.
Other issues	<p>Three error models are available for the catch-at-age part of the model:</p> <ul style="list-style-type: none"> <li>• errors attributed to the catch-at-age data. This is a strictly separable model (“effort-controlled version”)</li> <li>• errors attributed to the separable model of fishing mortality. This is effectively a VPA but uses the separable model to arrive at terminal fishing mortalities (“catch-controlled version”)</li> <li>• errors attributed to both (“mixed version”). For each age and year, F is calculated from the separable model and from the VPA type approach (using Pope’s approximation). The final estimate is an average between the two where the weighting is decided by the user or by the squared residual in that point.</li> </ul> <p>Four options are available for constraining the residuals on the catches:</p> <ol style="list-style-type: none"> <li>1. Each row-sum and column-sum of the deviations between fishing mortalities derived from the separable model and derived from the VPA-type (effort controlled) model are forced to be zero. This is called “unbiased separabilization”</li> <li>2. As option 1, but applied to logarithmic catch residuals.</li> <li>3. As option 1, but the deviations are weighted by the selection-at-age.</li> <li>4. No constraints on column-sums or row-sums of residuals.</li> </ol>
Program language	Visual Basic

## 1. Introduction

Separability assumption is widely used in various cohort models (Pope, 1974; Doubleday, 1976, Pope and Shepherd, 1982; Fournier and Archibald, 1982; Deriso et al. (1985), Kimura (1986), Gudmundsson (1986), Patterson (1995), etc.). A group of separable cohort model, named ISVPA, may serve as an example of comparatively simple stochastic separable cohort models (Kizner and Vasilyev, 1997; Vasilyev 1998, 1998a, 2001). Models of the ISVPA group are similar in many aspects to other separable cohort models and imply the existence of errors in catch-at-age data and in separable representation of fishing mortality coefficients. But their parameter estimation procedure is based on some principles of robust statistics that helps to diminish the influence of error (noise) in catch-at-age data on the results of the assessment. Besides the solution is guaranteed to be unbiased in chosen statistical sense. Special parameterization of the model makes it unnecessary to use any preliminary assumptions about the age of unit selectivity and about the shape of selectivity pattern. This helps to get unique solution in cases when catch-at-age data are noisy and auxiliary information is too controversial or is not available. Otherwise ISVPA may be used in order to outline stock tendencies from catch-at-age data taken alone.

For simplicity any model from the group we will further refer to as ISVPA model, if necessary giving concretization of the version used.

## 2. Basic relationships

The Instantaneous Separable VPA (or ISVPA) group of models is designed for stock assessment when catch-at-age data are noisy; auxiliary information may be incorporated, or not used at all (if it is not available or considered as unreliable). The word “Instantaneous” means that similarly to Cohort Analysis by Pope (1972) the catch is assumed to be taken “instantaneously”, that is within comparatively short period within a year. The approximation of “instantaneous” catch is absolutely correct for short fishing seasons, but it also can be regarded as being an approximate method for assessment of continuously exploited age-structured populations. It should be noted that the assumption of a constant fishing mortality coefficient during a year, that underlines conventional VPA, is also only an approximation. These two

hypotheses are in fact two opposite marginal simplifications in the frames of cohort models. The acronym ISVPA should not be confused with that of Integrated Stochastic VPA by Lewy (1988).

Let us remind that Pope's Cohort Analysis is based on the observation equation (Baranov's catch equation):

$$C_{a,y} = F_{a,y} / (F_{a,y} + M) * N_{a,y} [1 - e^{-(F_{a,y} + M)}] \quad (1)$$

( $a=1, \dots, m$ ;  $y=1, \dots, n$ ),

and the dynamic state equation:

$$N_{a,y} = (N_{a+1,y+1} e^{M/2} + C_{a,y}) e^{M/2} \quad (2)$$

( $a=1, \dots, m-1$ ;  $y=1, \dots, n-1$ ), where  $a$  - age index,  $m$  - total number of age groups,  $y$  - year index,  $n$  - total number of years,  $N_{a,y}$  - abundance of age group  $a$  in year  $y$ ,  $C_{a,y}$  - catch from age group  $a$  in year  $y$ ,  $M$  - instantaneous natural mortality coefficient (may be constant or a function of age). For simplicity  $a=1$  and  $y=1$  correspond to the first age group and first year in the available data respectively.

Equation (1) express the total catch from age group  $a$ , accumulated in the  $y$ -th year if the dynamics of the group abundance  $N$  and the accumulated catch  $C$  (at time  $t$ ) during the year are governed by the well known equations:  $dN/dt = -(F+M)N$  and  $dC/dt = FN$ , where  $F$  and  $M$  do not depend on  $t$  (indices are omitted). Equation (2) is traditionally regarded as a discrete approximation of a continuous process; it becomes an exact one if the catch  $C_{a,y}$  is taken instantaneously in the middle of the year  $y$ .

However, there are many exploited stocks with such short periods of fishing that the latter may be regarded as momentary. In such a case if the period of fishing falls in the middle of a year, equation (1) may be replaced by

$$C_{a,y} = \varphi_{a,y} N_{a,y} e^{-M/2}, \quad (3)$$

where  $\varphi_{a,y}$  plays the role similar to that of  $F_{a,y}$  in equation (1) but cannot be called a fishing mortality coefficient. Strictly speaking, it is the fraction of the abundance of the  $a$ -th age group, taken as catch in the middle of the year  $y$ . The model (2)-(3) may be regarded as "instantaneous" analogue of VPA. The word "separable" shows that the hypothesis of separability (i.e. of age selectivity of the fishery) is accepted.

In terms of ISVPA it means that

$$\varphi_{a,y} = s_a f_y \quad (4)$$

where  $f_y$  is proportional to the fishing effort (a year effect), while  $s_a$  is the selectivity of the fishery (an age effect). Further we will call them as effort factor and selectivity factor.

Selectivity factors in the model are normalized:

$$\sum_{a=1}^m s_a = 1 \quad (5)$$

It is clear that in reality the fishing season does not necessarily fall within the middle of the calendar year. For the model it means that instead of factors  $e^{M/2}$  и  $e^{-M/2}$  the Equations (2) and (3) must contain factors  $e^{\beta M}$ ,  $e^{(1-\beta)M}$  and  $e^{-\beta M}$ , where  $\beta$  is a given constant ( $0 < \beta < 1$ ). For simplicity in further explanations we will use  $\beta=1/2$ .

As can be seen, calculation of abundances in Equation (2) is undertaken directly through catch values. Catch values in this case are treated as true, the same way as in deterministic cohort models. But separabilization of the model makes it possible to look for unique values of  $N_{a,y}$ . . By this reason the version of the model determined by Equations (2)-(5) may be called ***catch controlled***. In this version of the model the role of separabilization consists only in estimation of terminal populations and this version may be regarded simply as a method of tuning of ordinary cohort analysis, while the loss function of the model (for example - sum of squared residuals between logarithms of real and theoretical catches) may be regarded as a measure of inseparability of the catch-at-age data (in logarithmic form) .

***The effort-controlled version of the ISVPA***, which do not treat catch-at-age data as true, is based on another dynamic state equation, resulting from substitution of the expression for theoretical catch  $\hat{C}_{a,y} = s_a f_y N_{a,y} e^{-M/2}$  instead of real catch  $C_{a,y}$  into Equation (2):

$$N_{a,y} = \frac{N_{a+1,y+1} e^M}{1 - s_a f_y} \quad (2')$$

Thus, in estimation of abundance by this version of the model it is implied that separable representation of fishing mortality is true and residuals are attributed to errors in catch-at-age

data. Here the value of loss function may be regarded as a measure of “precision” of catch-at-age data (if to assume that the fishery is fairly separable).

In practice in most cases both assumptions (that catch-at-age data are precise or fishery is well separable) are rather far from reality. If there are some ideas about their relative validity it is possible to use *mixed* version of ISVPA in which the equation of stock dynamics is a mixture (with the coefficient given by user) of equations (2) and (2’). In this version of the ISVPA the same weight (or “level of relative confidence”) of the two assumptions is used for all points.

Since often the user has no preliminary ideas about relative validity of the above mentioned assumptions and since the relative weight of these assumptions may be strongly different for different points  $(a,y)$ , the 4-th version of ISVPA named *mixed with weighting by points* is also available. In this version for *every point*  $(a,y)$  equations (2) and (2’) are weighted by reciprocal squared residuals between the given catch $(a,y)$  value and its respective “theoretical” value  $\hat{C}_{a,y} = s_a f_y N_{a,y} e^{-M/2}$  where  $N_{a,y}$  is calculated by equation (2) or (2’). These weights are recalculated on every iteration within the iterative procedure of the model parameters estimation (see below).

Equation (2) or (2’) is treated as an exact one and serves for calculation of the matrix  $\|N_{y,a}\|$  through  $M$  and  $\|C_{y,a}\|$  (in the catch controlled version) or  $M$  and the vectors  $s_a$  and  $f_y$  (in the effort controlled version). Equations (3)-(4), postulating the separability, or age selectivity of fishing, is regarded as approximate ones, and the unknowns  $M$ ,  $s_a$  and  $f_y$  are estimated so that to reduce the residual in (3) as much as possible (as a rule, the squared logarithmic error is meant). Equation (5) is a normalizing condition and is treated as an exact one.

Estimated values of  $\varphi_{a,y}$  may be recalculated into traditional instantaneous coefficients of fishing mortality  $F_{a,y}$  by the formula:  $F_{a,y} = -\ln(1-\varphi_{a,y})$ , which becomes obvious if to rewrite the equation (2’) as

$$\ln(N_{a,y} / N_{a+1,y+1}) = M - \ln(1-\varphi_{a,y})$$

and to compare it with traditional VPA equation:

$$\ln(N_{a,y} / N_{a+1,y+1}) = F_{a,y} + M.$$



### 3. Algorithm of the model

In general outline, for each version of the ISVPA the algorithm consists of a 'core', in which all the model parameters are evaluated from the iterative procedure at given natural mortality coefficient,  $M$ , and terminal fishing effort,  $f_n$ , and an outward 'shell', a loop in which the best  $M$  and  $f_n$  are fitted.

The 'core' is represented in the program *by 4 iterative procedures*. The three procedures described in details below are designed to ensure "unbiasness" of the solution, each - in its own sense.

The 4-th procedure is intended to produce the best fit to catch-at-age data, but the solution will be free from any restriction on bias. The 4-th procedure is rather time consuming derivative-free procedure, but experiments with very noisy data showed that if parameters are strongly interdependent and minimum is flat it works better (gives better fit) with respect to some of tested algorithms, including Marquardt-Levenberg and Simplex.

#### **Basic iterative procedure (procedure A).**

Within any ISVPA iterative procedure the given  $M$  and  $f_n$  are not changed. The calculations start with setting the initial values of the fishing effort,  $f_y$  at  $y=1, \dots, n-1$  and selectivity,  $s_a$ ; at  $a=1, \dots, m$  (the normalizing condition (5) must be kept). Each iteration consists of the following steps.

First, the terminal vectors  $\{N_{a,n}\}$  and  $\{N_{m,y}\}$  are evaluated from (3), then all other  $N_{a,y}$  are determined from (2) or (2'). After that the matrix of fractions  $\|\varphi_{a,y}\|$  is evaluated from the Equation

$$\varphi_{a,y} = \frac{C_{a,y}}{N_{a,y}} e^{M/2}, \quad (6)$$

and  $\{f_y\}$  and  $\{s_a\}$  are determined as

$$f_y = \sum_{a=1}^m \varphi_{a,y} \quad (7)$$

and

$$S_a = \frac{\sum_{y=1}^n \varphi_{a,y}}{\sum_{a=1}^m \sum_{y=1}^n \varphi_{a,y}} \quad (8)$$

To make the convergence better,  $s_m$  and  $s_{m-1}$  are replaced with their arithmetic mean:

$$S_m = S_{m-1} = \frac{\sum_{y=1}^n (\varphi_{m,y} + \varphi_{m-1,y})}{2 \sum_{a=1}^m \sum_{y=1}^n \varphi_{a,y}} \quad (9)$$

Note that the selectivity values remain normalized since the initial normalization.

Equations (7) and (8) are algebraic consequences of the relationship (4) which represents the hypothesis of separability of the fraction of the  $a$ -th age group abundance in the middle of the  $y$ -th year taken as catch. Strictly speaking, the symbol  $\varphi_{a,y}$  is allotted to the estimate of the fraction given by formula (6) at every iteration  $IT$ . To avoid confusion, its separable analog, which also can be evaluated at every iteration, will be designated as  $\varphi_{a,y}^{sp} = s_a f_y$ .

Assume that the convergence is already achieved, and  $\varphi_{a,y}$  and  $\varphi_{a,y}^{sp}$  are limits of the corresponding fractions at  $IT \rightarrow \infty$ . When we deal with the 'pure', completely separable data, convergence means that  $\varphi_{y,a} = \varphi_{y,a}^{sp}$ . However, in the general case, when the catch-at-age data do not correspond to completely separable fishing (and contain errors), the two fraction estimates,  $\varphi_{a,y}$  and  $\varphi_{a,y}^{sp}$  must differ. This difference may serve as a measure of non-separability in the data, thus appearing in the role of a random error,  $\varepsilon_{a,y}$ , in the fraction  $\varphi_{a,y}$  with respect to the separable fraction  $\varphi_{a,y}^{sp}$ :

$$\varphi_{a,y} = s_a f_y + \varepsilon_{a,y} \quad (10)$$

Now let us clear up the question of whether our separable estimates of  $\varphi$  are unbiased or not. Such an analysis requires calculation of the mathematical expectation of the random values

$\varepsilon$ . It is reasonable to regard such errors within each age group at  $y=1, \dots, n-1$  as being independent and equally distributed. When this is the case, the averaging of  $\varepsilon$  within the same age group furnishes the required estimation of the bias. At  $IT \rightarrow \infty$  relationships (5), (7) and (10) yield:

$$f_y = \sum_{a=1}^m (s_a f_y + \varepsilon_{a,y}) = f_y + \sum_{a=1}^m \varepsilon_{a,y}$$

or

$$\sum_{a=1}^m \varepsilon_{a,y} = 0, \quad (11)$$

for every year  $y$ . Similarly, at  $IT \rightarrow \infty$ , relationships (5), (8), (10) and (11) involve:

$$s_a = \frac{\sum_{y=1}^n (s_a f_y + \varepsilon_{a,y})}{\sum_{a=1}^m \sum_{y=1}^n (s_a f_y + \varepsilon_{a,y})} = s_a + \frac{\sum_{y=1}^n \varepsilon_{a,y}}{\sum_{y=1}^n f_y},$$

or

$$\sum_{y=1}^n \varepsilon_{a,y} = 0 \quad (12)$$

for every age group  $a$  (certainly, transformation (9) does not break this result). Relationships (11) and (12) prove that the separable estimates of  $\varphi$  supplied by this iterative procedure are unbiased.

### ***Weighted arithmetical mean procedure (procedure B)***

When the selectivity is strongly dependent on age, the errors corresponding to different age groups hardly can be regarded as equally distributed (although, relationship (10) shows that their mean over age also equals zero). In this case, a modified iterative procedure might be appropriate, in which inverse selectivity values serve as weights at the stage of calculating the efforts.

Within this, 'weighted' iterative procedure, relationship (7) is replaced with the following equation for calculating the efforts:

$$f_y = \frac{1}{m} \sum_{a=1}^m \frac{\Phi_{a,y}}{s_a}, \quad (13)$$

(which is also an algebraic consequence of the separability hypothesis), and the efforts are calculated from (13) taking the selectivity values from the previous iteration. Thereupon the current selectivity values are computed from (8).

Analysis of statistical sense of the solution for this procedure is similar to the previous one. At  $IT \rightarrow \infty$  relationships (5), (13) and (10) result in:

$$f_y = \sum_{a=1}^m (s_a f_y / s_a + \epsilon_{a,y} / s_a) = f_y + \sum_{a=1}^m (\epsilon_{a,y} / s_a)$$

or

$$\sum_{a=1}^m (\epsilon_{a,y} / s_a) = 0, \quad (11')$$

for every year  $y$ . Similarly, at  $IT \rightarrow \infty$ , relationships (5), (8), (10) and (11') will give:

$$s_a = \frac{\sum_{y=1}^n (s_a f_y / s_a + \epsilon_{a,y} / s_a)}{\sum_{a=1}^m \sum_{y=1}^n (s_a f_y / s_a + \epsilon_{a,y} / s_a)} = s_a + \frac{\sum_{y=1}^n (\epsilon_{a,y} / s_a)}{\sum_{y=1}^n f_y},$$

or

$$\sum_{y=1}^n (\epsilon_{a,y} / s_a) = 0 \quad (12')$$

for every age group  $a$ . Relationships (11') and (12') prove that the separable estimates of  $\phi$  weighted by selectivity factor, supplied by this iterative procedure are unbiased.

**“Logarithmic” (geometrical mean) procedure (procedure C)**

Logarithmic transformation of the relationships (3) and (4) leads to the third iterative algorithm, similar to the basic and the weighed arithmetic mean ones but dealing with logarithms of  $C$ ,  $\varphi$ ,  $s$ ,  $f$ , etc. Within this, logarithmic iterative procedure relationships (6) - (8), that are used at  $IT$ -s iteration, must be replaced with:

$$\ln \varphi_{a,y} = \frac{M}{2} \ln \frac{C_{a,y}}{N_{a,y}}, \quad (14)$$

$$\ln f_y = \frac{1}{m} \sum_{a=1}^m \ln \left( \frac{\varphi_{a,y}}{s_a} \right), \quad (15)$$

$$\ln s_a = \frac{1}{n} \sum_{y=1}^n \ln \frac{\varphi_{a,y}}{f_y}, \quad (16)$$

and

$$\ln s_m = \ln s_{m-1} = \frac{1}{2n} \sum_{y=1}^n \left( \ln \frac{\varphi_{m,y}}{f_y} + \ln \frac{\varphi_{m-1,y}}{f_y} \right) \quad (16a)$$

When evaluating  $f_y$  from (15), selectivities are taken from the previous iteration. At the end of each iteration, selectivities must be re-normalized so that to satisfy condition (5). This procedure can also be called "weighed geometrical mean procedure", as from (15) and (16) it immediately follows that  $f_y$  and  $s_a$  equal to the geometrical means of  $\varphi_{a,y}$  weighed by  $s_a$  and  $f_y$  respectively.

In order to understand the statistical meaning of the convergence point of this procedure, it is convenient to use the notion of estimated catch,

$\hat{C}_{a,y} = s_a f_y N_{a,y} e^{-M/2}$ , and present  $\varphi_{y,a}$  in the form:

$$\varphi_{a,y} = s_a f_y \frac{C_{a,y}}{\hat{C}_{a,y}} \quad (17)$$

As it was noted above, we are considering the convergence of the iterative procedure, i.e., the limits at  $IT \rightarrow \infty$  of all the variables participating in the model. Therefore the fractions  $\varphi_{a,y}$ ,

which is determined by equation (14) and figures in (15) and (16), can be replaced with that given by relationship (17), where  $\hat{C}_{a,y}$  is substituted by  $\hat{C}_{a,y}^*$ , the catch estimates supplied by the iterative procedure at  $IT \rightarrow \infty$ . This substitution implies:

$$\sum_{a=1}^m [\ln C_{a,y} - \ln \hat{C}_{a,y}^*] = 0 \quad (18)$$

and

$$\sum_{y=1}^n [\ln C_{a,y} - \ln \hat{C}_{a,y}^*] = 0. \quad (19)$$

The meaning of (18) and (19) is that the log-transformed estimates of catches are unbiased. It can be simply shown that this procedure provides unbiased estimates of logarithms of  $\varphi_{a,y}$ ,  $s_a$  and  $f_y$ .

## 4. Loss functions

In accordance with the assumptions about the error structure in the data the solution of the model may be based on standard minimization of sum of squared residuals or on minimization of more robust loss functions: median of distribution of squared residuals or absolute median deviation of residuals.

Minimization of the median, *MDN*, of squared residuals (that is, the use of the least median or LMSQ principle) instead of their sum (the classical LSQ-principle) sometimes is referred to be more resistant with respect to outliers, those elements of the data set which overstep considerably reasonable confidence limits and, hence, are suspicious of containing extremely high errors (O'Brien, 1997; Hampel et al., 1986).

According to this concept, an alternative ISVPA solution may be looked for as providing estimates of  $M$  and  $f_n$ , which secure minimum of the median of the distribution of the squared logarithmic residuals,

$$SE_{a,y} = (\ln C_{a,y} - \ln \hat{C}_{a,y}^*)^2$$

( $a = 1, \dots, m$ ;  $y = 1, \dots, n$ ). The corresponding loss function will be denoted as  $MDN(M, f_n)$ .

In practice, the median of a random series is estimated by rearranging its elements in a descending or increasing order and taking the central element of the new series or the mean of two central elements (depending on whether the total number of the elements is odd or even). However, when used within the framework of ISVPA, this estimate sometimes may cause a certain roughness of the surface  $MDN(M, f_n)$ . In order to make the loss function smoother, the median is estimated here as the mean of a number (for example, 10) central elements of the ordered series of  $SE_{a,y}$ . So, in this version of ISVPA, the iterative procedures for estimating the vectors  $f$  and  $s$  remain the same as described above, the only difference being the use of the behavior of the median as an indicator of their convergence. Numerical experiments ascertain workability of the three versions of the ISVPA iterative procedures combined with the LMSQ principle.

As was noted above, in order to smooth the median estimates, averaging over a number of central elements of the ordered series of squared residuals is suggested. Certainly, the number of central elements can vary from one or two to  $m-n$ , the total length of the series. However, in the latter case, the averaging results in estimation of the mathematical expectation and not the true median of the squared residuals. So, in fact, the suggested approach (when averaging over a number of central squared residuals is applied) can be regarded as a compromise between the true median minimization and the conventional least squares criterion. The advantage of this compromise is that, according to our experience, the use of the least squares approach leads to a sufficiently smooth loss function, while the minima of  $MDN(M, f_n)$  are better pronounced.

One of the central issues in fitting a model to real data is the choice of the fitting criterion. Statistically, the use of the LSQ criterion is equivalent to accepting the hypothesis of normality of the distribution of the residuals (in the case when the sum of squared logarithmic residuals is minimized, the errors themselves are supposed to be logarithmically normal). What is the reason for using the median minimization approach? What kind of iterative procedure matches well the LMSQ criterion? To illuminate the nature of combining LMSQ criterion with ISVPA, let us consider the third, weighed logarithmic version of the iterative procedure.

It was shown above that the logarithmically transformed theoretical estimates of catches are unbiased. Strictly speaking, it means only that the mathematical expectation of the corresponding residuals is zero. We, however, believe that in practice, the distributions of the logarithmic residuals often are almost symmetric. This is confirmed by our numerous computer

tests with both simulated and real data. Clearly, if a random value  $\varepsilon$  is distributed symmetrically the median of its squares,  $\varepsilon^2$ , indicates the compactness of the distribution of  $\varepsilon$ : the higher the median of  $\varepsilon^2$ , the greater the variance of  $\varepsilon$ . Conversely, the lower the median of the distribution of  $\varepsilon^2$ , the more compact is the distribution of  $\varepsilon$ . So, by minimizing the median of the squared logarithms of the catches residuals resulting from estimation of catches by means of the weighed logarithmic iterative procedure, the maximal allowable compactness of the distribution of the errors themselves is reached, thus providing a reasonable fit of the model to the catch-at-age data in the sense of the conventional maximum likelihood concept.

Such a statistical justification cannot be given to the median minimization approach when the first (**A**) or the second (**B**) version of the ISVPA iterative procedure is used, as neither of them impose any reasonable condition on the errors in logarithmically transformed catches. From this point of view for these versions the conventional least squares approach seems to be more appropriate.

From the other side, the approach when the quality of fitting is measured by some “window” in the distribution of residuals which does not include the tails of the distribution, may be considered as a mean to suppress the influence of outliers on the solution (because the residuals which corresponds to outliers, are located near the margin of distribution and will not influence the value of the median). From this point of view minimization of the median seems to be appropriate for procedures **A** and **B** also.

In addition to the two above mentioned ISVPA objective functions, the absolute median deviation  $AMD(M, f_n)$  - the median of the absolute deviations of model residuals from their median value, known as one of the most robust measures of scale (Huber, 1981), also may be used. According to the author’s experience in some cases (for example, when distribution of residuals, still having zero mean, has nonzero median)  $AMD$  gives more pronounced minimum with respect to  $MDN(SE)$  - minimization. But if the data are not informative (for example, if historical changes in catches and in stock are not pronounced)  $AMD$  may be not sufficiently sensitive and it may be better to use  $MDN$ .

Now let us say a few word about the procedure of estimation of the “best” ( in the sense of the loss function chosen) values of  $(f_n, M)$ . Its choice in the ISVPA was based on the following considerations:



- algorithmic simplicity, bearing in mind that in the *outer loop* only two (or even one, if  $M$  is considered as known) parameters are to be estimated;
- if the loss function surface has more than 1 minimum - possibility to start minimization in the vicinity of the required minimum and to arrive at it even if the surface is very flat (this implies that gradient methods may be ineffective).

As numerous simulation experiments have shown, the method, which was not fastest, but which allowed to precisely reach the minimum even if the error surface was very flat and the minimum was local, was the method of “lowering by coordinates” with successively diminishing steps. The step of the procedure (the increase in the tested parameter value) is fixed by the program and after the minimum is achieved with this step, the step is diminished by a factor of 10. After the minimum is achieved again, the step value is decreased again by the same factor, and so on, till the minimum is reached with the required precision by the tested parameter value.

It is necessary to mention that while minimization of sum of squared errors multiple minima are almost never encountered (here the problem is that for noisy data minimum of  $SSE$  is often reached at marginally high or low value of the tasted parameter), for median minimization the surface of the loss function (as a function of  $f_n$  and  $M$ ) may have complex structure. That is why before the final run with precise estimation of the model parameters it is recommended to make preliminary point-by-point scanning of the  $(f_n ; M)$  area with sufficiently small step (for example, 0.1 for  $f_n$  and 0.01 for  $M$ ). Program realization of ISVPA gives such a possibility.

## 5. Suppression of inter-iteration oscillations

When the level of noise in the initial data is high, the estimated effort and selectivity, as well as the sum of squared residuals,  $SSE$ , vs. the number of iteration,  $IT$ , contain a few visible slowly decaying modes of oscillations superimposed upon a certain rapidly stabilizing trends. These oscillations slow down the convergence of  $SSE$  to its limit,  $SSE^*$ , or of  $MDN$  to  $MDN^*$ , or  $AMD$  to  $AMD^*$  at  $IT \rightarrow \infty$ , thus becoming significant at the stage of searching for the minimum of  $SSE^*(M, f_n)$  or  $MDN^*(M, f_n)$ , as in practice, at every  $M$  and  $f_n$  the iterative process is stopped at a finite  $IT$ . The most notable in this context are the saw-tooth type oscillations with a 2-year periodicity, i.e., those of the highest frequency. Conventional method for filtering oscillations and extraction of trends from numerical series is moving averaging. We, however, are dealing with an iterative process, where at any iteration  $IT$ , the current selectivity,  $s_{IT}(a)$ , or the effort,

$f_{IT}$ , estimate is calculated after the previous value,  $s_{IT-1}(a)$  or  $f_{IT-1}(y)$ , was found. That is why, by defining the corrected selectivity and effort estimates at  $IT$ -th iteration,  $s'_{IT}(a)$  and  $f'_{IT}(y)$ , as

$$s'_{IT}(a) = \alpha s_{IT-1}(a) + (1 - \alpha) s_{IT}(a) \quad (20)$$

$$f'_{IT}(y) = \alpha f_{IT-1}(y) + (1 - \alpha) f_{IT}(y) \quad (21)$$

and by a proper choice of the coefficient  $0 < \alpha < 1$ , the desired filtration, similar to the moving averaging, can be achieved. According to (20), all the selectivity estimates, which were computed at the previous iterations, participate in the correction for the current,  $IT$ -th iteration. The same is valid for the effort (see (21)). So, the size of the averaging interval in this filtration procedure increases with the growth of  $IT$ . Nevertheless, as the weights of the last,  $IT$ -th, iterations remain constant, while the weights of the early iterations decay, the suggested filtering procedure can be regarded as an analog of a conventional moving averaging. The effective averaging interval is determined by the choice of  $\alpha$ : the smaller  $\alpha$ , the narrower the effective averaging interval. Experiments showed that the choice of  $\alpha$  do not influence the result: there are almost identical for tested diapason of  $\alpha$  from 0 to 0.95.

## 6. Treatment of zero catches.

Existence of zero values in catch-at-age matrix is known to be a rather complicated (and may be logically controversial when dealing with logarithmic residuals) problem and is solved differently in different methods. In ISVPA the following algorithm is applied:

1. If  $C_{a,y} = 0$ , then the value of  $\varphi_{a,y}$  is taken equal to its “theoretical” value, that is

$$\varphi_{a,y} = s_a f_y.$$

2. Residuals for points of zero catches are taken equal zero.

3. Stock abundance is computed as follows:

3.1. If  $N_{a+1,y+1} > 0$  and  $C_{a,y} = 0$ , than  $N_{a,y}$  is computed by (2.2).

3.2. If  $N_{a+1,y+1} = 0$  and  $C_{a,y} = 0$ , than  $N_{a,y} = 0$ .

3.3. If  $N_{a+1,y+1} = 0$  and  $C_{a,y} > 0$ , than  $N_{a,y}$  is computed by (2.3) -the same way, as for terminal points.

3.4. If  $N_{a+1,y+1} > 0$  and  $C_{a,y} > 0$ , than  $N_{a,y}$  is computed by equation (2.2) or (2.2') or their mixture, according to the version chosen.

## 7. Some other variants of optimization algorithms

Some other variants of ISVPA parameter estimation procedures were also tested while working at the program. For example, to make faster the parameter estimation procedure an attempt was made to exclude the estimation of natural mortality coefficient from the “outer loop” and to estimate this parameter within the “inner” iterative procedure along with  $\varphi_{a,y}$ ,  $s_a$  and  $f_y$ . For this purpose on every iteration, after the vectors  $s_a$  and  $f_y$ , are estimated, new matrix  $\varphi_{a,y}=s_a f_y$  is building up and a new parameter  $X$ , being the average value of  $e^{-M/2}$ , is estimated:

$$X_{a,y} = C_{a,y}/(\varphi_{a,y}N_{a,y});$$

$$X = \frac{1}{nm} \sum_{y=1}^n \sum_{a=1}^m X_{a,y}$$

After that a new value of natural mortality coefficient is estimated as  $M = -2LnX$ . Naturally, an initial guess for  $M$  is to be input before the start of the procedure along with initial guess for  $s_a$  and  $f_y$ . For initial guess it is possible to use any positive values of  $s_a$  and  $f_y$ , such as  $s_a f_y < 1$ . For  $M$  the initial guess may be taken from the diapason  $0 < M < 1$ .

Unfortunately experiments showed that this variant of procedure is suitable only for very “clean” data (with very low noise) and for practical purposes this procedure is not effective.

Experiments also proved the importance of organization of ISVPA parameter estimation procedure in form of two concentric loops: attempts to estimate  $f_n$  (or both  $f_n$  and  $M$ ) in frames of single loop along with other parameters was not successful: it was needed to use rather precise initial guess for all parameters, what is rarely possible in practice. This is explained by low curvature of loss function for real (that is noisy) data. Consequently, optimization by parameters  $f_n$  and  $M$ , which are most influenced by values of other parameters, does not work until the “best values” (for the tested values of  $f_n$  and  $M$ ) of other parameters are not estimated (or “almost” not estimated).

## 8. Estimation of ISVPA parameters without limitation on bias

In order to test experimentally the role of limitation on bias, imposed by the above described ISVPA procedures, an additional, free of such limitations parameter estimation procedure was developed.

For “direct” fitting of multi-parameter models the Marquardt-Levenberg and Gauss-Newton method are traditionally used (Bard, 1974), as it was done, for example, in CAGEAN (Deriso et al., 1985) and ICA (Patterson, 1994). But in our case implementation of these methods is complicated by normalization equation (2.5): parameters are becoming inter-dependent. Attempt to use Simplex-method (Schnute, 1982) was also unsuccessful: for the case of many parameters the procedure is very time-consuming and also requires very qualified initial guess for parameters (the result is extremely sensitive to its choice).

Because of the above mentioned, the procedure of “direct” search for the ISVPA parameters, free of limitations on bias, was finally arranged as follows. The same was, as it was done with “iterative” inner ISVPA procedures, the procedure was designed as two concentric loops. In outer loop optimization by  $(f_n, M)$  is made, while the parameters  $\{s_a\}$  and  $\{f_y\}$  (except  $f_n$ ) are estimated in the inner loop.

The inner loop is arranged as follows. Each parameter is optimized in succession, while the order of optimization appeared to be important. Starting from a set of initial guesses for all parameters  $s_1, \dots, s_m$  и  $f_1, \dots, f_{n-1}$ , optimization begins from  $f_{n-1}$ ; after that the value of  $f_{n-2}$  is optimized, and so on till  $f_1$ . After that, the best value (from point of view of the loss function) of  $s_1$  is estimated, the other values of  $s_a$  being changed by means of normalization equation (5). The found value of  $s_1$  is then “frozen up” and the “best” value of  $s_2$  is searched for (here the normalization equation (5) is applied to the rest of selectivity factors:  $s_3, \dots, s_m$ , ). Then the next,  $s_3$ , selectivity factor is estimated, and so on till  $s_{m-2}$ . The rest of selectivities,  $s_m = s_{m-1}$ , appears to be already estimated by the normalization equation. After that the procedure again returns to estimation of  $f_1$ , and the sequence of calculations is repeated till convergence.

The above described procedure gives the solution free from restrictions on bias. For “clean” catch-at-age data (simulated data without noise) the procedure gives absolutely correct estimates of all parameters (as well as “iterative” procedures **A**, **B** and **C**). For noisy simulated data and for real data the solution based on this “unrestricted” fitting procedure as a rule is much worse, while the final value of loss function may be lower than for “unbiased” solutions.

It is necessary to mention that implementation of the above described procedure of “parameter-by-parameter” optimization for *median* minimization may be problematic if one (or a group) of parameters  $s_1, \dots, s_m$  and  $f_1, \dots, f_{n-1}$  occasionally influences only those values of

residuals which are located on tails of distribution of residuals and, hence, do not influence the median value.

## 9. Dealing with auxiliary information

There is possibility to include up to 3 SSB indexes and up to 7 age structured stock abundance indexes into the model. In such a case ISVPA loss function will include additional components representing measures of discrepancy:

- for each SSB index : between logarithms of SSB from cohort part and from surveys;
- for each age-structured index: between logarithms of abundance ( $a,y$ ) from cohort part of the model and from surveys (corrected to estimated age-dependent "fleet catchabilities" or not).

It is also possible to fit the model not only on survey abundance-at-age data, but on survey age proportions and “weighted” survey age proportions. In fact, age-structured abundance indexes, when being used for tuning of cohort models, sometimes give unclear or controversial signals about stock size, more precisely - about the value of terminal fishing mortality coefficient ( $F_{term}$ ). In some cases the minimum of corresponding component of loss function of a model may be completely deteriorated, that is, the best fit is found for extremely low or high  $F_{term}$ . This indicates that abundance-at-age index data from surveys (or in cpue of a fishing fleet) are so far from the values calculated in cohort part of a model from catch-at-age data (theoretical values), that the best fit corresponds to almost zero (or extremely high) stock size in terminal year. It is not always clear why we have such a discrepancy. At least there could be two possible explanations: 1) age structure of abundance-at-age index from surveys (or for a fleet, used for tuning) is unrepresentative with respect to the whole stock (data are very noisy), and 2) there is a trend in catchability of surveys. Naturally, both the above mentioned factors may act simultaneously.

Considering the second reason (year-dependent factor in survey catchability), it is theoretically possible to make an attempt to estimate time trend in catchability, but this requires additional data and may make the model to be too flexible. That is why in some cases it is preferred to substitute fitting of the model to abundance-at-age index data by fitting on age composition (in proportion) of survey data (that is, by minimization of residuals between age composition of surveys and age composition of abundance derived from a model). Usually in such a case multinomial (Fournier et al., 1998) or, as it is done in COLERANE (Hilborn et al., 2000), robust-normal error model is used.

Influence of the first above mentioned reason (high level of noise in the survey data) may be diminished by robustization of the model, for example, by application of robust loss functions, such as the median of distribution of squared residuals instead of their sum.

In some cases survey data may have different quality in different years. For example, representativity of the data may correlate with stock abundance. In such a case a specific weights may be needed for specific years.

Let us assume lognormal error model. Then the residuals between “theoretical” (derived from a model) abundance-at-age  $N_{a,y}^{(th)}$  and index abundance-at-age  $N_{a,y}^{(Ind)}$  may be represented as:

$$res_{a,y} = Ln\left(\frac{N_{a,y}^{(th)}}{N_{a,y}^{(Ind)}}\right) = Ln\left(\frac{P_{a,y}^{(th)} \sum_{a=a \min}^{a \max} N_{a,y}^{(th)}}{P_{a,y}^{(Ind)} \sum_{a=a \min}^{a \max} N_{a,y}^{(Ind)}}\right) = Ln\left(\frac{P_{a,y}^{(th)}}{P_{a,y}^{(Ind)}}\right) + Ln\left(\frac{\sum_{a=a \min}^{a \max} N_{a,y}^{(th)}}{\sum_{a=a \min}^{a \max} N_{a,y}^{(Ind)}}\right) \quad (22)$$

where  $P_{a,y}^{(th)}$  and  $P_{a,y}^{(Ind)}$  are proportions of age group  $a$  in the “theoretical” and “index” stock abundance in year  $y$ . From expression (22) it is clearly seen that, when dealing with minimization of residuals between abundances, in fact for each point  $(a,y)$  we are simultaneously minimizing residuals between age compositions and between total abundances. It is also seen that the ratio of total abundances may be considered as a “weighting factor” for ratio of proportions.

As it was mentioned above, for minimization of residuals in age compositions (proportions) it is more traditional to assume multinomial or robust-normal error model. Nevertheless in the ISVPA we use logarithmic residuals, because experiments shows that in some cases lognormal error model seems to be at least not less appropriate (e.g. see Vasilyev 2003). To be comparable, age proportions in each year are calculated only for those age groups, which are simultaneously present both in stock and in index data.

Another option, which was also added to the model, consisted in possibility of tuning by minimization of residuals between logarithms of models-derived abundance  $LnN_{a,y}^{(th)}$  and index age structure  $LnP_{a,y}^{(Ind)}$ . In such a case model-derived estimates of total abundance serves as weighting factors for age proportion ratios (see expression (22)). This option could be helpful for stocks with strongly variable abundance, if representativity of survey data is strongly dependent

on stock size. As well as for catch-at-age and for tuning on index abundance-at-age data, minimization for age structures (or for abundance and index age structures) can be undertaken in the model by minimization of the sum of squared logarithmic residuals (SSE), or by minimization of more robust statistics: the median of distribution of squared logarithmic residuals (MDN). Possibility for minimization of absolute median deviations (AMD) – the median of distribution of absolute deviations between logarithmic residuals and their median value is also reserved.

Thus, for each age-structured index the discrepancy may be measured as traditional sum of squared residuals, or by MDN, or AMD. The measure may be stated independently for each of "fleet".

For SSB indexes the only available measure in the model is the sum of squared residuals (because, as a rule, available number of years of SSB surveys is rather low).

## 10. The program

Current realization of ISVPA is made in Visual Basic and can be run from any Windows environment. If Visual Basic is installed on your computer it will be enough to copy only exe – file. If not – use ISVPA set up package.

Input files are blank-separated text files and include:

- "necessary" files: catch-at-age by years, weight-at-age by years in the stock and maturity-at-age by years;
- "optional" files (may be not given): natural mortality by ages, up to 3 files with SSB estimates by years and up to 7 files with age-structured abundance indexes by years.

All input files must be positioned into **C:\vbisvpa** directory or its subdirectories.

Output files include: the file with records of minimization (minim.out), the file of results (its name is given by user) of initial ("basic") run, as well as bootstrap output files:

- 1) bootf.out - includes effort factor estimates by years and bootstrap runs;
- 2) bootm.out - includes natural mortality estimates by ages and bootstrap runs (if it was considered as unknown parameter);
- 3) boots1.out and boots2.out - include the estimates of selectivities (for first and second time intervals) by ages and bootstrap runs (the program gives possibility to fit 2 different selectivity patterns for 2 different successive time intervals);

- 4) bootssb.out - includes the SSB estimates by years and runs;
- 5) boottsb.out - includes the estimates of total stock biomass by years and runs;
- 6) bootntrm.out - includes terminal year abundance estimates by ages and runs.

The procedure of working with the program is the following.

1. First what is needed to be done while running the program is to enter the names of catch-at-age and weight-at-age files. If they are located directly in C:\vbisvpa directory - simply print their names (with extension). If they stand in some sub-directory of C:\vbisvpa - print the name of the file with the name of this subdirectory.
2. After that you will be asked about the **situation with natural mortality**: 1) to find  $M$  as age-independent value; 2) to find it as a simple quadratic function of age; 3) to use known values of  $M(a)$ . If option 2 is chosen, you will be asked to enter the age of minimum  $M$  (as a rule it may be taken equal to the age of 'mass' maturity). If option 3 is chosen, you will be asked to enter the name of file with known  $M(a)$  values.
3. Next you have to choose the method for parameter estimation. 4 options are available. Option 1 will produce solution with "unbiased separabilization"; option 3 - with "unbiased weighted separabilization"; option 2 will ensure "unbiased" estimates of logarithms of all parameters; option 4 will produce solution corresponding to best fit to logarithmic catches, not restricted by any condition on bias. While using option 4 be patient - it takes time. In most cases option 2 is recommended. It is strongly recommended **not to use option 4** when you minimize the median - error surface may be too "broken".
4. The next choice is what to minimize. It is possible to minimize sum of squared residuals in logarithmic catches, or median of distribution of squared residuals in logarithmic catches  $MDN(M, f_n)$ , or absolute median deviation  $AMD(M, f_n)$ . For noisy data minimization of  $MDN$  or  $AMD$  is recommended.
5. Selection of first and last year of analysis and the last year of first selectivity pattern (**the program gives possibility to fit 2 different selectivity patterns for 2 different successive time intervals**). After that it is needed to input the first and the last age groups. Naturally, they should be within the limits of the input data. After that you will be asked: is the oldest age in the data a "normal" age group, or it is +-group ?
6. Next question is about the "version" of the program (1. Catch-controlled, 2. Effort-controlled, 3. Mixed, 4. Mixed, weighted by points). Version 1 is preferable if fishery is known to be extremely non-separable. It also may be useful as a part of "mixed" versions 3 and 4. Version 2 is preferable if  $M$  is considered as unknown parameter and/or the data are very noisy.
7. If version 3 is chosen you will have to input relative weight of catch-controlled routine.
8. You may 1) scan the error surface or 2) look for precise solution. If scanning is chosen, you will be asked about minimum and maximum values of the parameter ( $f_{term}$  or ( $M$  and  $f_{term}$ )) and of "step". It is recommended to make scanning first - there could be several local minima of the loss function. Option 2 allows to find precise solution. If several local minima



exist, you may look for the solution corresponding to the required minimum - by proper choice of initial guess for the parameter and sufficiently small initial step. Please note that if “scan” mode was chosen, the output file will contain the result at **rough** minimum of the loss function. To get the result at precise minimum you have to start the program again and to choose the option “precise solution”. If “precise solution” is looked for - you have to input the value of initial guess for  $f_{term}$  or ( $M$  and  $f_{term}$ ) and of initial step for searching procedure.

9. Next you will have to set the value of “inter-iteration smoother”. In most cases any value within 0.5-0.9 will be OK. For very noisy data to suppress possible oscillations you may take the higher value - up to 0.9. Don’t worry about “precise” value of this parameter: if procedure converges - it is OK. Experiments proved that final result will be the same even for 0.95.
10. If you have chosen the median minimization, you will have to input the number of central elements of the ordered series of squared residuals (or residuals) to use as its measure. In most cases 10 points is OK. If error surface contain too many local minima it may be useful to increase the number of central elements; if minimum is too flat - you may diminish the number of central elements. Please note that this setting will be used for MDN or AMD measures everywhere (for indexes also, if one of these measures will be used for some of them).
11. Enter the portion of the year for peak of catches (since the model is based on Pope’s approximation of “instantaneous” catch). If fishing goes on uniformly all over the year - enter classic 0.5.
12. Enter the name of output file. It will be in C:\vbisvpa directory.
13. You have possibility to make output of currents results on screen. Output on screen makes the calculations slower, but it is comfortable to see what’s happening.
14. Input maturity-at-age file name.
15. You will be asked to include SSB surveys or not. If “yes”, you will have to input names of files with SSB surveys by years (up to 3).
16. If you have age-structured abundance indexes, you may use up to 7 different indexes. If “yes”, input their names.
17. If any auxiliary information is used, you will be asked to input weight for catch-at-age-derived component in the overall loss function (any value is allowable, including 0).
18. If SSB surveys are included - for each of them input weights for components of the overall loss function, representing measures of their closeness to cohort part -derived estimates of SSB (for SSB indexes only one kind of measure is available - sum of squared residuals between their logarithmic values).
19. Input portion from start of the year before the moment when surveys are made (the same for all SSB indexes).
20. If SSB surveys are included – for each of them input the values of standard deviation of lognormal distribution, which will be used in stochastic runs.

21. If SSB surveys are included - state how to treat each of them: as absolute or relative index.
22. If age-structured indexes are included - input portion from start of the year before the moment when age-structured survey is made (for each kind of survey).
23. If age-structured indexes are included - state index of what they are (mature part, whole stock, or immature part).
24. If age-structured indexes are included - for each of them input weights for components of the overall loss function, representing measures of their closeness to cohort part- derived estimates of abundance.
25. If age-structured indexes are included - for each of them answer the question: to estimate age-dependent catchabilities or not (if “not” is chosen then it will be assumed that  $q(a)=1$ ).
26. If age-structured indexes are included - choose for each of them what measure of closeness of fit will be used: MDN, SSE, or AMD.
27. If age-structured indexes are included – choose what you want to compare in tuning : 1) logarithmic abundances(a,y) from cohort part of the model and logarithmic abundances(a,y) in survey; 2) logarithmic abundance(a,y) (from cohort part of the model) and logarithmic age structure(a,y) of surveys; 3) logarithmic age structure of the stock(a,y) (from cohort part) and logarithmic age structure(a,y) of surveys.
28. If age-structured indexes are included –for each of them input the values of standard deviation of lognormal distribution, which will be used in stochastic runs.
29. When calculations are finished, you may make stochastic runs. Current version of the program gives possibility to run parametric conditional bootstrap with respect to catch-at-age, (assuming that errors in catch-at-age data are log-normally distributed, standard deviation is estimated in basic run), combined with adding noise to indexes (assuming that errors in indexes are log-normally distributed with specified values of standard deviation).

If something goes wrong or in unwanted direction, it is always possible to **stop the program** by clicking the button “stop”. The program will return to initial (input) screen and you may run it again. The only what is necessary to remember when using stop by user is that if option of “direct search” of inner parameters is used, you have to let the program to finish at least one inner cycle (that is to finish calculation of inner parameters for at least one  $f_{term}$ ) and to stop it after that (if not – interrupt will cause error and abortion of the program).

**Note:** current version gives possibility to use surveys for terminal+1 year (that is for year without known catch-at-age) Fishing pattern in this year is assumed equal to that of “true” terminal year. In such a case all input files should be entailed to include data for this year (it is becoming terminal one); catch-at-age file should include zero values of catch-at-age for this year.

## References

1. Anon. 1999. Reports of the Working Groups on the Assessment of Mackerel, Horse Mackerel, Sardine and Anchovy (1999). ICES CM 2000/ACFM.
2. Bard Y. 1974. Non-linear parameter estimation. - NY, Academic Press, 1974. - 349 p.
3. Deriso R.B., T.J. Quinn II and P.R. Neal. 1985. Catch-age analysis with auxiliary information. Can. J. Fish. Aquat. Sci., 42, N 4: 815-824.
4. Doubleday W.G. 1976. A least squares approach to analysing catch at age data. ICNAF Res. Bull,12: 69-81.
5. Fournier D. and Archibald C.P. 1982. A General Theory for analyzing catch at age data. Can. J. Fish. Aquat. Sci.,39: 1195-1207.
6. Fournier, D. A, J. Hampton, and J.R. Sibert. 1998. MULTI FAN-CL: a length- based, age structured model for fisheries stock assessment, with applications to South Pacific albacore. Can. J. Fish. Aquat. Sci. 55: 1-12.
7. Gudmundsoon, G. 1986. Statistical considerations in the analysis of catch-at-age observations. J. Cons. int. Explor. Mer, 43: 83-90.
8. Hampel, F. R., Ronchetti, E. M., Rousseeuw, P. J. and Stahel, W. A.. 1986. Robust Statistics. The approach based on Influence Function. John Wiley & Sons, NY.
9. Hilborn, R., et al. 2000. COLERANE. A generalized age structured stock assessment model. Users manual. Version 1.
10. Huber, P. J. 1981. Robust statistics. John Wiley & Sons, NY.
11. Kimura, D.K. 1986. Variability, tuning and simulation for the Doubleday-Deriso Catch-at-Age model. Can. J. Fish. Aquat. Sci. 46: 941-949.
12. Kizner Z.I. and D.Vasilyev. 1993. Instantaneous Separable VPA (ISVPA) with determination of natural mortality coefficient. ICES Statutory Meeting (1993) C.M. 1993/D:2. 45p.
13. Kizner Z.I. and D.A.Vasilyev. 1997. Instantaneous Separable VPA (ISVPA). ICES Journal of Marine Science, 54, N 3: 399-411.
14. Lewy P. 1988. Integrated stochastic virtual population analysis: estimates and their precision of fishing mortalities and stock sizes for the North Sea whiting stock. J. Cons. int. Explor. Mer. 1988. Vol. 44. P. 217-228.
15. Patterson K.R. 1995. Technical reference for the Integrated Catch-at-Age Programmes, Version 1.2 . SOAFD Marine Laboratory. Aberdeen.
16. Pope J.G. 1972. An investigation of the accuracy of virtual population analysis. Int. Commn. Northwest Atl. Fish. Res. Bull. 1972. N9. P. 65-74.
17. Pope J.G. 1974. A possible alternative method to virtual population analysis for the calculation of fishing mortality from catch at age data. ICNAF Res. Doc. 74/20. 16 pp.
18. Pope J.G., Shepherd J.G. 1982. A simple method for consistent interpretation of catch-at-age data. Cons. int. Explor. Mer.,40: 146-184.
19. Vasilyev D.A. 1998. Separable Methods of Catch-at-age Analysis From Point of View of Precautionary Approach. ICES Study Group on the Precautionary Approach to Fishery Management (Copenhagen, 3-6 February 1998). Working Paper N 11. 7 pp.
20. Vasilyev D. 1998a. Separable cohort procedures with internal property of unbiasedness of the solution. ICES C.M. 1998 / BB:3, 11 pp.
21. Vasilyev D. 2001. Cohort models and analysis of commercial bioresources at informational supply deficit. Moscow, VNIRO Publishing, 2001. 98 pp.
22. Vasilyev D. 2003. Is it possible to diminish the impact of unaccounted time trends in age structured surveys' catchability on the results of stock assessment by means of separable cohort models ? ICES CM 2003/X:03. 13 pp.