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Using a genetic algorithm to optimize a data-limited catch rule

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Many data-limited fish stocks worldwide require management advice. Simple empirical management procedures have been used to manage data-limited fisheries but do not necessarily ensure compliance with maximum sustainable yield objectives and precautionary principles. Genetic algorithms are efficient optimization procedures for which the objectives are formalized as a fitness function. This optimization can be included when testing management procedures in a management strategy evaluation. This study explored the application of a genetic algorithm to an empirical catch rule and found that this approach could substantially improve the performance of the catch rule. The optimized parameterization and the magnitude of the improvement were dependent on the specific stock, stock status, and definition of the fitness function. The genetic algorithm proved to be an efficient and automated method for tuning the catch rule and removed the need for manual intervention during the optimization process. Therefore, we conclude that the approach could also be applied to other management procedures, case-specific tuning, and even data-rich stocks. Finally, we recommend the phasing out of the current generic ICES "2 over 3" advice rule in favour of case-specific catch rules of the form tested here, although we caution that neither works well for fast-growing stocks.

Keywords: data-limited, empirical catch rules, FLR, FLife, genetic algorithm, ICES, management strategy evaluation, MSY

Introduction

The majority of the world's fish stocks are data-limited, and analytical stock assessments do not exist (Rosenberg et al., 2014). Nevertheless, fisheries scientists and managers are often requested by stakeholders to advise on fishing opportunities in order to ensure the sustainability of fisheries activities.

ICES provides advice on fishing opportunities for many fish stocks in the Northeast Atlantic. For this purpose, fish stocks are classified into six categories, depending on the availability of data and the applicability of assessment methods (ICES, 2012, 2019a). Data-rich stocks fall into the highest category (category 1). For these stocks, analytical stock assessments offer quantitative information about stock metrics, and ICES provides advice based on a framework that includes considerations of the precautionary approach (Garcia, 1996) for biological risk and target fishing levels that are defined by reference points following the maximum sustainable yield (MSY) principle (ICES, 2019a). The lowest category is category 6 and includes data-poor bycatch stocks with negligible landings. In between are data-limited stocks, and for these, ICES bases its advice on a precautionary approach (ICES, 2012).

ICES category 3 data-limited stocks are stocks for which survey-based assessments indicate trends in stock dynamics (ICES, 2012). Even though some survey indices exist for these stocks, it is not always possible to apply simple stock assessment methods, such as biomass dynamic models or simplified integrated models (e.g. extended simple stock synthesis; Cope *et al.*, 2015). This might be because of short time-series, conflicting signals from the catch, catch per unit effort, survey and length data, lack of contrast in these data, or model convergence issues. Management procedures based on empirical rules are an alternative and can sometimes perform at least as well as those based on analytical methods (Carruthers *et al.*, 2014; Geromont and Butterworth, 2015). For category 3 stocks, ICES typically applies a "2 over 3" rule to an index of abundance (the average of the last two values divided by the average of the three values preceding those) and has introduced MSY principles for stock status evaluations based on MSY proxy methods (ICES, 2018b). However, this approach considers solely the application of a precautionary buffer to reduce the catch advice based on the "2 over 3" rule in case of a non-favourable stock status and does not include any MSY targets. It is therefore not explicitly aligned towards MSY.

Fischer *et al.* (2020) deployed a management strategy evaluation (MSE, Smith, 1994; Punt *et al.*, 2016) approach to simulation test an alternative catch rule that includes an MSY target, which is based on an empirical rule of the form:

$$A_{y+1} = C_{y-1}\, r\, f\, b. \tag{1}$$

This harvest control rule (the *rfb*-rule) sets the catch advice for the following year (A_{y+1}) on the recently observed catch (C_{y-1}) multiplied by three components; a biomass trend r, an exploitation proxy f, and a biomass safeguard b. Component r represents the recent stock trend derived from a biomass index, f is calculated by comparing the recent mean length in the catch to a length-based proxy for F_{MSY}, and b reduces the catch when the biomass index falls below a threshold.

The *rfb*-rule is currently being considered by ICES (ICES, 2017d, 2018c, 2019b) as a potential successor for assessing category 3 data-limited stocks. The simulations of Fischer *et al.* (2020) showed that its performance is crucially dependent on the life-history of the stock, and in particular on the von Bertalanffy growth parameter k. The *rfb*-rule performed reasonably well for stocks with $k \leq 0.32\,\mathrm{year}^{-1}$ by keeping these stocks at or above B_{MSY}, but very poorly for stocks with higher k (fast-growing and small pelagic stocks), resulting in increased risks of stock collapses in these cases.

In an MSE context, the term tuning describes the process of adjusting the control parameters of a management procedure to improve performance statistics for the purpose of meeting specific management objectives in a simulation (tRFMO, 2018). This concept has also been considered at the International Whaling Commission to adapt management procedures to balance management objectives such as risk, stock status, and aboriginal subsistence whaling needs (Givens *et al.*, 1999). Fischer *et al.* (2020) made some attempts to improve the performance of the *rfb*-rule by manually tuning the rule by the addition of multipliers (to change the target level) and catch constraints (to limit catch variability). The results showed that the *rfb*-rule was mainly dominated by the stock trend (component r), whereas the remaining components had less influence on the newly advised catches. The logical course of action is to apply weights to the three components in order to reduce or increase their influence. The application of weights should not just be a process of adding arbitrary correction factors but implemented with consistent and logical rules. Trying to manually modify a single component of the *rfb*-rule or a limited combination of components to improve performance might be feasible with a grid search; however, such a manual optimization task is an onerous activity and decisions are potentially arbitrary. Givens *et al.* (1999) note that depending on the way optimizations and approximations are specified, outcomes might give preference to different approaches, e.g. by focusing only on specific management goals. If the components are going to be tuned on a case-specific basis and their interactions considered in a multi-dimensional search, then there are an almost infinite number of scenarios and potentially confounding results between parameters, which means traditional approaches are impractical.

In the absence of predefined and clearly articulated management objectives, the results of such a tuning exercise must be carefully examined, and this can easily lead to a time-consuming activity. For example, trade-offs between opposing objectives need to be considered, such as maximizing catch and biomass or reducing depletion risk and catch variability. Moreover, trust is a crucial element and stakeholders will need to agree to the procedure and accept outputs and revisions in the light of new developments. Therefore, the application of an automated or semi-automated optimization procedure without the need for manual intervention is desirable. For this approach, the objectives of the optimization process must be precisely defined and be formalized as an objective function.

In this study, we explore the use of a genetic algorithm (GA) as an optimization method. Genetic algorithms belong to the more general class of evolutionary algorithms which are inspired by the principles of biological evolution (Darwin, 1859) and can be used as an optimization procedure. In a GA, the functional behaviour of genetic operators is mimicked in order to create variability in a population, which is then subjected to selection in a competitive environment (Holland, 1992).

The GA approach was already well developed in the 1970s but did not gain much attraction in the scientific community initially (Holland, 1992). However, with the development of faster and more advanced computers, its application became more feasible. To date, GAs have been applied to optimization problems in various scientific fields, including the design of integrated circuits, communication networks, and stock market portfolios (Holland, 1992). In fisheries science, GAs have, for example, been applied to the optimization of bioeconomic models (Mardle *et al.*, 2000), or fitting stock-recruitment models (Chen *et al.*, 2000) and growth functions (Taylor and Mildenberger, 2017).

Numerous other optimization methods exist; however, not all of them are equally applicable to specific optimization problems. We chose the GA approach because it is a flexible optimization approach, allows the inclusion of computing-intensive fitness functions, and has been shown to perform well for various optimizations. It is also able to consider many possible solutions simultaneously within one generation, and it is, therefore, less prone to converging on local optima (Chen *et al.*, 2000).

The genetic algorithm can be applied to the optimization of management procedures that include harvest control rules such as the *rfb*-rule. For a control rule to be optimized, there is a need for it to be adaptable. This adaptability can be achieved by making the existing components of the rule more flexible (e.g. by changing the definition of a component) or through the inclusion of additional parameters (e.g. weighting components or a multiplier) that can be used for tuning. An individual of the population in the genetic algorithm is defined by its genetic material (the genotype). In the context of a control rule, parameters could be considered as genes. All parameters together form the genotype of an individual. Such a genotype must be translated in order to obtain observable traits (the phenotype). This translation corresponds to running an MSE projection with the parameters of the control rule, and summary statistics could then characterize its phenotype.

Figure 1 illustrates the principles of a genetic algorithm. The initial population (the first generation) in the genetic algorithm consists of many individuals, each with a different set

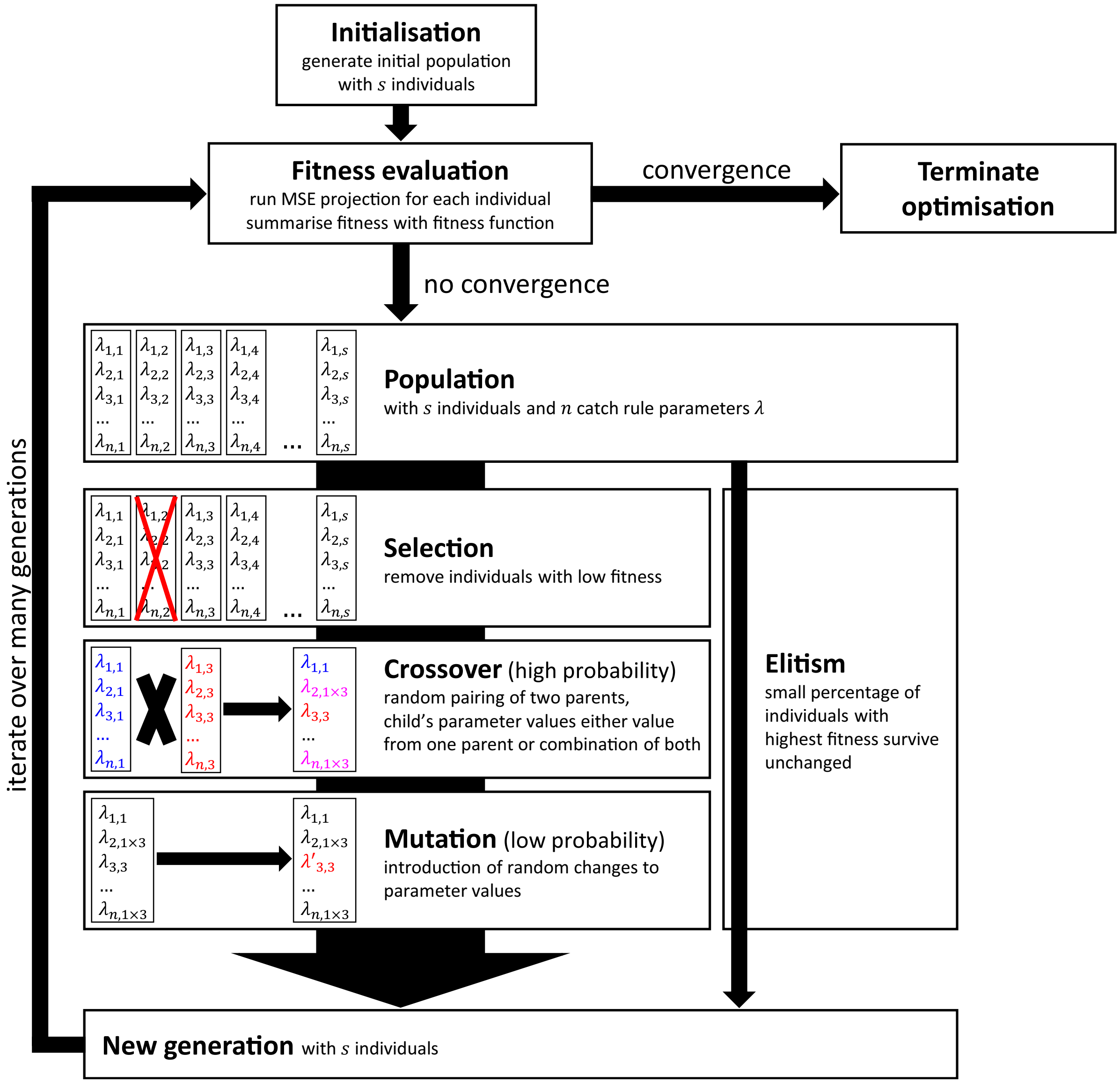

Figure 1. Conceptual representation of the genetic algorithm as an optimization procedure for a management procedure.

of parameters. This population would include the default parameterization of the rule, as well as randomly chosen parameterizations. For the population to evolve, the fitness of each individual must be evaluated with a fitness function, e.g. by comparing summary statistics for predefined targets or thresholds. Prior to creating the second generation, natural selection is applied to the initial generation, and only the fittest individuals survive and form a reproductive population. This reproductive population is the basis for the next generation and their genes (control rule parameters) are passed on to the next generation; however, natural variability is introduced through two genetic operators: crossover and mutation. The individuals in the new generation are generated by combining the parameters of two parent-individuals (crossover), as well as introducing random changes to the parameters (mutation). Furthermore, an elitist strategy allows the survival of some of the individuals with the highest fitness values. Elitism is useful to ensure that the best performing parameterizations do not disappear, and that there is no deterioration in the performance over the generations. This process is then repeated for every subsequent generation until convergence criteria are reached, and the optimization terminates.

In the present study, we explore the application of the genetic algorithm to the optimization problem of the data-limited catch rule from Equation (1). By doing so, we aim to improve the performance of the generic catch rule, and, more generally, evaluate whether the approach can be used for higher-k stocks for which the default catch rule parameterization showed poor performance (Fischer *et al.*, 2020). We also compare the results of this catch rule, both its default and optimized settings, to the current ICES "2 over 3" advice rule for ICES category 3 data-limited stocks.

Methods

Operating models

The 29 stocks in Fischer *et al.* (2020) were used for the operating models and these covered a wide range of life-history traits

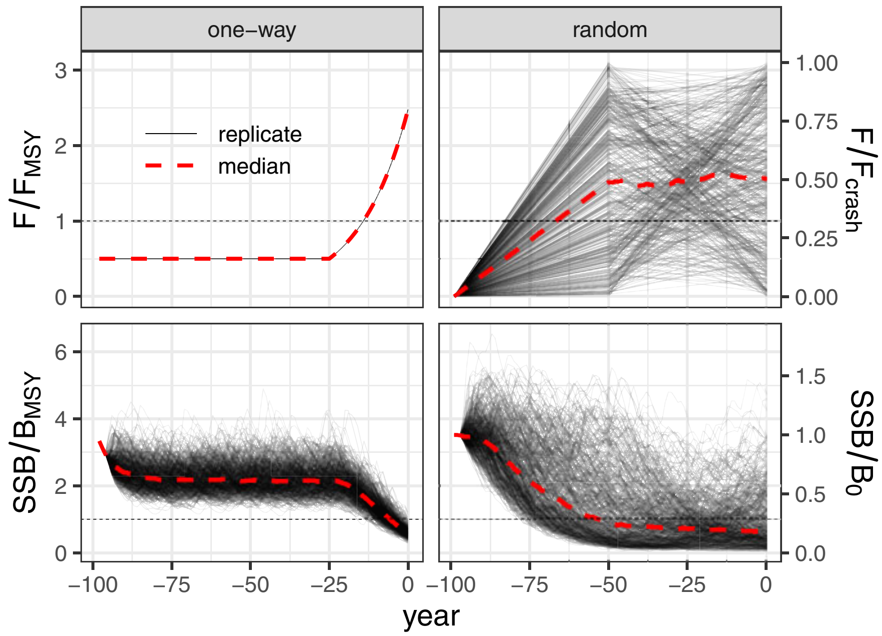

Figure 2. Comparison of the two fishing histories in the operating models, shown here for pollack. The black curves represent the 500 simulation replicates and the dashed horizontal lines indicate F_{MSY} and B_{MSY}.

(the stocks and their life-history parameters are listed in Supplementary Table S1). Age-structured operating models were created using the FLR (Kell *et al.*, 2007) package FLife and were conditioned using life-history parameters.

Two fishing histories were created starting from an unfished state for a period of 100 years ($y = -99, \ldots, 0$, enough for slower-growing stocks to respond to changes in exploitation) and with 500 simulation replicates (Figure 2). The approach of using alternative fishing histories was chosen to cover different possible exploitation patterns, including a pattern of overexploitation against which the default *rfb*-rule was already tested, and as a way to compare the catch rule performance depending on the exploitation history. The baseline was the "one-way" fishing history from Fischer *et al.* (2020), in which stocks were fished for 75 years at $0.5F_{MSY}$, and then the fishing mortality was increased exponentially to $0.8F_{crash}$ over the following 25 years, where F_{crash} is defined as the lowest fishing mortality that causes the stock to collapse in equilibrium. This fishing history meant that the stocks were highly depleted and declining at the end of the fishing history. An alternative fishing history ("random") was generated with random fishing trajectories. This was achieved by defining the fishing mortality at three points in time; starting from an unfished state ($F_{y=-99} = 0$), setting fishing mortality after 50 and 100 years by drawing from independent uniform distributions [$F_{y=-50} \sim U(0, F_{crash})$ and $F_{y=0} \sim U(0, F_{crash})$], and using a simulation replicate-specific linear interpolation for the intermediate years. This random fishing history covered a wide range of fishing patterns, including increasing, stable, and decreasing fishing mortality, and combinations thereof (see Figure 2).

Management procedure

After the 100-year fishing history, a management procedure based on a modified version of the *rfb*-rule defined in Equation (1) was implemented for 50 years (years 1 to 50). In order to make the rule more flexible, additional elements were introduced:

$$A_{y+1} = C_{y-1}\, r^{e_r}\, f^{e_f}\, b^{e_b}\, x. \tag{2}$$

The newly introduced exponents e_r, e_f, and e_b allowed the weighting of the three components r (biomass trend), f (exploitation proxy), and b (biomass safeguard). The multiplier x worked by modifying the advised catch, e.g. by increasing the catch (less precaution) or decreasing it (more precaution). The components of the *rfb*-rule are multiplicative; consequently, the multiplier can be considered as working on the total catch advice or any individual component (e.g. by changing the target of the *f*-component). Setting $e_r = e_f = e_b = 1$ corresponds to the default *rfb*-rule parameterization without weighting, $e_j < 1$ reduces the influence of any component j (r, f or b) and makes it less reactive to the underlying data, with $e_j = 0$ removing it altogether, and $e_j > 1$ giving component j more weight by making it more reactive. The r component reflects the trend in a biomass index time series and defaults to the average of the last two years' values divided by the average of the three preceding years' values, which corresponds to the current implementation of the "2 over 3" rule within ICES. Component r was adapted so that it corresponded to an average of n_1 years divided by n_2 years of the biomass index (I) and the most recent year was defined as an offset n_0 to the intermediate (assessment) year y:

$$r = \frac{\sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)}{\sum_{i=y-n_0-n_1+1}^{y-n_0-n_1} (I_i/n_1)}. \tag{3}$$

Components f and b were kept unchanged:

$$f = \frac{\overline{L}_{y-1}}{L_{F=M}}, \tag{4}$$

where $\overline{L}_{y-1}$ is the mean catch length above the length of first capture and $L_{F=M}$ a theoretical MSY reference length assuming $M/k = 1.5$ and $F = M$ based on Beverton and Holt (1957) and proposed by Jardim *et al.* (2015); and

$$b = \min\left\{1, \frac{I_{y-n_0}}{I_{\text{trigger}}}\right\}, \quad (5)$$

with $I_{\text{trigger}} = 1.4 I_{\text{loss}}$, where I_{loss} is the lowest observed biomass index value in the historical fishing period. This relationship is an analogy to the rationale for ICES data-rich stocks, where, in the absence of better knowledge, a trigger biomass level (used as the breakpoint of a hockey-stick harvest control rule) can be set relative to a biomass limit reference point, which corresponds to the lowest observed biomass (ICES, 2017a, b).

The final parameter of this flexible *rfb*-rule was the frequency of advice (v), which defines the number of years the catch advice is kept constant before applying the rule again. The default was $v = 2$ years, i.e. biennial advice as is standard for category 3 data-limited stocks within ICES (ICES, 2012, 2018a).

Errors were assumed to be log-normal, and observation uncertainty was applied on top of the age-aggregated biomass and length indices with $SD = 0.2$. Variability was implemented for recruitment, assuming a Beverton–Holt stock-recruitment model with $\sigma_R = 0.6$. The generation of the operating models and the formulation and quantification of uncertainty were explored in detail previously, and considered appropriate (supplementary material of Fischer *et al.*, 2020).

Recruitment variability and random observation errors were compiled prior to running the MSE and were identical for all stocks and runs; therefore, the results of a projection with a specific catch rule parameterization were fully reproducible and comparable.

Summary statistics

Five summary statistics were selected to evaluate the performance of the *rfb*-rule, which were computed over the entire 50-year projection period and all 500 simulation replicates. These were the medians of SSB/B_{MSY}, F/F_{MSY}, Catch/MSY, and ICV (inter-annual catch variability, defined as $|(C_y - C_{y-v})/C_{y-v}|$, where C_y is the catch for the year y and v the frequency of advice, e.g. $v = 2$ for a biennial advice) and the B_{lim} risk [defined as the number of times SSB is below B_{lim} over all years and replicates, expressed as a proportion, with B_{lim} defined as the SSB where recruitment is impaired by 30%; see Fischer *et al.* (2020) for detailed descriptions of these metrics].

Optimization procedure

The *rfb*-rule was optimized by altering its parameters with a genetic algorithm as an optimization procedure. The eight parameters of the *rfb*-rule (n_0, n_1, n_2, e_r, e_f, e_b, v, x) described above were included in the optimization procedure, and a specific set of these eight parameters was seen as one individual in one generation of the algorithm. The population size was set to 100, i.e. in every generation, 100 parameter sets were simulated. The first generation contained *rfb*-rule parameter suggestions, which included (i) the default *rfb*-rule, (ii) the default *rfb*-rule with an annual catch advice (i.e. $v = 1$), (iii) using the most recent data without lags (i.e. $n_0 = 0$), (iv) constant catch, and (v) combinations where one or more of the *rfb*-rule components were turned off (i.e. $e_j = 0$ for one or more components, j), and comprised a total of 35 suggestions (see Supplementary Table S2). The remaining 65 individuals of the first generation were created randomly.

The simulation for each individual included running a full-feedback MSE projection over the 50-year projection period and 500 replicates. Subsequently, the fitness of the 100 individuals was evaluated against a predefined fitness function. The fitness function, ϕ, summarizes the output of one MSE projection and assigns a numerical value to its fitness. The summary statistics defined above were used as the basis for the fitness function definition. The *rfb*-rule investigated here is designed to provide management in compliance with MSY. Therefore, the deviation of SSB, , and catch from their MSY reference point can be used:

$$\phi_{\text{SSB}} = -\left|\frac{\text{SSB}}{B_{\text{MSY}}} - 1\right|, \quad (6)$$

$$\phi_F = -\left|\frac{F}{F_{\text{MSY}}} - 1\right| \text{ and} \quad (7)$$

$$\phi_{\text{Catch}} = -\left|\frac{\text{Catch}}{\text{MSY}} - 1\right|. \quad (8)$$

Absolute values are used here because both an under and overshooting of the MSY reference points is considered unfavourable. The remaining two summary statistics can be used similarly because both risk and ICV should be reduced:

$$\phi_{\text{risk}} = -B_{\text{lim}} \text{ risk, and} \quad (9)$$

$$\phi_{\text{ICV}} = -\text{ICV}. \quad (10)$$

SSB/B_{MSY}, F/F_{MSY}, Catch/MSY, and ICV in Equations (6), (7), (8), and (10) are, as defined above, the medians over the 50 years and 500 replicates per simulation, i.e. one value per simulation. B_{lim} risk in Equation (9) is a single value per simulation.

The genetic algorithm worked by evaluating the fitness function, and the optimization procedure progressed by maximizing the value of this fitness function. In this case, the summary statistics used in the fitness function indicated better performance when their absolute values were smaller, i.e. a smaller deviation from their target. To account for this, their absolute values were made negative so that the maximization deployed in the optimization procedure aimed at increasing values for the fitness evaluations.

The final fitness function could then be any one of the Equations (6–10) or the sum of an arbitrary combination thereof. Several fitness functions were explored, and the default fitness function used was:

$$\phi_{SSB+Catch+risk+ICV} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk}} + \phi_{\text{ICV}}. \quad (11)$$

After running the 100 MSE projections (each one corresponding to an individual) in one generation of the genetic algorithm and calculating the fitness of each individual, natural selection was applied to generate the reproductive population (Figure 1). The probability of selecting an individual was proportional to its fitness. In the creation of the next generation, natural variability was applied to the parameters. Individuals were randomly grouped into reproductive pairs. In these pairs, crossover occurred with a probability of $p = 0.8$ and meant that an offspring individual with eight parameters was generated as a combination of the parameters of two parent individuals. Mutation introduced random changes to the parameters by drawing from a uniform distribution and had a probability of $p = 0.1$. Elitism was set to 5%, i.e. within each generation, the individuals were ranked by fitness and the top 5% were passed into the next generation without changes. This process was repeated over many generations. A termination occurred if either (i) a maximum of 100 generations was reached or (ii) due to stationarity if no improvement in the fitness was observed within 10 consecutive generations. The genetic algorithm was run with the R package GA (Scrucca, 2013).

Current ICES management

The generic advice rule for category 3 data-limited stocks, as currently applied by ICES (2012, 2019a), was simulated. This served as a benchmark against which the new *rfb*-rule (and its optimized parameterizations) could be compared, and also offered insights into the performance of the current rule. The catch advice is biennial and based on the "2 over 3" rule (see Fischer *et al.*, 2020), which is essentially Equation (2) where C_{y-1} is set to the previously advised catch A_{y-1}, r is the default of Equation (3) with $n_0 = 1$, $n_1 = 2$, and $n_2 = 3$, the weights are set as follows: $e_r = 1$, $e_f = 0$, $e_b = 0$, the multiplier set to $x = 1$, and a precautionary buffer (b_{PA}) is introduced, i.e.

$$A_{y+1} = A_{y-1} \frac{\sum_{i=y-2}^{y-1} (I_i/2)}{\sum_{i=y-5}^{y-3} (I_i/3)} b_{PA}. \tag{12}$$

In addition to that, an uncertainty cap limits the change in the catch advice to no more than 20%. The precautionary buffer reduces the catch advice if the stock is estimated to be in an unfavourable condition based on a comparison with proxy reference points estimated, e.g. by the surplus production model in continuous time (SPiCT, Pedersen and Berg, 2017) or length-based analyses. In the current ICES system, if such an assessment exists, the results are either used solely for informing on the stock status, or the "2 over 3" rule is applied on the biomass estimates from this assessment. Stock status is evaluated as positive if both $F \leq F_{MSY}$ and $SSB \geq 0.5B_{MSY}$, and negative if either or both conditions are not met (ICES, 2019a). If the status is negative, the catch advice is reduced by 20%; however, once the buffer is applied, it can only be considered again 3 years later. This parameterization of the precautionary buffer is based on an MSE evaluation conducted by (ICES, 2017c) in which various sizes and intervals for the application of the precautionary buffer were tested depending on the stock status evaluated by the SPiCT assessments. This evaluation was conducted for 12 fish stocks and three initial exploitation levels ($0.5F_{MSY}$, F_{MSY}, $2F_{MSY}$), and a total of 36 million SPiCT assessments were run.

In the present study, the stock status evaluation was approximated based on the pooled sensitivity of these SPiCT assessments run by (ICES, 2017c). This yielded a true positive rate of 0.99 (detection of a positive stock status, as defined above, by the model when the true state in the operating model was positive) and a true negative rate of 0.42 (detection of a negative stock status by the model when the true state in the operating model was negative). The stock status approximation was implemented here by extracting the stock status from the operating model and adding uncertainty to this evaluation by drawing from a binomial distribution $B(1, p)$, where p is the success rate (0.99 for positive and 0.42 for negative stock status), independently for each simulation replicate and year. This approach was a simple approximation appropriate for the analyses here; however, it has the caveat that the identification of correct stock status by SPiCT was assumed to be a random process defined by the success rate, irrespective of other possible factors influencing performance. More complex model approximations could be considered in future analyses.

Scenarios

The scenarios explored were:

(1) Fitness function explorations. Pollack (pol, *Pollachius pollachius*) was chosen as a typical example stock (k = 0.19 year^{-1}, a medium value within the range for which the *rfb*-rule performed reasonably;) Fischer *et al.* (2020) to test the influence of different formulations of the fitness function and fishing histories.

(2) Catch advice interval. The impact of the interval for which the catch advice is set was explored for the example pollack stock.

(3) Stock-specific optimization. The genetic algorithm was applied independently to all 29 stocks using the fitness function formulation selected in the first step in order to test the approach for different life-histories.

(4) Stock groups. The stocks were split into three groups using their von Bertalanffy k value (low: $0.08 \leq k \leq 0.19$; medium: $0.20 \leq k \leq 0.32$; high: $0.32 \leq k \leq 1$; unit for k: year^{-1}), based on the results of ICES (2018c) and Fischer *et al.* (2020). Here, the stocks within a group were combined, and identical catch rule parameters applied and projected forward simultaneously. The fitness function was defined as the sum of the fitness values per stock. This scenario was used to explore the behaviour of the optimization procedure when applied to a group of life-histories, e.g. fast-growing compared to long-lived species, and to test whether a generic catch rule parameterization could be applied. [Note: there was an overlap at $k = 0.32$ year^{-1} between the medium and high groups because turbot (tur, *Scopthalmus maximus*) belonged to the group for which the *rfb*-rule worked, whereas it did not work for tub gurnard (gut, *Chelidonichtys lucerna*).]

(5) Current ICES rule. The performance of the *rfb*-rule and its optimized parameterizations were compared to the ICES "2 over 3" advice rule for category 3 data-limited stocks as a direct comparison of the new rule with the currently applied advice rule.

Results

Fitness function explorations

For the fitness function explorations with pollack, the genetic algorithm terminated after 16 to 27 generations (well before the 100-generation cut-off), depending on the fitness function definition and fishing history. The optimized *rfb*-rule parameters depended on the specific fitness function (Table 1). For five of the six runs, the "2 over 3" ratio of the biomass index was kept, whereas the offset between the last biomass index year and the intermediate year was always removed ($n_0 = 0$). In general, the weighting of component r of the *rfb*-rule did not change substantially; however, components f and b were down-weighted, and the advice interval v and the multiplier x remained at or around their

Table 1. Default and optimized catch rule parameters

	Operating model			**Genetic algorithm**			**Catch rule parameters**							
	Fishing history	**Stock**	**k (year^{-1})**	**Fitness function ϕ**	**Generations**	**Fitness improvement (%)**	**n_0**	**n_1**	**n_2**	**e_r**	**e_f**	**e_b**	**v**	**x**
Default parameters														
	One-way						1	2	3	1	1	1	2	1
	Random						1	2	3	1	1	1	2	1
Fitness function explorations														
	One-way	pol	0.19	ϕ_{SSB}	27	100	0	2	3	1.2	0.7	0.8	3	1.06
	One-way	pol	0.19	ϕ_{Catch}	19	100	0	2	3	1.0	0.4	0.4	2	1.00
	One-way	pol	0.19	$\phi_{SSB+risk+ICV}$	16	48	0	2	3	1.0	0.5	0.5	2	1.03
	One-way	pol	0.19	$\phi_{SSB+Catch+risk+ICV}$	18	64	0	2	3	0.9	0.4	0.5	2	1.03
	One-way	pol	0.19	$\phi_{SSB+F+Catch+risk+ICV}$	26	72	0	2	2	1.1	0.4	0.3	2	1.01
	Random	pol	0.19	$\phi_{SSB+Catch+risk+ICV}$	26	57	0	2	3	0.7	0.3	0.4	2	1.02
Stock-specific optimization														
	One-way	ang3	0.08	$\phi_{SSB+Catch+risk+ICV}$	25	70	0	3	3	1.3	0.4	0.7	3	1.06
	One-way	rjc2	0.09	$\phi_{SSB+Catch+risk+ICV}$	23	66	0	3	4	1.2	0.7	0.6	3	1.02
	One-way	smn	0.11	$\phi_{SSB+Catch+risk+ICV}$	21	71	0	2	3	0.8	0.2	0.3	2	1.02
	One-way	wlf	0.11	$\phi_{SSB+Catch+risk+ICV}$	23	83	0	2	3	1.0	0.5	0.3	2	1.07
	One-way	meg	0.12	$\phi_{SSB+Catch+risk+ICV}$	24	89	0	2	3	1.0	0.4	0.7	2	1.24
	One-way	lin	0.14	$\phi_{SSB+Catch+risk+ICV}$	23	60	0	3	3	1.2	0.6	0.5	3	1.01
	One-way	rjc	0.14	$\phi_{SSB+Catch+risk+ICV}$	35	60	0	2	3	1.1	0.6	0.4	2	1.00
	One-way	syc	0.15	$\phi_{SSB+Catch+risk+ICV}$	34	65	0	3	3	0.9	0.3	0.3	2	1.01
	One-way	sdv	0.15	$\phi_{SSB+Catch+risk+ICV}$	14	62	1	2	3	1.0	0.1	0.1	2	0.98
	One-way	ang	0.18	$\phi_{SSB+Catch+risk+ICV}$	19	57	0	2	3	0.9	0.3	0.3	2	0.99
	One-way	ang2	0.18	$\phi_{SSB+Catch+risk+ICV}$	24	57	0	2	3	0.9	0.5	0.6	2	1.02
	One-way	pol	0.19	$\phi_{SSB+Catch+risk+ICV}$	18	64	0	2	3	0.9	0.4	0.5	2	1.03
	One-way	had	0.20	$\phi_{SSB+Catch+risk+ICV}$	35	77	0	2	3	0.9	0.3	0.8	2	1.08
	One-way	nep	0.20	$\phi_{SSB+Catch+risk+ICV}$	11	76	1	2	3	1.0	0.0	0.3	1	1.00
	One-way	mut	0.21	$\phi_{SSB+Catch+risk+ICV}$	20	75	0	2	3	0.8	0.4	0.6	2	1.10
	One-way	sbb	0.22	$\phi_{SSB+Catch+risk+ICV}$	21	59	0	2	2	0.9	0.5	0.7	2	1.06
	One-way	ple	0.23	$\phi_{SSB+Catch+risk+ICV}$	28	75	0	2	2	0.9	0.4	0.4	2	1.07
	One-way	syc2	0.23	$\phi_{SSB+Catch+risk+ICV}$	30	68	1	2	3	1.0	0.2	0.2	2	1.01
	One-way	arg	0.23	$\phi_{SSB+Catch+risk+ICV}$	14	64	0	2	3	0.9	0.2	0.2	2	1.00
	One-way	tur	0.32	$\phi_{SSB+Catch+risk+ICV}$	32	75	0	2	2	0.9	0.4	0.4	2	1.09
	One-way	gut	0.32	$\phi_{SSB+Catch+risk+ICV}$	22	51	0	2	2	0.8	0.3	0.6	2	1.02
	One-way	whg	0.38	$\phi_{SSB+Catch+risk+ICV}$	27	58	0	2	3	0.6	0.6	0.7	2	1.00
	One-way	bll	0.38	$\phi_{SSB+Catch+risk+ICV}$	28	52	0	2	3	0.7	0.4	0.9	3	1.00
	One-way	lem	0.42	$\phi_{SSB+Catch+risk+ICV}$	28	50	0	3	3	0.6	0.3	0.8	3	1.03
	One-way	ane	0.44	$\phi_{SSB+Catch+risk+ICV}$	14	42	0	2	3	0.8	0.8	0.7	2	1.01
	One-way	jnd	0.47	$\phi_{SSB+Catch+risk+ICV}$	25	55	0	3	3	0.3	0.4	1.4	3	0.94
	One-way	sar	0.60	$\phi_{SSB+Catch+risk+ICV}$	25	48	0	2	3	0.6	0.8	1.3	3	0.96
	One-way	her	0.61	$\phi_{SSB+Catch+risk+ICV}$	24	51	0	2	3	0.4	0.5	1.1	2	0.96
	One-way	san	1.00	$\phi_{SSB+Catch+risk+ICV}$	25	45	0	2	2	0.3	0.5	1.1	2	1.00
Stock groups optimization														
	One-way	Low-k	0.08–0.19	$\phi_{SSB+Catch+risk+ICV}$	15	68	1	2	3	1.0	0.0	0.2	2	1.00
	One-way	Medium-k	0.20–0.32	$\phi_{SSB+Catch+risk+ICV}$	19	67	0	2	3	0.8	0.2	0.8	2	1.07
	One-way	High-k	0.32–1.00	$\phi_{SSB+Catch+risk+ICV}$	34	28	0	3	3	0.6	0.4	1.0	3	1.00

Shown are the results for the fitness function explorations with the pollack stock, the stock-specific optimization for all 29 stocks, and the optimization where stocks are split into three groups based on k. See Equations (2) and (3) for definitions of the parameters.

default values. In the one-way fishing history, the median of the SSB increased after the implementation of the default *rfb*-rule from its depleted state, but overshot B_{MSY}, peaked at just below $2B_{MSY}$, and then equilibrated at around $1.5B_{MSY}$ at the end of the 50-year projection period (Figure 3a). All tested fitness functions resulted in median SSB trajectories without the initial SSB peak and terminated closer to B_{MSY}. Despite exhibiting similar SSB trajectories, trade-offs between the summary statistics were evident (Figure 3c). The fitness functions with only a single component (ϕ_{Catch}, ϕ_{SSB}) led to parameter combinations which resulted in values of the corresponding summary statistic being close to their targets; however, the remaining summary statistics did not always improve for ϕ_{SSB} (although it did for ϕ_{Catch}). Adding additional components to the fitness function alleviated this and

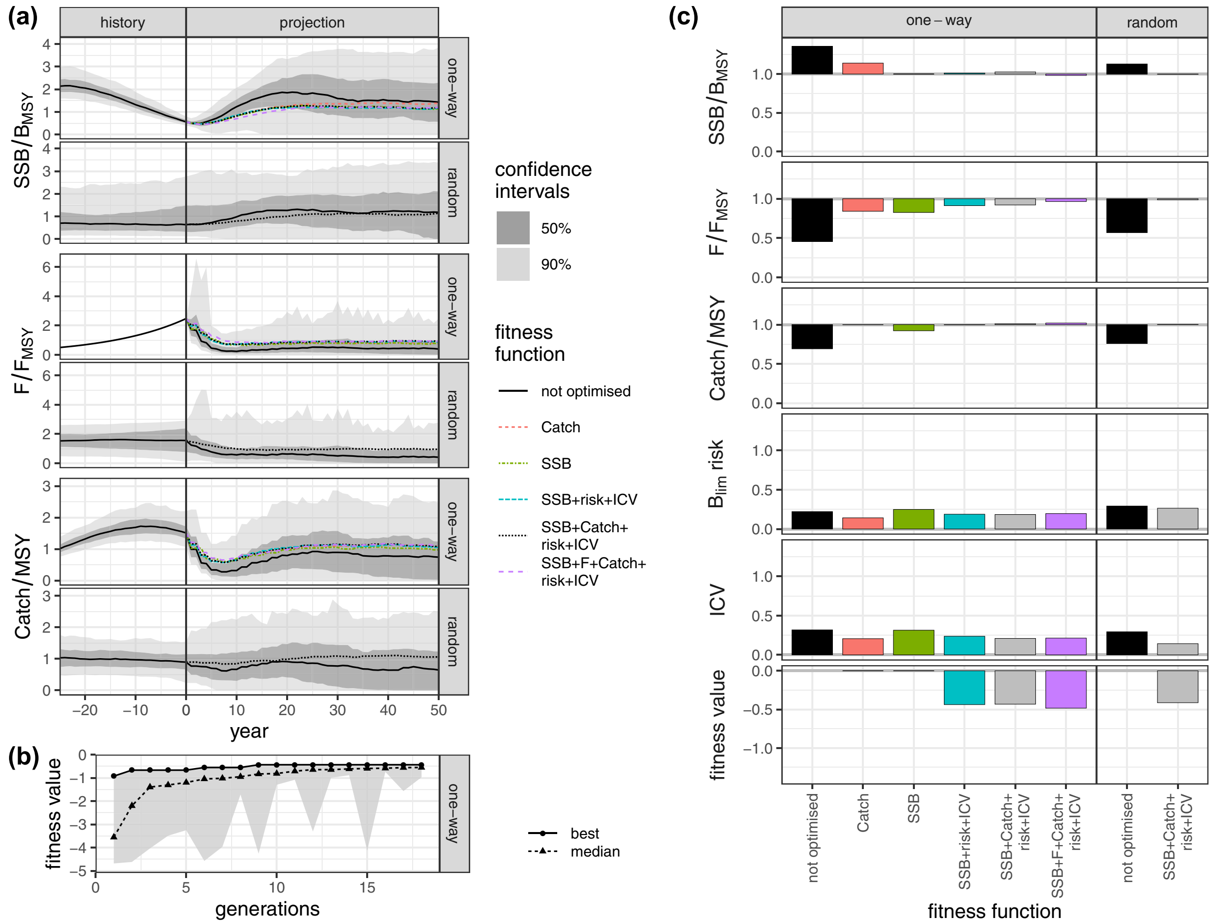

Figure 3. Results of the exploration of fitness functions for pollack. (a) The trajectories of the default *rfb*-rule (labelled "not optimized", including confidence intervals) and median trajectories for the optimized *rfb*-rule of several fitness functions are shown. Presented are the historical fishing period ("history") and the subsequent application of the *rfb*-rule ("projection"), for the "one-way" and the "random" fishing history. (b) The progress of the search procedure of the genetic algorithm for the $\phi_{\mathrm{SSB+Catch+risk+ICV}}$ fitness function is visualized. The shaded area indicates the total range of observed fitness values. (c) The summary statistics for the default *rfb*-rule parameterization in comparison with the optimized solutions, both for the one-way and random fishing history are shown. The height of the bars indicates the deviation (up or down) from the target of the optimization (MSY reference points for SSB, *F*, and catch; 0 for B_{lim} risk and ICV). No fitness value is shown for the non-optimized rule.

improved the respective summary statistics. The progress of the optimization process with a genetic algorithm is visualized in Figure 3b for the one-way fishing history with the fitness function including SSB, catch, risk, and ICV. The best fitness values in each generation (with a population size of 100) converged quickly, and the algorithm terminated after 18 generations due to stationarity, because no further improvement within 10 consecutive generations was made.

For the alternative historical fishing history (random), only the $\phi_{\mathrm{SSB+Catch+risk+ICV}}$ fitness function was explored, and improved the performance of the *rfb*-rule, as seen for the stock trajectories and all summary statistics (Figure 3a and c). The SSB, and catch moved closer to the MSY reference points and reached this state earlier, and risk and ICV were reduced. This fitness formulation ($\phi_{\mathrm{SSB+Catch+risk+ICV}}$) was selected for further analysis because it offered a balance between achieving MSY (for both SSB and catch), reducing risk and minimizing inter-annual variations in the catch. Ideally, a decision on which components to include in the fitness formulation would be closely aligned to management objectives.

Catch advice interval

The impact of the frequency of setting the catch advice was explored for pollack in the one-way fishing history by fixing the interval and then optimizing the *rfb*-rule for the remaining parameters with the genetic algorithm and using $\phi_{\mathrm{SSB+Catch+risk+ICV}}$. The maximum fitness was obtained with a biennial catch advice. When setting an annual or triennial catch advice, the fitness deteriorated by 20 and 12%, respectively when compared to biennial catch advice (results not shown).

Stock-specific optimization

The stock-specific optimization of the *rfb*-rule led to stock-specific catch rule parameters and substantially improved fitness of the rule for all stocks (Table 1). The components of the fitness function are summarized in Figure 4a. For the low- to medium-*k* stocks ($k \leq 0.32\,\mathrm{year}^{-1}$), SSB, *F*, and catch summary statistics were moved close to their MSY reference points. This meant a reduction in SSB for many stocks compared to the default *rfb*-rule, which is reflected in a slight increase in risk and decrease in catch

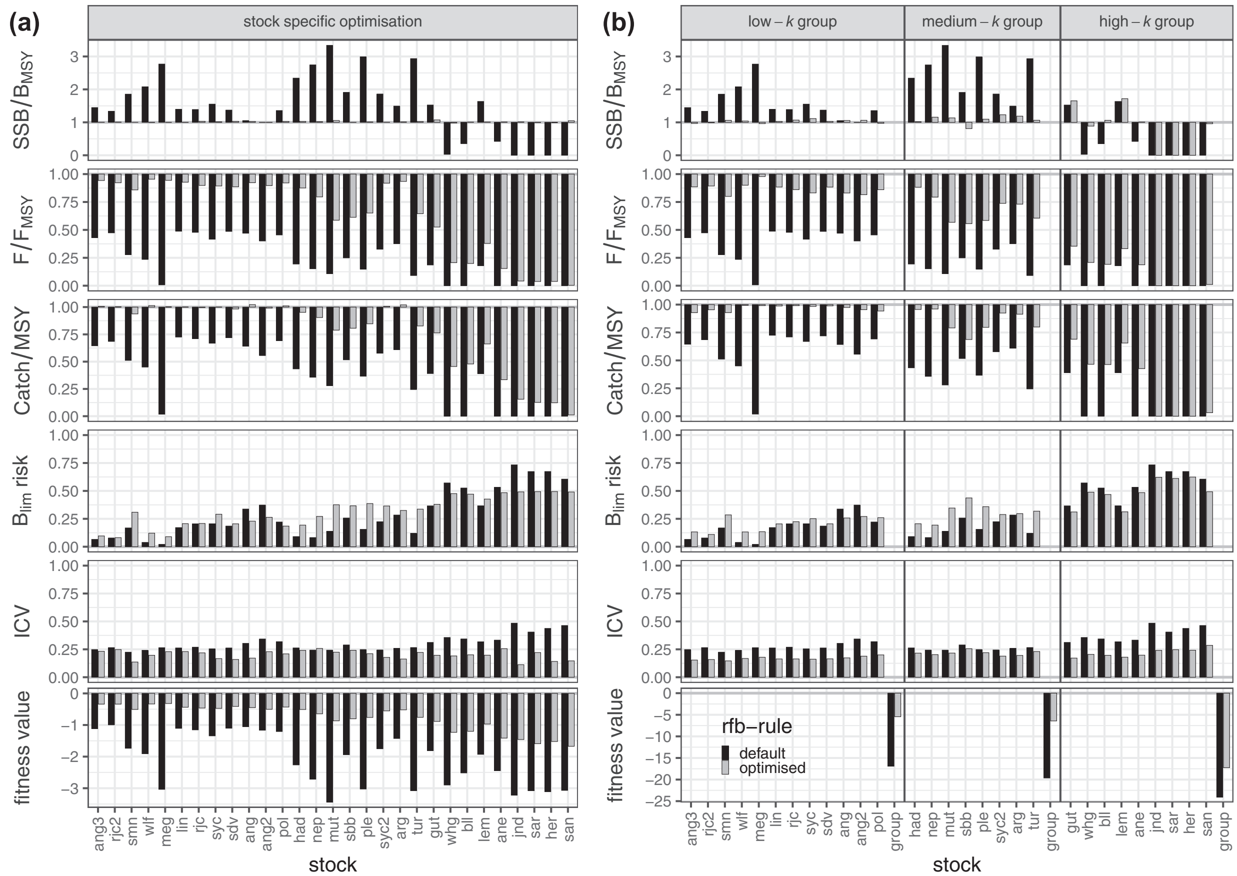

Figure 4. Summary statistics for all 29 stocks of the MSE, for the default and optimized *rfb*-rule parameterization, and the one-way fishing history. The fitness function corresponds to "SSB+Catch+risk+ICV" in Figure 3. The stocks are sorted by the von Bertalanffy growth parameter k in ascending order from left to right. (a) shows the results of stock-specific optimizations in which the genetic algorithm was run independently for all stocks and in (b) the optimization was conducted for three stock groups based on k. For the groups in (b), only one fitness value exists per group, which is the sum of the values for the stocks in the group. The stock abbreviations are defined in Supplementary Table S1.

variability. For most high-k stocks ($k \geq 0.32\,\text{year}^{-1}$), some improvement of the performance was achieved; however, the catch was still low and fitness value improvements were less pronounced than for stocks with lower k.

Stock groups

The optimization for the stock groups based on k (low, $0.08 \leq k \leq 0.19$; medium, $0.20 \leq k \leq 0.32$; high, $0.32 \leq k \leq 1$; unit for k: year^{-1}) was able to improve the performance of the *rfb*-rule compared to its default parameterization (Table 1, Figure 4b). When the fitness values from the stock-specific optimization are summed up by stock group and compared to the fitness of the stock group optimization, then the total improvement was always better for the stock-specific optimization. The overall improvement for the low and medium-k groups was close to the stock-specific optimization. For the high-k group, the improvement was less pronounced and the *rfb*-rule showed poor performance.

Current ICES rule

The current ICES "2 over 3" advice rule for category 3 stocks (with uncertainty cap and precautionary buffer) was compared to the *rfb*-rule (Figure 5). The performance of the "2 over 3" rule was dependent on the stock and fishing history. At first glance, the performance of the "2 over 3" rule appeared better compared to the default *rfb*-rule when considering fitness, except for some high-k stocks. However, the optimized *rfb*-rule consistently performed better than both of them throughout. In the one-way fishing history, the "2 over 3" rule resulted in SSB values at or below B_{MSY}, with low SSBs for some medium k stocks, and generally high B_{lim} risks.

The performance of the default *rfb*-rule by stock was similar for SSB, F, catch, and ICV when comparing fishing histories (one-way vs. random). In contrast, the performance of the "2 over 3" rule was highly influenced by the fishing history prior to its implementation, with low SSB values for some of the medium-k stocks, and generally high levels of B_{lim} risk under the one-way fishing history.

For better comparability, the uncertainty cap of the "2 over 3" rule (limiting catch advice variability to no more than 20%) was added to the default parameterization of the *rfb*-rule (see Supplementary Figure S1). For most stocks, this moved the performance of the *rfb*-rule closer to the "2 over 3" rule. Some stocks exhibited an increased B_{lim} risk, whereas the risk was reduced for others.

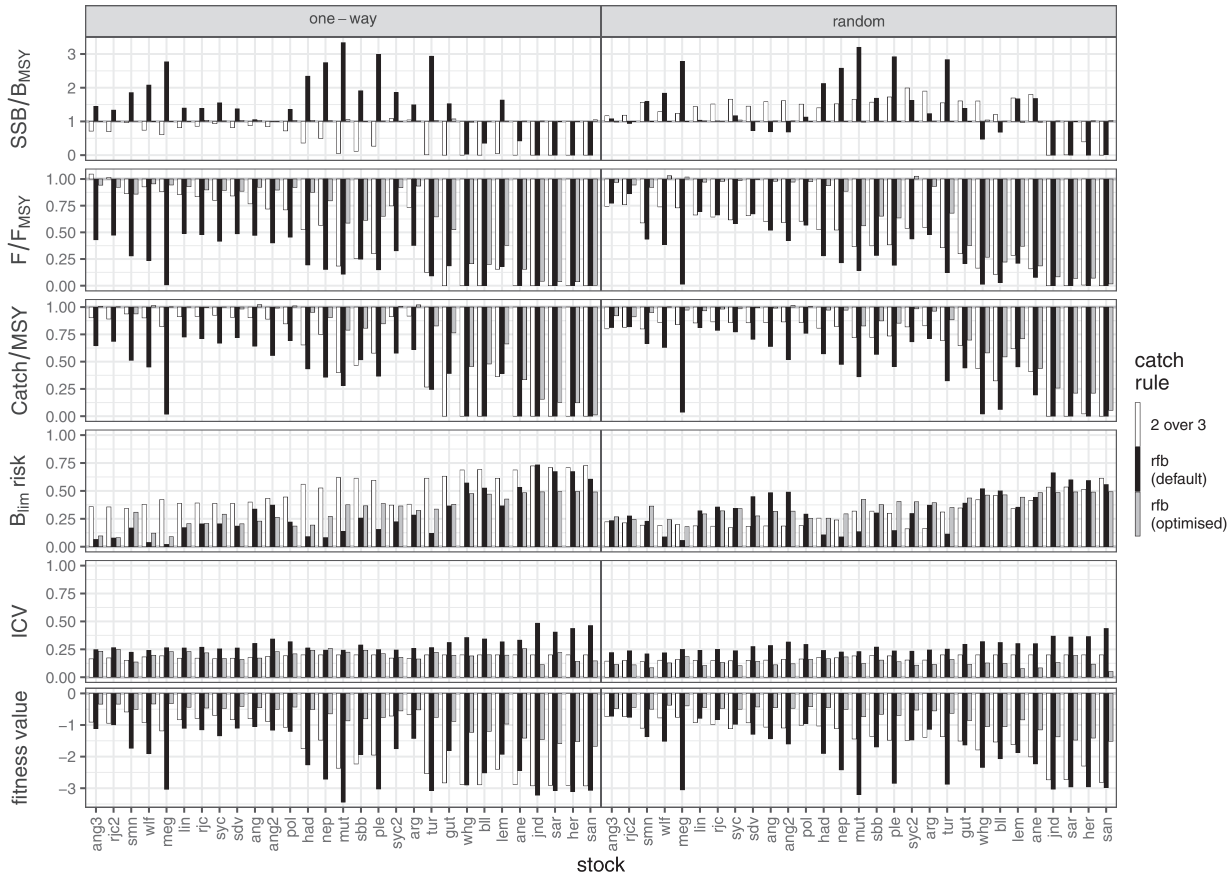

Figure 5. Comparison of the summary statistics of the current ICES management procedure and the default and optimized *rfb*-rule for two fishing histories. The fitness function corresponds to "SSB+Catch+risk+ICV" in Figure 3. The stocks are sorted by the von Bertalanffy growth parameter *k* in ascending order from left to right.

Discussion

The main aim of this study was to explore the application of a genetic algorithm to the optimization of the performance of a data-limited catch rule (the *rfb*-rule). The results presented provide evidence that the *rfb*-rule performance can be substantially improved. The improvement was dependent on the simulated stock (i.e. defined by life-history) and the definition of the fitness function.

The optimization of the *rfb*-rule was performed for 29 stocks, which were generated based on life-history parameters and relationships to develop age-structured operating models, and provides a theoretical basis for developing hypotheses about population dynamics. The reason for this approach was that these stocks are considered data-limited, and therefore analytical stock assessments do not exist. Fischer *et al.* (2020) conducted extensive sensitivity analyses on the assumptions and parameterizations of the operating models such as steepness, recruitment variability, and observation uncertainty. Even though the operating models are based on real stock units, they might not necessarily exactly represent the stocks (e.g. fishing histories were simulated to represent certain conditions); nevertheless, they cover a wide range of life-histories. The purpose of this study was, therefore, only to a lesser extent to provide stock-specific tuning parameters for the *rfb*-rule. If stock-specific tuning of the rule is required, it is recommended that additional data be gathered to fine-tune the operating models and apply the optimization procedure set out here.

For most stocks, the optimized *rfb*-rule parameterization included a biennial catch advice interval. Therefore, not unexpectedly, when this interval was fixed to a different value in the optimization procedure for pollack, the performance of the rule deteriorated. This result is an indication that updating the advice more frequently does not necessarily result in better management, particularly when ICV is considered an important component of the fitness function. ICES usually provides biennial catch advice for category 3 data-limited stocks, which reduces the operational effort for conducting stock assessments for the many data-limited stocks compared to an annual cycle. Nevertheless, for most stocks, the usual 1-year time lag for the survey data was removed in the optimized *rfb*-rule parameterization. Essentially, this means that data up to the intermediate year are used to provide the catch advice for the following advice year. This situation is feasible in an ICES setting where, for many stocks, scientific catch recommendations for the advice year are released in the middle of the intermediate year. Consequently, survey data from the beginning of the intermediate year are available and can be included in the analyses. In the present simulations, surveys were timed to occur at the start of the year.

Previous work by Fischer *et al.* (2020) revealed that the *rfb*-rule performs poorly for stocks with higher von Bertalanffy growth parameter k values ($k \geq 0.32\,\text{year}^{-1}$). Despite making the *rfb*-rule much more flexible by allowing the reduction of the time lag and introducing weighting of the catch rule components, the rule still did not perform markedly better for these stocks, and caused low yields and a high risk of dropping below biomass reference points. For the remaining low- to medium-k stocks ($k \leq 0.32\,\text{year}^{-1}$), the performance improvements through the genetic algorithm were substantial, both for stock-specific as well as the broader k-group optimization. Therefore, we must consider that, for higher-k stocks, the *rfb*-rule cannot provide reliable management options which are compliant with precautionary and MSY principles, and alternatives need to be found.

Higher-k stocks are inherently more dynamic, i.e. exhibit more inter-annual variability and have high population growth rates. Therefore, they respond more quickly to changes in fishing behaviour, environmental forcing, and errors in the feedback control rule. Alternative management procedures, such as simple constant harvest rate-based rules using an index of relative abundance (e.g. an acoustic survey), might provide better management without the need to enforce MSY reference levels. In addition, the *f*-component of the *rfb*-rule based on mean catch length and an F_{MSY} proxy may not be optimal for these species, and alternative length-based indicators that track incoming year-classes and identify future abundance may potentially perform better. Lessons can also be learned from the management of fisheries targeting fast-growing and pelagic stocks in other parts of the world, such as for Pacific sardine (PFMC, 2019) or the South African pelagic fishery (Cochrane *et al.*, 1998; De Oliveira and Butterworth, 2004).

The first step in addressing the optimization of procedures for managing marine living resources, like any other optimization problem, requires the specification of management objectives. Different stakeholders may have vastly different preferences for utility functions (Fishburn and Kochenberger, 1979), and fisheries management, like many other real-world problems, must consider multiple objectives due to the potentially conflicting interests of different asset and stakeholder groups (Rindorf *et al.*, 2017), e.g. fishers, policymakers, environmentalists, wholesalers, retailers, consumers, and scientists. In an ideal set-up of an MSE exercise, all stakeholders are involved from the beginning and have their say in the selection of management objectives as well as inevitable trade-offs. In reality, it can be challenging to receive any interaction from stakeholders; for example, even though methods workshops in ICES are open to the public, feedback about management objectives sometimes has to be explicitly requested, or such management objectives assumed by analysts (ICES, 2020).

Alternative tuning algorithms to the optimization deployed here exist (e.g. Givens *et al.*, 1999). Optimization towards achieving some minimum performance (e.g. conservation considerations) is possible but is likely to reduce the overall performance by forfeiting yield. The implications of including specific risk thresholds are a subject of future work.

Several fitness functions were explored and resulted in different catch rule parameters and performance metrics. When only a single component, e.g. SSB, was included, the SSB metric reached levels very close to its optimum (B_{MSY}); however, other important metrics such as B_{lim} risk and ICV were neglected. The fitness function selected here can be considered partially arbitrary, although based on careful consideration by the authors; it appears to balance the objective of achieving MSY (for both SSB and catch) while reducing risk and minimizing inter-annual catch variability. The weighting of the fitness function elements can be a point of discussion, and specific stakeholders might favour alternative parameterizations. Furthermore, equal weighting was applied to the deviation of performance metrics from their MSY level (up or down). In terms of SSB, dropping below B_{MSY} should be reduced when considering conservation, whereas the opposite is less critical. Nevertheless, the fitness function included B_{lim} risk, and therefore, low stock levels triggered a different response in the optimization.

Any improvement can only be as good as the definition of the fitness function, and the optimization is purely based on evaluating this fitness function, ignoring any other feature. Therefore, fitness functions must be carefully designed, and it should be recognized that there might not be a single fitness function covering all aspects. The type of fitness function used in this study could be tailored for stock-specific case studies, as it included all metrics important for the objective of a specific management system to account for trade-offs. The development of case-specific control rules is an improvement over the current approach of one rule for all.

Uncertainty in the stock dynamics could also have been explored, because these are data-limited stocks, and there is uncertainty in processes such a growth, maturity, natural mortality, and recruitment dynamics. This can be done by developing multiple operating models for each stock and then averaging the fitness function over these. In the present study, we explored the application of the optimization approach with operating models from Fischer *et al.* (2020) and, for simplicity, did not include additional uncertainty considerations. Nevertheless, future case-specific evaluations could include this. Another important concept that could be explored is the monetization of the outcome of applying a specific management procedure, e.g. by quantifying the monetary value of exploiting a fish stock with the price of premiums for an insurance against economic risks of the fishery (Mumford *et al.*, 2009). Such an evaluation would allow the comparison of the application of new catch rules compared to traditional management rules, or even the benefit of optimizing management procedures, and should be considered in future studies.

The types of simulations, as run here with the genetic algorithm included in a full-feedback MSE framework, are highly computationally demanding. The simulations, in particular for the runs combining several stocks, had CPU runtimes of up to several thousand hours. Therefore, it is implausible to attempt to run these simulations on personal computers, and instead a high-erformance computing (HPC) cluster with massive parallelization techniques was utilized. The computations were spread simultaneously over numerous computing nodes and hundreds of CPU cores to reduce the runtime to mere hours. Specifically, a hybrid parallelization approach was adopted where the individual projections of the MSE (catch rule parameterizations) were parallelized by executing them on different computing nodes with the message passing interface (MPI; Walker, 1992), and the MSE projections themselves were parallelized within computing nodes.

For the purpose of this study, the MSE simulations were based on FLR's standardized MSE framework (Jardim *et al.*, 2017) and this was linked to a genetic algorithm optimization approach, adapted for massive parallelization. The outcomes presented here provide evidence that it is possible to link the two and that management procedures can be improved successfully with this approach. The FLR MSE framework has recently been gaining popularity for conducting MSEs within the ICES community, and has, for example, been used to evaluate long-term management plans of North Sea gadoid stocks (cod, haddock, whiting, and saithe, ICES, 2019c) based on an EU-Norway request to ICES. This evaluation included running an MSE for data-rich stocks and a fully analytical stock assessment (SAM, Nielsen and Berg, 2014) in the feedback loop, which caused substantial computational complexity. In order to optimize a management procedure (maximize yield while maintaining precautionary risk considerations), an exhaustive grid search with manual interventions was conducted over two harvest control rule parameters (F_{target} and B_{trigger}). With a framework which includes machine intelligence for the optimization, like the one developed for the data-limited *rfb*-rule here, the computational effort could likely be greatly reduced, thereby reducing computational expenses and also shortening the runtime required for obtaining results. Therefore, the optimization procedure explored here in a data-limited context could also be applied to data-rich situations.

The application of a genetic algorithm as an optimization procedure piloted here was specific to an empirical management procedure considered by ICES. Nevertheless, the use of this approach is not limited to ICES or Europe and can be applied in any management system. The optimization is aimed at satisfying concrete management objectives, formalized in a fitness function. Therefore, any management objective (be it for data-rich, data-limited, or data-poor situations) can be included, as long as it is possible to characterize the objectives mathematically.

The settings for the genetic algorithm (maximum number of generations, convergence criteria, population size, mutation, and crossover probabilities, etc.) might be, at least partially, considered arbitrary, and were a compromise between reducing computational complexity (computing time, memory demand, etc.) and at the same time providing a reliable optimization. The optimization process is entirely reproducible, but it is based on a stochastic process and therefore dependent on random numbers. The set-up of the search itself can be considered an optimization problem (hyperparameter optimization). Due to the nature of the optimization procedure, it cannot be guaranteed that the optimized solution is indeed the global optimum of the multi-dimensional parameter space (Holland, 1992). Nonetheless, the solutions presented here are a substantial improvement to the base case (the default catch rule parameters) and can be quantified with the fitness values and its components. An optimization with a genetic algorithm has the benefit that the progress can be observed directly, and the path leading to the final solution can be traced back. Other machine learning methods, such as neural networks, might also be used; however, they might be regarded as black boxes which provide results, but it is not always possible to describe them in a way humans can understand.

Finally, the performance of the *rfb*-rule analysed in this study was compared to the current ICES advice rule for category 3 data-limited fish stocks (i.e. the "2 over 3" rule with an uncertainty cap and a precautionary buffer; ICES, 2012, 2019a). At first glance, the performance of the "2 over 3" rule might appear better than the default *rfb*-rule, particularly when considering the random fishing history. However, the behaviour of the rule is highly influenced by the stock and its status prior to the implementation, as shown previously (Jardim *et al.*, 2015; ICES, 2017c; Fischer *et al.*, 2020) and again here for the two fishing histories. The "2 over 3" rule is aimed at maintaining a status quo and does not include any target. Therefore, we recommend phasing out its use within ICES and propose the *rfb*-rule tested in this study as an improved successor. The reasoning in favour of the new catch rule is that (i) it includes an MSY based target in addition to the index trend, (ii) it underwent extensive MSE testing prior to its implementation, (iii) it yields more stable outcomes irrespective of the stock status, and (iv) its flexibility allows case-specific optimization. Nonetheless, we cannot recommend the *rfb*-rule for higher-k stocks due to its poor performance, even when optimized. For such stocks, alternative management procedures, such as constant harvest rates, should be investigated.

Data availability

Input data, software code, and summarized results as presented in this study are available from GitHub at https://git.io/JkllU.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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