Chapter 11
Personalized Portfolio Optimization Using Genetic (AI) Algorithms

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1 Introduction to Robo-Advisory and Algorithm-Based Asset Management for the General Public

The takeover of the financial advisory service using robots (so-called "robo-advisors") in the classic field of wealth management, asset management and personalized investments started as a new emerging trend after the 2008 global financial crisis. New and tighter regulations on banks and insurance companies led technology-based financial companies (i.e. "fintechs") to offer "robo-advisory" services. The first robo-advisors were still considered to be real exotics. However, this situation changed significantly around 2015. This was quickly recognized as a "booming" market, also driven by the impressive development of the US market for robo-advisor offerings. Typical of the first generation of online asset managers was the exclusive use of the so-called passive investment strategies and products. The main selling proposition of robo-offerings lies in their low overall cost level, which was combined with a fast and seamless digital sales and on-boarding process. The development of this selling proposition was propelled by the use of low-cost ETFs. The use of AI and mathematical algorithms was not a top priority at that time. Rather, the "robo-advisory" consisted of digital on-boarding and risk profiling processes, which enabled the classification of customers and their mapping to appropriate risk levels. Users were typically divided in up to ten risk levels, and one out of ten standard portfolios appropriate to the customer's personal risk level was selected. All these new "robo-advisors" offered an easy entry point for new customers for their investing. Secondly, the offer represented an innovative opportunity for banks to address new consumer segments.

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Robo-advisors served as a starting point for shifting financial advisory processes to digital channels. According to the Boston Consulting Group [1], which surveyed 42,000 adults in 16 countries, customers worldwide are becoming increasingly digital. As of 2017, only 15% called for exclusively face-to-face advice, while hybrid advice offers and purely digital offers were preferred by approximately 42% of the customers. Two years earlier, in 2015, approximately 37% of the customers still preferred face-to-face (F2F) advice, and only 25% preferred digital offers and channels.

The COVID-19 pandemic has accelerated the adoption of digital channels across industries. According to a McKinsey survey [2], industries across various regions experienced an average of 20% growth in "fully digital" between November 2020 and April 2021, building on previous gains earlier in the pandemic. Still, some 44% of digital consumers say that they don't fully trust digital services. The ways companies can build and establish trustworthy relationships with consumers differ by industry. Consumer trust in banking is overall the highest among all industries. This rapidly advancing digitization asks for the employment of new methods and processes to meet the needs of new customer groups. The latter include, above all, personalized solutions that respond to individual needs and provide customers with tailored offers at the push of a button.

In recent years, virtual assistants and robo-advisory supported the advisory process. Specifically, artificial intelligence, supported by genetic algorithms, results in a paradigm shift that is significantly advancing the client relationship processes of the financial services industry. Processes that were previously considered impossible to digitize, such as the generation of portfolio proposals, can now be automated and digitized.

Likewise, personal interaction is digitally supported. Personal interaction between (bank) customers and their advisors can also be digitally supported, e.g. by online advisory solutions. In a (digital) advisory meeting, digital solutions make it possible to combine the competencies and skills of the human advisors with the bank's research and business intelligence in real time for the benefit of the retail customer. Digital tools and processes are increasingly becoming an integral part of hybrid sale processes and are proven as particularly valuable in supporting advisors. Digitization does only simplify and improve the customer experience. It also enables financial institutions to improve and optimize the quality of their customer advisory offerings. At the same time, it enables advisors to offer highly personalized products and services, i.e. optimized and personalized portfolios.

The remainder of this chapter is structured as follows: Section 2 following this introductory section describes traditional portfolio optimization methods along with their limitations. Section 3 introduces genetic algorithms and their merits for portfolio optimization. It also presents our novel, flexible approach to portfolio optimization, which leverages genetic algorithms, along with relevant validation results. Section 4 summarizes and papers and draws main conclusions.

2 Traditional Portfolio Optimization Methods

The primary goal in creating optimized investment portfolios is to generate robust and well-diversified portfolios. In contrast to genetic algorithms, traditional methods are one-step optimization models. The proposed portfolio is the direct result of the calculation process based mainly on the historical price data of the considered assets or asset classes. Similarly, the objective function is one-dimensional with potential parameters the maximum volatility, Sharpe ratio targets or a predefined minimum return that meets certain investment risk and performance parameters. The following two subsections present the two most common concepts that have been employed for several years to perform portfolio optimization

2.1 The Modern Portfolio Theory

The most prominent traditional method is the modern portfolio theory (MPT) which was published by Harry Markowitz in 1952 and for which he has received the Nobel Prize for economics in 1990. The goal of MPT is to create a diversified portfolio consisting of a variety of assets to be prepared for future uncertainties. The risk/return ratio of a broadly diversified portfolio is superior to any investment in just one single asset – no matter how well chosen. The MPT is a one-step method that simply maximizes the portfolio return subject to a given risk constraint. Portfolios compiled with the modern portfolio theory have some limitations. The major one is the high sensitivity to the given input data and the lack of not being able to handle multiple input factors.

A major issue of MPT is the estimation of the input parameters' "expected returns" and "variances" which are required for the calculation of optimal portfolios. The assumption of the future values of these parameters is based on data from the past, which are used for predictions of future developments. Consequently, in the MPT, effective values deviate from the estimated values, which leads to misallocation and thus to only optimal portfolios in theory, but not in reality. Many studies have shown that the application of the MPT leads to serious problems in practical usage. Especially the estimation/forecasting errors in the determination of the expected return have a large impact on the portfolio structure. The implications of an estimation error in determining the correlation are rather small.

Portfolios generated based on the Markowitz theory are mathematically correct but deliver no feasible results in practice. The method generally overweighs assets with high estimated returns, negative correlations and small variances. Experience shows that portfolios often generate higher losses than expected because the MPT does not cover extreme risk scenarios which happen more frequently than expected. It also systematically underestimates the risk of loss and overestimates the opportunity for gain. Furthermore, it fails to protect against risk stemming from diversification, especially in times of turbulent markets. The assumption of a normal

distribution of returns does not correspond to reality. Extreme price movements occur much more frequently than the normal distribution suggests. Therefore, the risks of loss tend to be systematically underestimated, and profit opportunities are rather overestimated as in reality volatility and correlations strongly deviate from theoretical assumptions. Thus, despite its scientific foundation, the MPT is not very widely used in practical operations within financial services, and its acceptance within asset management is rather limited.

2.2   Value at Risk (VaR)

As stated above, one of the main parameters required to generate optimized portfolios that need to be quantified is portfolio risk. In the 1990s, value at risk (VaR) was established among banks and asset managers to measure the risk of trading portfolios. VaR has been widely implemented in the regulatory frameworks of the financial sector and is used to quantify requirements, within the internal risk management of banks, for ongoing back-testing and for stress-testing. VaR is a key risk measure for determining the highest expected loss. It is defined as the highest expected loss of a security that will not be exceeded with a predefined probability within a fixed period of time. Today, VaR is a standard risk measure in the financial sector.

For the calculation of the potential loss and to determine the VaR, the following three parameters are required: the holding period of the positions in days, weeks or months; the reference period – for example, 1 year; and the so-called confidence level in per cent, which is referred to as confidence probability. The VaR is usually recalculated daily by financial institutions. VaR has established itself as a valuable tool for risk managers. In portfolio management, however, the method is highly controversial. The value-at-risk concept assumes that events in the future will behave as events have behaved in the past. This assumption is especially wrong if a crisis phase arises after a longer period without severe market turbulences. To put it bluntly, VaR can also be interpreted as a fair weather risk measure. The highest possible loss of a portfolio is ignored. VaR is therefore not "black swan proof". Rare events that strike cruelly break the back of VaR.

3   Portfolio Optimization Based on Genetic Algorithms

3.1   The Concept of Evolutionary Theory

The theory of evolution and the concept of natural selection have their origin in biology and have found their way into various fields such as mathematics, physics and computer science. These concepts inspired new powerful optimization methods

for solving complex mathematical problems that depend on a large number of parameters. Many optimization problems comprise tasks and models that resemble evolutionary processes, which are very similar to biological processes. Specifically, the word evolution originates from Latin and its meaning is "slow development". Moreover, the theory of evolution, founded by Charles Darwin in 1859, states that all animal and plant species we know today evolved from other species. Also, relevant research had recognized that living things, even if they belong to the same species, have different characteristics. Some are larger; others are better camouflaged or faster than their peers. Creatures whose traits are particularly favourable for survival have the most offspring. They pass on their genes to the next generation, ensuring that their species become better and better adapted to changing living conditions. In millions of years of evolutionary history, nature has produced organisms perfectly adapted to the surrounding environment. Darwin referred to this form of development as natural selection: Only the offspring of a species that have the best adaptation to their environment survive.

In this context, genetic algorithms are commonly considered and employed to solve problems that are associated with evolutionary processes. This class of algorithms represent one of the most modern and best available methods for solving highly complex tasks.

3.2 Artificial Replication Using Genetic Algorithms

Genetic algorithms are primarily suitable for optimizing and finding solutions to complex tasks [3]. In the evolutionary process of biology, genes of organisms are subject to natural mutation, which results in species diversity or genetic variability. The effects of mutated genes on new generations can be positive, negative or neutral. Through reproduction (recombination) of individuals, species adapt to changing conditions over a long period of time. This process is artificially reproduced by software solutions, where the quality of different parameters and solutions is evaluated with fitness functions to allow comparability and selection of solutions. The repetition of this process is continued until a defined termination criterion is reached. The result of the natural selection is the solution with the highest fitness score.

3.3 Genetic Algorithms for Portfolio Optimization

To enable the next generation of portfolio construction, advanced algorithms need to be developed. The genetic theory enables the development of algorithms that build robust and dynamic portfolios based on multiple input parameters. A concrete set of such algorithms are introduced and described in the following paragraphs.

3.3.1 Multiple Input Parameters

Genetic algorithms are capable of considering multiple input parameters. This ability is the foundation for meeting clients' diversified needs in terms of their investments in assets and securities. Modern wealth management faces a diverse group of clients with varying (investment or risk) goals, personal needs and many different focus points. Hence, there is a need to develop optimization algorithms and build an artificial intelligence engine to aid investment propositions for various client groups. The latter groups range from wealth management and private banking to retail clients.

Possible input parameters to these optimization algorithms include asset prices, dividends, volatility, correlation parameters as well as diverse asset breakdowns such as currencies, regions, asset classes and credit ratings. Furthermore, it is possible to consider additional parameters such as economic data, different types of ratings (e.g. sustainability ratings), individually defined investment themes (e.g. investments in renewable energies, healthcare, technology, megatrends, gold, aging society, infrastructure, impact investing) and more. Overall, there is a need for algorithms that consider and use a wide array of datasets.

3.3.2 Data Requirements

To meet the challenges of a modern optimization algorithm based on multiple input parameters, a vast number of data points from usually different data sources are required. Some of the most prominent examples of data sources that are used for portfolio optimization include:

- Financial market price data fetched from several market data providers
- Financial asset master data fetched from several data providers
- Customer risk profile data fetched directly from the financial institution
- Mutual fund, ETF and structured product allocation and breakdown data fetched from several market data providers
- Individual data points received from financial institutions and maintained as customer-specific data points
- Customer economic outlook fetched directly from financial institutions based on questionnaires and customer (risk) profiles

3.3.3 A Novel and Flexible Optimization Approach Based on Genetic Algorithms

Our approach to developing a genetic optimizer for portfolio optimization seeks to improve the quality of asset allocation of a portfolio of financial assets (e.g. stocks, bonds, funds or structured products) with respect to quantitative and qualitative financial criteria. It utilizes concepts of genetic algorithm, including an evolutionary

iterative process of portfolio modification and a subsequent evaluation of the quality of the financial portfolio, via a scoring assessment method (i.e. "fitness" assessment). Specifically, in the scope of our approach, a "fitness factor" evaluates a specific quality of a portfolio. Furthermore, a "fitness score" represents an overall metric to describe the quality of a portfolio, i.e. it evaluates the quality of the portfolio across multiple factors.

We offer flexibility in the use of different fitness factors, which helps in defining the objectives of the optimization process based on different customer "optimization preferences". Hence, users can design and assign weights to the factors that are important to the individual investor. It enables the users to integrate their market views using a functionality that is conveniently characterized as "frozen". This functionality fixes the weights of holdings an investor wants to have untouched, i.e. the holdings that he/she does not want to be considered in the scope of the optimization process. Given this flexibility of the methodology, the optimization provides highly customized portfolios based on clients' needs.

The genetic algorithm is also designed to reach a recommended portfolio within a very short period of time, as the speed of execution is one of the key drivers behind the potential adoption of this methodology. Given that there are multiple stages of iterations that need to be optimized based on a large underlying product universe with hundreds or thousands of assets to select from, the optimizer shall provide a solution within a response time of less than 8–10 s.

An additional goal for the optimizer is to ensure the compatibility of genetic optimization with other optimization methods and potential strategies. For example, a traditional mean-variance optimization can be defined by a Sharpe ratio factor, which will enable the genetic optimization process to generate results for portfolios with the highest Sharpe ratio. As another example, a strategic approach based on a certain asset allocation strategy can be defined by an asset class allocation factor, which will enable the genetic optimization process to recommend a portfolio according to the strategic asset allocation of a financial institution or asset owner.

Note also that our methodology provides multi-asset support: It can work with all different asset classes and product types, including stocks, bonds, funds, ETFs and structured products, as soon as the needed price and master data are available from relevant data sources.

3.3.4   Fitness Factors and Fitness Score

A "fitness score", as we designed it, is calculated as the weighted aggregate of a number of factors. These factors represent mathematically determined formulas based on certain criteria of the given financial assets. The corresponding weightings of the fitness factors can be defined individually for each optimization request or can be predefined as constants based on standard definitions. In general, the sum of the weighted fitness factors gives the total fitness score. Each of these fitness factors is a parameter of the total fitness score, covering a certain aspect or financial criteria for the given financial assets. One fitness factor may have an offsetting or amplifying

character with another fitness factor. Nevertheless, the factors are generally designed based on independent and uncorrelated attributes of the financial assets.

The fitness functions are applied to the complete portfolio, which is getting optimized. They can take into account all financial holdings within the investment portfolio, including equities, bonds, mutual funds, structured notes and cash. Each fitness factor is assigned with a given weight which determines the magnitude of the impact of that factor on the optimization process. Fitness factors considered for the fitness score can cover various parameters, including but not being limited to the examples presented. Hence, a flexible framework allows the creation of basically any fitness factor related to the investment assets of the asset universe, subject to the condition of data availability about the asset.

Fitness score will be calculated as:

$$FS = \sum_{i=0}^{n} w_i \ F_i$$

$i = 1,2,...,n.$
F_i is the corresponding fitness factor
w_i is the corresponding weight for each fitness factor i.

All fitness factors are scaled from 0.0 to 1.0. The weight of the fitness factors can be any number from 0.0 to 1.0.

The weights work in a relative way meaning the fitness factors with high weight will affect the resulting portfolio more than the fitness factors with low weight. For example, if the weight of Factor A $= 0.9$ and Factor B $= 0.1$, the resulting portfolio will be impacted by Factor A more than by Factor B. The genetic algorithm framework enables the development of fitness factors considering various financial key figures, portfolio-related constraints as well as characteristics of the underlying assets.

Fitness factors can be quite flexible created with different targets, which can be grouped in general as follows:

Risk/Return-Related Fitness Factors
- *Volatility-capped performance factor* minimizes the difference between the return of the recommended portfolio and the target return of the client under the condition that the recommended portfolio has a volatility that is not higher than the risk limit. The risk limit (in %) is in most cases linked to the risk level.
- *Portfolio volatility factor* measures the risk of the recommended portfolio; it minimizes the volatility of the recommended portfolio compared to the current or defined model portfolio.
- *Portfolio performance factor* measures the performance of the recommended portfolio; it maximizes the return of the recommended portfolio.
- *Sharpe ratio factor* measures the Sharpe ratio of the target goal allocation portfolio.

Portfolio Constraint-Related Fitness Factors
- *Product diversification factor* measures is the diversification of different financial products within a portfolio.
- *Reuse of existing asset factor* measures reuse of the investor's existing holdings for the new portfolio. The objective of that factor would be to reduce turnover of holdings in the customer's portfolio and primarily define whether an asset should be kept within a customer's portfolio. The so-called frozen assets can be completely excluded from the optimization calculations.
- *Preferred asset factor* measures the use of preferred assets (premier funds or other defined preferences) in the recommended portfolio.
- *FX minimization factor* minimizes the foreign exchange (FX) exposure in implementing the recommended portfolio by reducing FX transactions. It measures for each currency (cash and securities denominated in these currencies) in the recommended portfolio what percentage of such currency is already in the existing portfolio.
- *Preferred currency factor* measures the extent of the recommended portfolio that complies with the investor's preference for the investment currency.

Asset Characteristics' Related Fitness Factors
- *Asset class allocation factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to selected or predefined asset classes.
- *Sustainability/ESG allocation factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to ESG/sustainability criteria/rating.
- *Region allocation factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to specified regional preferences based on asset breakdowns.
- *ETF allocation factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to ETFs as a "low-cost" investment product selection.
- *Core/satellite allocation factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to assets tagged as core investments or satellite investment products.
- *Sentiment factor* measures how well the recommended portfolio follows a given target portfolio/target allocation with respect to a sentiment dataset or criteria/rating.

3.3.5 Phases of the Optimization Process Utilizing Genetic Algorithms

Genetic algorithms are utilized to discover the best portfolio out of all possible portfolio construction options considering the user-defined constraints defined and described above as fitness factors. Genetic algorithms are built based on the evolutionary processes of our nature. Guided random search is used for finding the

Table 11.1 Sample portfolio ranking table

	Weighted fitness factor 1	Weighted fitness factor 2	Weighted fitness factor 3	...	Fitness score (weighted sum of all factors)
Portfolio 1	0.13	0.29	0.14		**0.88**
Portfolio 2	0.10	0.07	0.03		**0.24**
Portfolio 3	0.34	0.16	0.21		**0.90**
...					
Portfolio 254	0.01	0.01	0.00		**0.05**
Portfolio 255	0.03	0.06	0.05		**0.20**
Portfolio 256	0.29	0.18	0.31		**0.83**

optimal portfolio, starting with a random initial portfolio. The following iteration process and the concept of natural selection filter portfolios in each generation based on its fitness score. The optimal portfolio results as the one with the highest fitness score after a predefined number of iterations.

Optimization Process

After receiving the inputs, the first generation of portfolios will be generated. There will be [256] portfolios in every generation. The number in brackets ([ ]) is an adjustable parameter which is determined through a qualitative and quantitative assessment. A random generation process is used for this calculation. The first portfolio of the first generation will be the input portfolio (from the data input). The financial assets and their weights within the portfolio are randomly assigned. The fitness score, which is the weighted aggregate of different factors, is calculated for all portfolios as shown in Table 11.1. The portfolios are then ranked according to their scores.

Within the further process, portfolios with fitness score in the top 50% range will be selected, while the bottom 50% will be discarded as illustrated in Fig. 11.1.

The "surviving" 50% [128] portfolios will be treated as parents to generate [128] offsprings. Each child is generated by two adjacent parents: For example, the first portfolio will be combined with the second one, the second one with the third one and so on. The [128]th portfolio will pair with a randomly created new portfolio. Mutation is performed by introducing new financial assets, rather than from existing portfolios. These steps will be repeated for [100] times. After this automated genetic calculation, the portfolio with the highest fitness score is selected as the "fittest portfolio" and the final output.

3.3.6 Algorithm Verification

The described and developed methodology has undergone an extensive verification process with a wide range of combinations of different inputs. The input variables include 5 sets of portfolios, 5 sets of preferred currencies, 11 sets of fitness factor
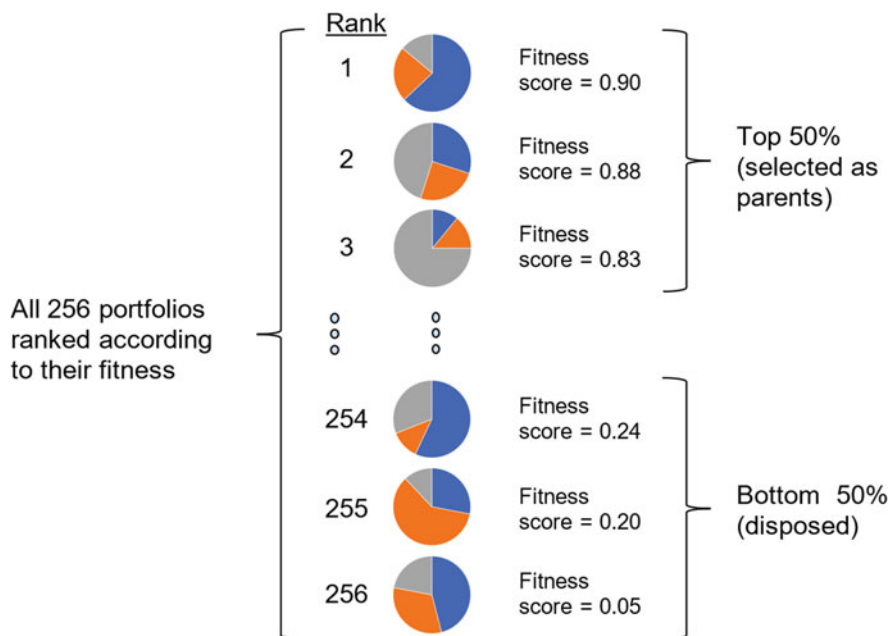
Fig. 11.1 Sample portfolio selection table

weights, 6 sets of frozen amounts and 5 different product universes. It has already been tested with over 8000 different predefined test cases. The resulting response time, fitness score and other related metrics have been examined and compared.

Fitness Improvement

By changing the selected inputs of the 8000+ cases, the improvement of the fitness score of these optimized portfolios achieved a level of 30% on average as shown in Fig. 11.2 and Table 11.2. This result is consistent with the traditional portfolio theory, while providing more customization for a client such as the currency of the assets, maximum risk acceptance, etc. would lead to "better results".

Convergence Test

Additional analysis has been done to study the behaviour of the algorithm by plotting the fitness score of the portfolios in each generation. Figure 11.3 illustrates an example of how the fitness of the portfolios improves over the different generations. It can be observed that there is a greater dispersion in "fitness quality" in portfolios of earlier generations, while portfolios of later generations are yielding
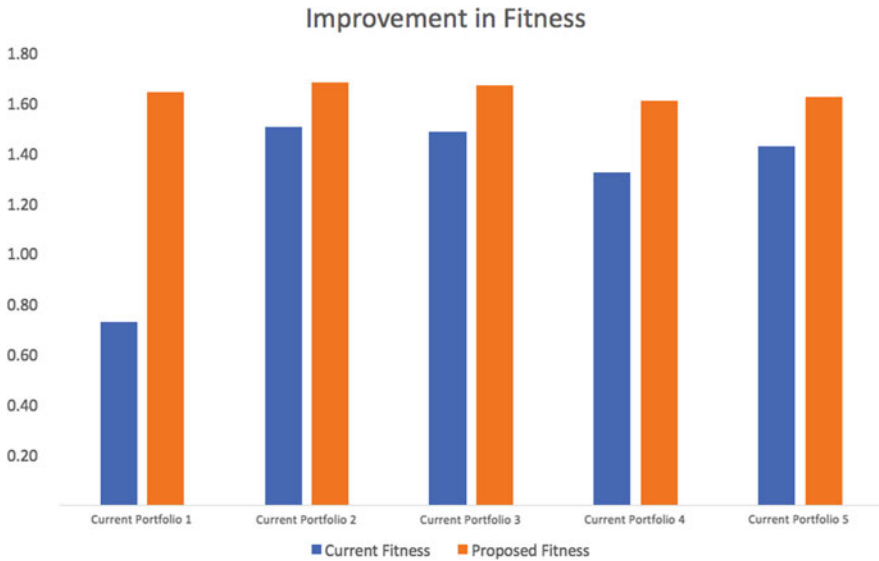
Fig. 11.2 Portfolio fitness improvement

Table 11.2 Sample portfolio ranking table

(Average results)	Fitness	Return (%)	Volatility (%)	Sharpe
Before optimization	1.26	4.77	14.04	0.36
After optimization	1.64	8.22	13.11	0.69

generally higher fitness scores. It can also be observed that through the optimization process, the fitness score of each individual portfolio gradually converges to a level where there is no or only a marginal room to increase the fitness score further.

3.3.7 Sample Use Case "Sustainability"

In the past years, "Green" or ESG (environmental, social and governance) compliant investments are in growing demand among institutional and retail investors. Assets under management in ESG funds and corresponding ETFs have recently grown disproportionately strongly. Among other things, this has to do with the fact that many new sustainability products have been launched and regulators are increasingly demanding compliance with and disclosure of sustainability criteria, thus also creating drivers for change. New regulations, for example, the EU Disclosure Regulation 2019/2088, introduce disclosure requirements regarding sustainability in the financial services sector.

The proposed optimizer framework based on genetic algorithms enables the development and consideration of fitness factors for various criteria, including sustainability. It will also be possible to develop a fitness factor for each of the
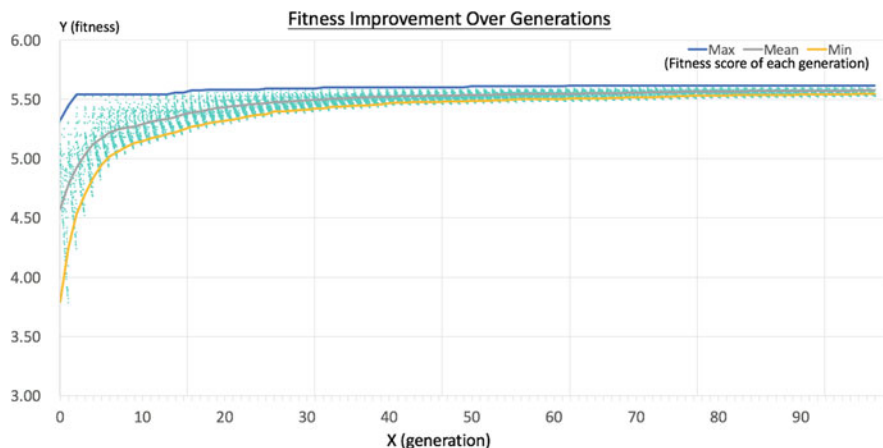
Fig. 11.3 Fitness improvement over generations

17 Sustainable Development Goals (SDGs) proposed by the United Nations to generate specific portfolios that meet certain ESG/sustainability requirements. As a first step, an additional sustainability fitness factor was developed to optimize assets classified as sustainable according to qualitative criteria. It enables users to select the percentage weighting of the desired ESG compliance or sustainability grade of a portfolio proposal. The fitness factor ensures that the desired weighting or even exclusivity for ESG compatible investments in the portfolio is targeted.

Sustainability Fitness Factor Test Series

The created sustainability fitness factor was verified in an extensive test series. The underlying investment universe of this test series consisted of 127 mutual funds, of which 31 were classified as sustainable, and for the second batch of tests, a restricted investment universe of 30 mutual funds, including 9 sustainable funds, marked as sustainable selection. The optimization was performed over a 5-year period using live market data. In total, 3100 portfolios were generated with different preferences for volatility targets, different regions, ETF allocation and sustainability targets.

The sustainability preference was set as follows (Fig. 11.4):

(a) No preference for sustainability, i.e. 0% fixed weight for the sustainability fitness factor
(b) Sustainable assets preferred, i.e. soft target for sustainability weight of approximately 60% allocation in the portfolio
(c) Exclusive allocation with sustainable assets 100%

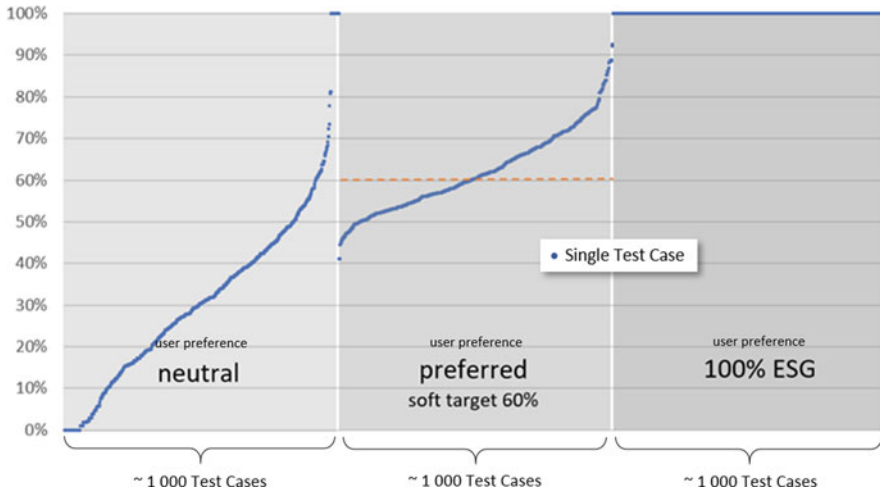**Fig. 11.4** Result of sustainability fitness factor test series, where from left to right the number of test cases and on y-scale the result of each single case is displayed within the blue line

Test Series Results

The preference (a) results show an intensive allocation of sustainable funds, with 93% of all portfolios containing sustainable funds. The median weighting was 30.5%, the first quartile (25th percentile) was 16.1%, and the third quartile (75th percentile) achieved an allocation of 44.1%. This "neutral" result can be taken as reference since the sustainable fitness factor had – as no preference was selected – no influence on the allocation of sustainable funds. The allocation of those funds is the result of risk/return factors as well as other selected preferences.

The preference (b) results confirm the proper function of the algorithm since the sustainable fitness factor was in use as a soft target. Nevertheless, it was not the only criteria the genetic algorithm had to consider. The fitness factor with the highest weighting was the volatility-capped performance factor to ensure the given volatility target is met. Also, the soft target for the sustainable fitness factor of 60% allocation was very well achieved. The median weighting was 60.4%, and first quartile (25th percentile) amounted to 54.3%, and the third quartile (75th percentile) achieved an allocation of 68.7%. Overall, 788 or 72% of all portfolios had an allocation of sustainable funds in the targeted range between 50% and 70%.

The preference (c) results were 100% achieved and the optimizer allocated only sustainable funds to the portfolios. The results of this test series confirmed the functioning of the genetic algorithms as well as the chosen configuration of the test setup.

4 Summary and Conclusions

This chapter presented a personalized portfolio optimization system, which was developed in the scope of the H2020 INFINITECH project. The system aims to define, structure and develop an end-to-end process that digitizes a "private ranking" like advisory journey to enable personalized and professional advisory services to the general public. This includes the personal risk assessment of the user resulting in a risk score or SRRI (synthetic risk and reward indicator), based on a new designed UI/UX setup, the definition and selection of personal investment preferences such as sustainability/ESG criteria, regional preferences or sentiment preferences. The solution aims to have further "customized" preferences as potential enhancements, including but not exclusively based also on additional "third-party content" providers.

The core of the portfolio construction and optimization process utilizes genetic algorithms based on the concept of evolution theory. It applies an iterative approach and natural selection process to generate portfolio proposals based on a wide range of individual and customized preferences with different investment goals. Preferences are defined and set up as fitness factors which can cover risk-/return-related key figures, various portfolio constraints (e.g. diversification and asset characteristic variables such as sustainability, asset class breakdowns or sentiment data). The goal of the overall approach is to enable advisors and potentially end customers to directly manage smaller portfolios (i.e. <25k €) in a professional investment advice manner. The solution is designed and implemented as a SaaS (software as a service) tool. Therefore, it can be flexibly integrated with existing advisors, banks, insurance or brokerage online systems. The proof of concept of this open framework solution has been validated based on a substantial test series, including several self-calculated fitness factors. As part of ongoing developments, the solution will be enhanced by adding a "sentiment fitness factor". The latter will be provided by a sentiment analysis service provider, which will act as an independent third-party data source.

The final goal for the system is to provide a set of predefined fitness and optimization factors, which shall be offered as a SaaS solution. This SaaS solution will become available for integration with existing backend solutions from financial institutions or alternatively provided via APIs which can be approached from other system providers that need to service their clients based on the presented approach to portfolio construction and optimization. Hence, such system providers will have the opportunity to leverage the presented approach and algorithms while offering them to customers based on their own UI/UX settings.

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