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Kilian Wagen, Grégoire Siegwart, 470M bronze medal at WCS Genoa 2019. Photo: Sailing Energy

SWISS SAILING TEAM ATHLETE PORTFOLIO OPTIMIZATION

by
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Abstract

The Olympic Sailing sport is subject to complexity, uncertainty and change. We explored this challenging sport with an interdisciplinary approach, using well-known tools in Economics and Finance for a new interpretation of success in Olympic Sailing. With this work, we offer an exploration with new lenses of an eminent domain for Swiss Sailing Team. To address the topic, we firstly studied the role and the contribution of the luck. So, we computed the ratio between the variance of the winning percentages for a large sample of Olympic classes elite sailors and the variance of the hypothetic scenario where the luck is the only factor in who wins and loses the sailing races. We identified that Olympic Sailing sport is a skill-based discipline, and the medallists are affected only for 10% to 20% by luck. Secondly, we analyzed in-depth the performance of the elite Swiss sailors. In total, we designed two predicting models, and we qualitatively validated both by keeping into account the luck and the risk. We are persuaded that these predictions could be used for goal setting. The first was elaborated by using the power-law functions; by doing so, we characterized the learning curve of each Swiss sailor and projected it into the future. In the second, by using the economics principle of the production functions and performing multilinear regressions, we identified how the different factors that define the performance in Olympic sailing are interconnected and contribute to the improvement of the results. We empirically found that this particular production function has an increasing return to scale. The predictions performed lead to the conclusion that some of the elite Swiss athletes have the potential to achieve a medal at the XXXII Olympic Games. In the last milestone of this work, we assessed the risk and return of the Swiss Sailing Team athlete portfolio. For that, we initially borrowed from Finance some tools of the modern portfolio theory, and we run the first round of optimizations to highlight the contribution of each member to the success of the whole team. In the end, we defined a more sophisticated multi-criteria objective function by using, on the one hand, the experience of the Swiss Sailing Team management, and on the other hand the finding of this work. We concluded the analysis by computing how much each of the sailors in the portfolio contributes to the success of the whole team while keeping into account different scenarios of the multi-criteria objective function. So, a new route for an enhanced decision-making process and a prospective rewarding methodology has been drafted.

[…]

“La via del mare segna false rotte, ingannevole in mare ogni tracciato,
solo leggende perse nella notte perenne di chi un giorno mi ha cantato
donandomi però un'eterna vita racchiusa in versi, in ritmi, in una rima,
dandomi ancora la gioia infinita di entrare in porti sconosciuti prima...”

Odysseus, F.Guccini

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Content

1 Introduction

1.1 Olympic Sailing

The sailing sport was first contested at the Olympic games in Paris 1900 and, except for the 1904 Summer Olympics held in St. Luis (Missouri, USA), sailing was always part of the Olympic program. The sailing disciplines represented at the Olympic games changed over time, trying to follow the equipment and sport evolution. During the first editions, the sport was dominated by bigger boats, sailed by crews composed by several members, up to 12 people. Starting from Paris 1924 and increasingly after the 1950 edition, the role of smaller and one-design oriented boats became more relevant. At the XXXII Olympic Games edition in Tokyo[1] (August 2020), a mixture of dinghy boats, high-performance classes and windsurfs will represent sailing. The competitors will battle for a total of 10 medals to win. As it follows in the list below, 6 events are for males, 4 events for females and 1 event is held with mixed crews:

- Men's Events:
  - 470 Class – Two-person dinghy men,
  - 49er – Two-person high-performance skiff men,
  - Laser – One-person dinghy men,
  - RS:X – Windsurfer men,
  - Finn – One-person dinghy (heavyweight) men.
- Women's Events:
  - 470 Class – Two-person dinghy women,
  - 49er FX – Two-person high-performance skiff women,
  - Laser Radial – One-person dinghy women,
  - RS:X – Windsurfer women.
- Mixed event:
  - Nacra 17 – Two-person high performance (foiling) catamaran.

During the Olympics, as well as during all the events for this type of sailing classes, the races that compose a regatta are sailed in a fleet racing format where one-design boats (tight Class measurement rules) sail around a course delimited by anchored floating buoys in a group. The courses can be of different shapes, but all of them offer a complete challenge incorporating upwind, reaching and downwind sailing angles.

A variable set of races, 2 to 3 per day for a total of 10 to 15 races, defines the final ranking of the event which award to the first 3 with respectively a gold, silver and bronze medal. The scores are awarded according to finishing positions in each race, and each boat can discard their worst score. The so-called "Low System Point" is, therefore applied, as defined by the Racing Rules of Sailing [1]. To win the medals, the ten best competitors (with the lowest accumulated scores) have to compete in the Medal Races, which is weighed the double of the fleet races. So, the point scored is doubled and added to the opening series' score.

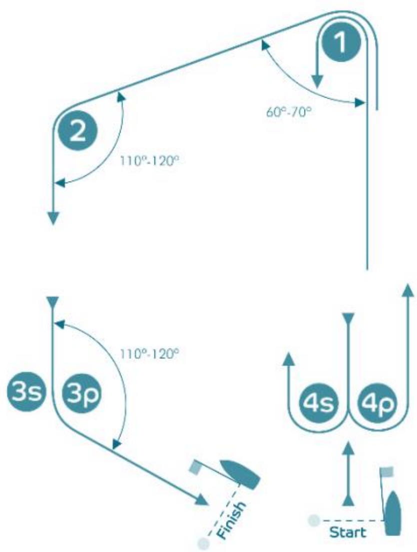


Figure 1: Inner-loop trapeze sailing course, the wind direction is intended from the top of the page. Source: World Sailing.

[1] www.olympic.org/tokyo-2020

1.1.1 Qualification System for the Olympic Games

World Sailing is the governing body for the sport of sailing[2], and it is recognized by the International Olympic Committee[3] (IOC), which is the authority responsible for organizing the modern Summer and Winter Olympic Games. World Sailing, in agreement with the IOC, defines the Olympic Classes periodically, trying to follow or anticipate the evolution of the discipline. Then, an athlete or a team that intends to compete at the Olympic Games have to go through a Qualification System [2] which is defined by the international sailing federation and ratified by the International Olympic Committee.
In a glance, the Qualification System aims to select which are the Nations that will take part in each of the Olympic Sailing events. This process starts about two years before the Olympic Games, and it ends only a few months before the opening. Generally speaking, because there are some exceptions, a National Sailing Federation have to reach a specific minimum performance in the results to guarantee its attendance with one or more athletes or teams.

	2018 WC	2018 Asian Games	2019 Pan Am Games	2019 WC	Europe	North America	South America	Africa	Asia	Oceania	Host	Tripartite	Total Boats	Total Athletes
Men														
Windsurfer	10	0	0	8	1	1	1	1	1	1	1	0	25	25
One Person Dinghy	14	1	2	5	2	1	1	2	2	2	1	2	35	35
One Person Dinghy (Heavyweight)	8	0	0	4	1	1	1	1	1	1	1	0	19	19
Two Person Dinghy	8	0	0	4	1	1	1	1	1	1	1	0	19	38
Skiff	8	0	0	4	1	1	1	1	1	1	1	0	19	38
Women														
Windsurfer	11	0	0	9	1	1	1	1	1	1	1	0	27	27
One Person Dinghy	18	1	2	10	2	1	1	2	2	2	1	2	44	44
Two Person Dinghy	8	0	0	6	1	1	1	1	1	1	1	0	21	42
Skiff	8	0	0	6	1	1	1	1	1	1	1	0	21	42
Mixed														
Multihull	8	0	0	5	1	1	1	1	1	1	1	0	20	40
													250	350

Figure 2: Nation quota allocated to each Olympic Class during the Qualification Events. Source: World Sailing

Anyhow, for a National Sailing Federation, the achievement of one or more nation quotas is not the target. Despite the famous quote of Pierre de Coubertin (founder of the International Olympic Committee), which was saying that "the important thing in life is not to win but to compete," athletes, federation managers and coaches want to win, so the target is the Olympic Medal. Therefore the Qualification System is a filtering process to identify the best sailors in the world and bring them together every four years.

1.1.2 A complex sports discipline

The Racing Rules of Sailing [1], in one of its rules, to define a regulate the propulsion of the boat says: "a boat shall compete by using only the wind and water to increase, maintain or decrease her speed. Her crew may adjust the trim of sails and hull, and perform other acts of seamanship". So here it is, in a nutshell, all the complexity of this sport discipline. First of all, a racing boat, as many racing equipment for other sports, it is the object of continuous evolution, research and development. Within the regulatory constraints (Class Rules), the boat builders, the sail designers, the spars and foils manufacturers continuously improve their products to offer the best performance. Frank Bethwaite in his

[2] www.sailing.org
[3] www.olympic.org/the-ioc

book *High Performance Sailing* [3] and Tom Whidden with Micheal Levitt in *The Art and Science of Sails* [4] tried to resume this complexity in a book available to the public. However, to learn the seamanship required to maintain and decrease the speed of a boat or to trim the sails and the appendixes of the hull efficiently take time. In general, as a rule of thumb, as skilled sailor acquired the experience over decades because it is not enough to read a book to learn how to read the wind, the waves and the currents. The experience is a crucial part of the learning process. Even for the coaches, it is not always a simple job to identify the weaknesses or to define the tapering process to peak the performance in a particular moment of the season. Some experienced coaches describe their training methodology in sailing, as Jim Saltonstall did in *Race Training* [5]. However, on top of that, each World-Class coach has to add his/her own experience as former-athlete, sports scientist, engineer, or any discipline-specific education that brought him/her to become a professional sailing coach. In this dissertation, we will investigate into this complexity because only since a few years, the National Sailing Federations are starting to acquire data systematically to analyze the performance. Before that time, in particular, for the Olympic Sailing, a veil of excuses due to the complexity rejected the idea of study the problem analytically and with a data-driven approach. Against the prevailing trend and despite its size, the Swiss Sailing Team is rather advanced in this domain, and this master thesis is another step forward in this direction.

1.2 Swiss Sailing Team

Swiss Sailing Team[4] is the department for the sport of performance of Swiss Sailing[5]. Therefore it is organizing and promoting the Olympic sport pathways and related junior classes. SST focuses its resources on obtaining prestigious results at international events such as continental championships, European series, World Cup series, world championships and ultimately, as the highest pinnacle, the Olympic Games. Swiss Sailing Team is acknowledged by the World Sailing and Swiss Olympic Association[6], the Swiss National Olympic Committee.

The teamwork of the SST staff is based on shared values such as excellence, information flow, perfectionism, innovative spirit, motivation, commitment, open communication and solution-oriented conflict management. In SST management is possible to find authentic passion-driven people striving to achieve the best results. The elite Swiss sailors define themselves as “Young & Hungry.”

The Swiss Sailing Team trains four different elite levels and two youth levels. In the elite, from the highest to the lowest level, we find the *Olympiakader-cadre Olympique*, the *Nationalkader (cadre national)*, the B-*Kader (cadre-B)* and the C-*Kader (cadre-C)*. In the youth, we have the *Youth Team* and the T*alentpool*. The team membership is regulated by the Kaderreglement (Règlement des athletes du cadre) [6]. On top of that, the Swiss Olympic Association defines the guidelines for the talent selection, supporting the use of the PISTE [7] (Prognostisch Integrativen Systematischen Trainer-Einschätzung) methodology, which is integrated into the conceptual framework for the sport and athlete development in Switzerland (FTEM) [8].

1.2.1 The object of the research

The declared target of SST for the XXXII Olympic Games (Tokyo 2020) is to win a medal. This work aims to contribute to move in that direction and to help the management to support their decision during the last year before the event and possibly for the following Olympic cycles. This work will be organized into three main milestones. In Chapter 2, we will focus on the research on the role of luck in the sailing sport. Starting from the idea that Mauboussin presented in his book *The Success Equation* [9], we generalized the concept and applied to the Olympic Sailing sport. To achieve the computation

[4] www.swss-sailing-team.ch

[5] www.swiss-sailing.ch

[6] www.swissolympic.ch

of the Luck Contribution, we will have to develop a sampling methodology to select the events and the sailors that we need to consider for the statistical analysis. In total, we will consider 169 of 226 World-Class events from 2012 to 2019, and 482 sailors selected from a broader set of 1676 athletes. In the central section, Chapter 3, we will focus on the results and the performance of the former and current elite Swiss athletes. In total, we will analyze 14 Swiss athletes arranged on 9 different boats[7] involved in two different Olympic cycles, Rio 2016 and Tokyo 2020. While doing so, we will formulate assumptions [10] [11] to interpolate their Race Results time series, and we will use data stored in the SST Performance Development Processes to define how Technique, Tactics & Strategy, Physical and Mental preparation, Equipment and Know-How are interconnected and contribute to the improvement of the Race Results. This approach will allow formulating some predictions for the future Race Results and some insights for the management to help the Sailing Team to improve as a whole. In the third and last milestone (Chapter 4), we will study the elements that characterize the team success and risks. At first, we will use methods [12] [13] derived from the Financial Markets to assess the risk and return of the SST Athlete Portfolio. Using the mean-variance analysis, we will perform the first round of optimization. Then, we will dive into the SST Olympic Project Review and, on one side we will offer to the SST Selection Committee predictive tools to define future targets for the athletes, on the other side we will use this internal assessment tool to design the Objective Function for SST. After that, based on a multi-criteria decision analysis approach [14], we will study different scenarios, and we will compute the contribution of each athlete to team success. In the end, the set Keep Performance Indicators will offer the opportunity to the SST management to enhance the rewarding system, by using a combination of dynamic prospective and retrospective evaluations [15].

Despite the wiliness to achieve an Olympic medal, we have to remind that SST act within a set of constraints. Financial resources, human resources and athlete recruitment are some of those. Moreover, the regulations of the International Olympic Committee, the World Sailing, the Swiss Olympic Association and Swiss Sailing itself define managerial limitations, scopes and roles. SST respects its position within this framework and acts in the interest and for the success of its athletes. The purpose of this work has to be seen as an explorative study for a deeper understanding of the dynamic of the Olympic Sailing sport.

Figure 3: from the top right, clockwise; the RS:X (windsurfing class), the 49er (two-person high-performance skiff class), the 470 (two-person dinghy class), the Nacra 17 (two-person high-performance catamaran), the Finn (one-person heavyweight dinghy class) and the Laser Radial (one person dinghy class). Photos: Sailing Energy.

[7]We will focus on the following Olympic boat classes: RSX, 49er, 470M, 470F, Laser Radial, Nacra 17 and Finn. In agreement with the SST management, we decided to neglect one of the members of the elite Swiss team, the Laser Standard sailor. The reason for this omission lies in lack of data concerning that specific athletes. He joined the team only recently, coming from another nation and SST does not own about this athlete the same amount of information as for the others, which developed within the Swiss Federation. In the future, when more data will be available, it will be possible to extend the analysis.

1.2.2 The sources of the data

All the Race Results data presented in this dissertation have been collected from official sources of information. The results of the World Cup Series (formerly known as Sailing World Cup) are available on the World Sailing website. The results of the Olympic Games are reachable from the official website of the International Olympic Committee or via the international sailing federation. The results of the World Championships are available on the websites of the international class association of each Olympic sailing class, or via the World Sailing website. The results of the Olympic Test Event of 2015 are available on a dedicated website, but a link can be found on the World Sailing website too. Therefore all the race results, the names of the competitors and dates of the events are publicly available. In this thesis, we will always refer to the Swiss sailors by naming the boat class on which they are competing and not their name.

Swiss Sailing Team opened for us the access to internal and confidential data, such as the Performance Development Process (PDP) of each elite sailors, the physical tests and the latest Olympic Project Reviews (OPR). This confidential data have been extensively used during this dissertation, but only the results obtained with those are here presented. To offer the highest level of transparency, all the statistical analysis that has been performed on the data are presented in the annex. The details concerning the content of the Performance Development Process and the Olympic Project Reviews will follow respectively in the sections 3.3.1 and 4.2.

1.3 The Full House of Elite Sports

Sports managers increasingly consider Sports Data Analytics. Historically, the American baseball league (MLB) played a role in the evolution of sports data science [16]. In the early seventies, Bob Davids funded the Society of American Baseball Research (SABR) [17] which aimed to study that specific sport discipline statistically. This approach becomes so dominant that George William James coined the term “sabermetrics” [18] to identify that specific type of empirical studies. Many other popular sports, where the interest of the public, the growth of the business, and the entertainment are prevailing, followed the same pathways soon after. In the United States, the National Hockey League and the National Basket Association are nowadays using a similar methodology. In Europe, the club in the European Football Association (UEFA) developed predictive and statistical tools for their players and to predict the injuries. Last but not least, the Professional Golf Association does the same. Therefore all around the planet, many business models started, and the market for sports analytics is expected to reach almost $4 billion by 2022 – Forbes.com writes [19].

Since the begin of the last century, the transition from amateur to professional players has begun for the most popular sport discipline in North America and Europe [20]. With the rise of professionalism in the sport arts, all the aspects of the disciplines involved in this process significantly improved. Stephen Jay Gould, in his book *Full House* [21], depicted how the statistical indicators evolved and how to interpret such kind of trends. Gould explains how misconceptions about statistics can lead people to misunderstand the role variation plays in driving trends in complex systems. One misconception people often have to focus too narrowly on averages or extreme values rather than the full spectrum of variation in the entire system [22].
“Moreover, - Gould writes - the rise in general excellence and consequent shrinkage of variation does not remove the possibility of transcendence. In fact, I would argue that transcendence becomes all the more intriguing and exciting for the smaller space now allocated to such a possibility, and for the consequently greater struggle that must attend the achievement. When the norm stood miles from the right wall (the extreme of the performance), records could be broken with relative ease. But when the average player can almost touch the wall, then transcendence of the mean marks a true outer limit for conceivable human achievement. I would carry the argument even further and point out that a norm near the right wall pushes the very best to seek levels of greater accomplishment that otherwise might

never have been conceptualized. […] Call it foolish, but acknowledge that human greatness often forms a strange partnership with human obsession, and that the mix sometimes spells glory—or death (page 75) [21]"

1.3.1 Professionalism in Sailing Sport

In this dissertation, we investigated the performance and the results of elite sport sailors, these men and women are fulltime dedicated to the sports discipline. Nowadays, an athlete that wants to reach an Olympic Medal must be afloat about 200 days a year, for an average of 3 hours a day. On top of that, we have to account the physical and mental preparation, the boat preparation, the equipment testing and tuning. Then, if the location is presenting extreme weather condition (humidity and temperature), the nutrition and the acclimatization to the racing venues become increasingly important. In-depth theoretical knowledge of meteorology [23], racing rules, and other technical or tactical [24] aspects have to be kept in the account, so additional time have to be considered for that. Therefore, despite the lack of big sponsors or significant remuneration for the athletes, the sailors that intend to conquer an Olympic medal are professional athletes, as they spend all their time (and most of their resources) to achieve their goal. Since 2019, Swiss Sailing Team started a process to professionalize the position of its athletes, and in Switzerland, the *Spitzensport der Schweizer Armee* (*Sport d'élite dans l'Armée Suisse*) [25] offers the possibility to elite athlete above a significant level to earn a salary while focusing on their discipline. Regardless of these possible financial contributions or the support of the sponsors, in Olympic Sailing, the remuneration is not the driver for the athletes, that is just enough to cover the costs. Generally speaking, the athletes that chose this lifestyle do that for internal intrinsic motivation, and the passion for the sailing discipline drives them. In his book "*Perseverare é Umano*"[8] (perseverance is human), the sports psychologist Pietro Tarabucchi depicted this peculiar obsessive attitude of passion-driven athletes accurately.

In 1951, Stanley Ogilvy, an accomplished Star boat[9] sailor, a Ph.D. mathematics professor and a prolific sailing writer, wrote in his book *Successful Yacht Racing* [26]: "Aside from winning a token prize [for winning a race] there is no material reward for excellence. No professional managers wait on the dock, anxious to sign up the day's winners on their teams" [27]. Now, even if the first part of the sentence may hold in most of the cases still, the second is changing considerably in the last two to three decades. Today's federation managers are professional and professional sailing coach education has been developed in most countries active in this sport. Professional circuits, like America's Cup, GC32, TP52, SailGp, Volvo Ocean Race are looking at the Olympic pathway as the source of the most competent and skilled athletes. Olympic Sailing remains a niche sport of performance discipline, but simultaneously, the house is progressively getting full.

1.4 Methods

This thesis comes as a conclusion of a Continuing Education (MAS) in Management, Technology and Economics (MTEC) at the Eidgenössische Technische Hochschule Zürich (ETHZ). The methods that we used to address the milestones of this work are oriented to solve the real problems that the Swiss Sailing Team required to investigate. In this section, we will present some of the tools that we encountered during the recent education; with a particular focus to some economic and financial constructs that we used to develop interdisciplinary parallelisms with the sport of performance.

[8] The title "*Perseverare é Umano*" is twisting the meaning of the quote attributed to Seneca "Errare humanum est, sed perseverare diabolicum", which is translated to: "To err is human, but to persist in error is diabolical".
[9] A former Olympic Class

1.4.1 Multinomial Distributions

In Chapter 2, to compute the contribution of the luck in the Olympic Sailing sport, we will take into consideration complex probabilities constructs. Therefore, the use of multinomial distribution will be required. The multinomial distribution is the generalization of the binomial distribution, which is addressing the discrete probability distribution of the number n of successes in a sequence of N independent events (for example sports matches), each having a win or a loss outcome. In the binomial case, for each event, a probability p for winning and a probability $q = 1 - p$ for losing are defined [28]. In the general form, for N independent events each of which leads to the success for exactly one of k possible outcomes, with each one having a given fixed success probability, the multinomial distribution gives the probability of any particular combination of numbers of successes for the various outcomes [29].

Applied to the sailing sport, where the competition is not based on the outcome of a match with one team winning and the other loosing, but on a ranking list, we will use the multinomial distribution to study combinations of probabilities in the function of different position in the ranking. For example, we will investigate the combined probability of being n-times a medallist, being m-times in the Medal Race (top 10) without winning the medal, and $(N - n - m)$-times out of the Medal Race over a set of N competitions.

Then, while dealing with the combined probability constructs, we will use the covariance matrix and its proprieties. In the covariance matrix, each diagonal entry is the variance of a (binomially distributed random) variable, and the off-diagonal entries are the covariances, which in the specific case of a multinomial distribution are always negative. In fact, for a fixed n, an increase in one component of a multinomial vector requires a decrease in another component.

Bias-variance trade-off

While dealing with the sampling process to select reliable and viable World-Class sailing events to use for the required statistics, we will have the opportunity to benefit from the experience of the SST management. In fact, we have to acknowledge that not all the events that are labelled top-class have the number and the quality of participants to be accounted for that. In particular, it happens that events held in a remote location or a certain period of the season are not compelling for the top sailors. Therefore, based on the bias-variance tradeoff principle, we will define which events to keep into consideration and which to discard. The bias-variance tradeoff is the property of a set of events whereby sets with a higher bias in parameter estimation have a lower variance of the parameter estimates across samples.

1.4.2 Law of Diminishing Returns and Learning Curves

In Chapter 3, we will analyze the Race Results time series of elite Swiss sailors. To define how to interpolate this particular series, we will make some assumption. As previously mentioned, we will focus on experienced sailors, with a significant career. In Switzerland, the best athletes start to be part of the Talentpool by the age of 12. Then, when they are developing without long stagnation while changing into new Junior Classes[10], they are expected to achieve the criteria for Youth Team by the age of 16-17. After that, but before 19 years old, they will pass to an Olympic Class by keeping the status of Youth Team member. Only after having proved a certain level in the junior categories of the Olympic classes, they will start their Olympic campaign. All the development process is described in the *Nachwuchsförderungskonzept* (*Concept de promotion de la rèleve*) *2019-2024* [30], published on the official website of Swiss Sailing. In the sketch of Figure 4, on a graph time-performance, we present the area of investigation in the spotlight of this thesis visually.

[10] Due to age restriction, the athletes have to change Class at the age of 15 and then again before they are 19.

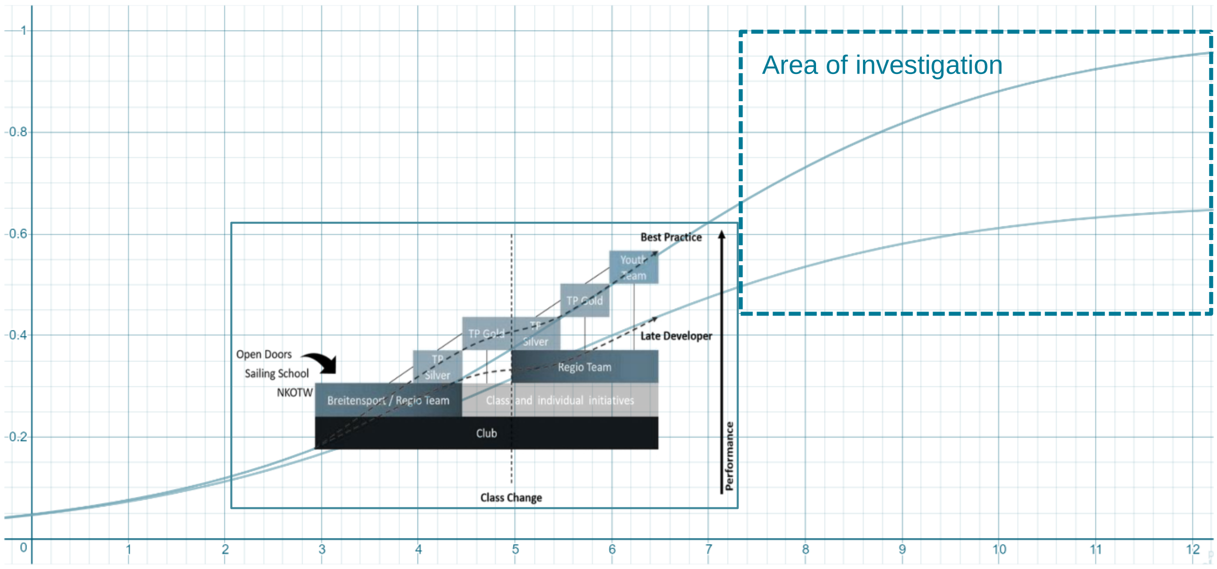


Figure 4: qualitative representation of the assumed performance and result development over time. On the x-axis, we set the time, on the y-axis the keep performance indicator, in particular, the Race Results and the items composing the Performance Development Processes. The overlaid sketch contoured with a solid line is the qualitative representation of the juniors' performance evolution [30]. The dashed box represents the area of investigation of this work, the experienced elite sailors.

Looking at Figure 4, it is possible to understand that, above a certain level, the performance obeys to a law of diminishing returns. The Race Result and the sportive performance, in general, will keep improving until the plateau. The maximum level of the performance will depend on endogenous and exogenous factors, and later in this dissertation, we will investigate further about that.
Here we want to stress the characteristics of the curves within the dashed box of Figure 4. In processes that implies successive refinements and diminishing returns, these can be known as learning curves. In this work, following some of the studies available in the literature [31] [10], we will assume those elite sailors, in the phase of the career that we are analyzing respect this trend.
A common and appropriate way to mathematically represent the learning curves as a function is by using the power laws. In Chapter 3, we will use this mathematical description to interpolate the data series of the Race Results for the elite Swiss sailors.

Production Function

When we face the challenge to build a predicting model for the Race Results in section 3.3, we will need to define a mathematical relation between the items of the Performance Development Process and the Race Results themselves. Therefore, we will assume that the results in the competition are the outputs of a production function which the inputs are the factors of the PDP. This assumption holds on the idea that in economics is the relation between quantities of inputs (capital, labour, land, raw materials, machine hours, etc.) and quantities of output. The production function is a crucial concept for the neoclassical economic theories, and it is extensively used to define the marginal product (diminishing returns) and to identify allocative efficiency. In the parallelism with the sport of performance, we think that an athlete needs to have a certain amount of skills in different domains (inputs) to achieve the targeted a Race Result (output). In this work, we are interested in discovering how the inputs contribute to the success of the athletes, in order to give to the SST management, the knowledge to support the team for what matters the most. Within the family of the production function, the Cobb-Douglas is a particular functional form [32] widely used to represent the technological relationship between the amounts of two or more inputs and the amount of output that can be produced by those inputs [33]. At the end of Chapter 3, we will see that this form will be interestingly representing our model.

Linearization and multiple regression

For processing the data, we had to proceed with linearization processes. In fact, while operating with data interpolated with power-law function, we passed in a logarithmic scale domain. This mathematical process will allow us to linearize the regression of our data and to compute the information we will need to assess the prediction model. The details of the linearization process will be presented at the proper time. To study the causal relation between the Race Results and the Performance Development Processes, we will first study the cross-correlation between all the inputs of the linearised production functions and its output. After that, we will perform multiple linear regressions to find the causal relationship between the inputs and the output.

To perform this process successfully, due to the amount of the data, their structure and the issues of asynchronicity that we will encounter, we will proceed with a fixed regressor design. To validate the quality and pertinence of the models developed, we will refer to the most common statistical indicators, the coefficient of determination and the probability value, otherwise known as significance. On the one hand, the coefficient of determination R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides a measure of how well-observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model [34]. On the other hand, the probability value (p-value) is, for a given statistical model, the worst-case probability that, when the null hypothesis is correct, the statistical summary would be greater than or equal to the actual observed results. [35]

1.4.3 Optimization

In Chapter 4, we explored two optimizations processes. The first approach is based on a mean-variance analysis. Initially introduced by Herry Markowitz [13] in 1952, the modern portfolio theory (MTP) was later awarded with the Nobel Prize in Economics. The theory offers a mathematical approach for assembling a portfolio of assets such that the expected return is maximized for a given level of risk. It is a formalization and extension of diversification in investing, the idea that owning different types of financial assets is less risky than owning only one kind. Its key insight is that an asset's risk and return should not be assessed by itself, but by how it contributes to a portfolio's overall risk and return. It uses the standard deviation of asset prices as a proxy for risk [36].

In this dissertation, we will apply an analogy between the assets of a financial portfolio and the athletes that are part of the Swiss Sailing Team. For each athlete, we will define the volatility of his/her Race Results and the mean of the distribution. By doing that, we will have the first insight into the contribution that each athlete brings to the whole team.

Within this first approach, we will compute the Sharpe Ratio for each member of the elite Swiss team, in order to examine his/her the performance by adjusting for his/her risk. In finance, as defined originally by William F. Sharpe in 1964 [12], this ratio captures the risk premium (or excess return) per unit of risk.

The second approach stems from a multi-criteria evaluation framework. So, we will dive into the internal Olympic Project Reviews to identify the principal Keep Performance Indicators that SST managers use seasonally to assess the success of their athletes. As a result of this analysis, based on the pieces of evidence reached in Chapter 3, we will offer to the management an algorithm for the interpretation of the athletes' results, and a methodology to set Result Target defined by the predictive model. Then as a conclusion of the full work, by applying a multi-criteria decision analysis approach [14], we will compute some relevant scenarios for the Objective Function we will define in 4.3. To define the Objective Function, we will use a combination of classic Keep Performance Indicators that SST defined historically relevant and newly made indexes designed by the experience collected over this dissertation. The study of the relevant scenarios will identify the contribution of each athlete to the SST success, and simultaneously will offer the possibility to frame new rewarding processes, as proposed by Sornette, Wheatley and Cauwels in *The fair reward problem* [15].

2 Luck Contribution

The first goal we intend to achieve is to define the Luck Contribution in the Olympic Sailing Sport. To do so, we refer to *The Success Equation* of Mauboussin [9]. In the book, the author proposes a methodology to assess the contribution of the luck for a given sports discipline. He applied to several sports and ranked them into a continuum, form pure luck, like the slots machines or the roulette games and pure skills, like it seems to be for chess players.

2.1 Skills-Luck continuum in Sports

As Mauboussin writes in the fourth chapter of *The Success Equation*, the “method for placing activities on the continuum is based on what is known as true score theory. That theory provides a method for measuring the relative contributions of skill and luck. It is essential to emphasize that this is a model of how the world works. We do not ever know what true skill is, and skill changes over time. For example, an athlete gains or loses skill with age. The skill also changes depending on circumstances. For example, a tennis player may be looking into the sun” [9].
The method proposed by the author is based on the following steps:

- “The first step is to consider a sufficiently large number of teams that have played the same number of games”;
- “The second step is to examine each team's performance”;
- “The third step is to calculate the standard deviation of the winning percentages”;
- “The fourth step is to determine what the standard deviation would look like if luck were the only factor in who wins and loses the games.” Given by:

Equation 1

$$Standard\ Deviation\ of\ Luck = \sqrt{p * \left(\frac{1-p}{N}\right)}$$

- “Now that we know two of the three variables in the equation, we can go to the final step, solving for the variance of skill”:

Equation 2

$$Var(Skills) = Var(Observed) - Var(Luck)$$

“This analysis allows us to look at the ratio of variance (luck) to variance (observed) in order to determine the contribution of luck. […] We can use this method to rank sports leagues by the relative contribution of luck in shaping the winning percentages of teams, offering a convenient way to place the leagues on the luck-skill continuum” [9].

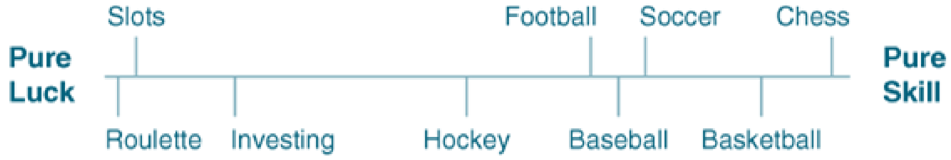


Figure 5: the Skills-Luck continuum, Mauboussin, *The Success Equation* [9].

2.2 Generalization for Olympic sailing

The approach proposed by Mauboussin in his book *The Success Equation* [9] is a method that can be applied to sports based on a seasonal tournament where each team has to play matches that can result only on a win or a loss. Therefore, as we intend to apply the same methodology to sailing, we need to generalize the concept of Luck Contribution to a type of competition where the winner is the athlete or the team that results first after a series of scored races which combined give the overall results. If we compare it with a team sport, such as football, basketball, etc., the probability of being ranked first in a regatta, or at least to win a medal, is strongly affected by the number of the participants. As explained in the first chapter, the ranking of Olympic sailing disciplines is based on the "Low System Point." Therefore we are forced to generalize because a 50-50 chance is not more a valid assumption for the victory of a regatta, and we need to approach the chance of success differently. In sailing, it exists even a "match-racing" format, which is comparable with the team sports tournament. That format would not require this type of generalization, but it is not applied for Olympic Sailing.
Strictly speaking, the winner of a sailing event (regatta), as the Olympic Games, is the athlete or the team who wins the gold medal, which would it gives, once qualified for the Olympic Games, a theoretical chance to win that is equal to:

Equation 3

$$p_{gold\ medal} = \frac{1}{K}.$$

As shown in Figure 2, the number K of teams or athletes attending each event is not constant, but it varies. Therefore the theoretical probability differs for each Olympic event. However, generally speaking, National Sailing Federations are generally chasing medals, so it is reasonable to consider the three medallists as winners. The pure chance to be a medallist is trivially three times larger than the chance of winning the gold. Also, at the Olympic Games, the best eight competitors for each discipline are awarded with the Olympic Diploma. That award is given to the first eight because that is traditionally the size of the finalists' pool in many Olympic sports. As previously mentioned, in Olympic Sailing, the Medal Race is the final battle for the medals, where the best ten boats of each class compete together. Therefore, a broader, more tolerant and less competitive approach could consider all the ten finalists as winners amongst the full fleet of competitors. In this case, the theoretical chance of being a finalist results to be ten times bigger than winning the gold.

2.2.1 Multinomial distribution approach

Swiss Sailing Team and many other National Federations achieve their mission by winning a medal at the Olympic Games or to a World-class event, such as World Cup Series or World Championships. So, for this dissertation, we define that any medal is a victory. Therefore there are three winners per each event. The theoretical definition of that probability is:

Equation 4

$$p_{medal} = \frac{3}{K}.$$

Later, in the dissertation, the theoretical probability p_{medal} will be compared with the mean value of the distribution to evaluate the reliability of this assumption. For now, we can consistently assume that, for a given probability of winning a medal in a single event with an average number of participants $\bar{K}$, the probability of winning n times a medal during N events is given by:

Equation 5

$$\Pr(medal\ n\ times \mid N) = \binom{N}{n}\ p_{medal}{}^{n}(1 - p_{medals})^{N-n}\ .$$

The same type of approach can be repeated for other probabilities, like, for example, to finish the race within the top 10 and therefore to be a competitor of the Medal Race. Then, it can be interesting to consider the probability $p_{4th-10th}$, which represent the probability of being in the Medal Race but not winning any medal. So, we can to compute the probability of being m times in the top 10 without winning a medal and $N - m$ times to be worse during N events with $\bar{K}$ we obtain:

Equation 6

$$\Pr(m\ times\ between\ 4th\ and\ 10th\ and\ N - m\ times\ loss \mid N)$$
$$= \binom{N}{m}\ p_{4th-10th}{}^{m}\ (1 - p_{medal} - p_{4th-10th})^{N-m}\ .$$

So far, we used binomial distributions function, but using a trinomial distribution formulation we can combine the probability of winning n medals, to be m times in the Medal Race without winning the medal and $N - n - m$ times to be worse during N events with $\bar{K}$ competitors, thus obtaining:

Equation 7

$$\Pr(n\ times\ medal, m\ times\ between\ 4th\ and\ 10th\ and\ N - n - m\ times\ loss \mid N)$$
$$= \binom{N}{n, m, N - n - m}\ p_{medal}{}^{n}\ p_{4th-10th}{}^{m}\ (1 - p_{medal} - p_{4th-10th})^{N-n-m}\ .$$

With an increasing level of complexity, in order to carry the most significant amount of information, we can use multinomial distribution function to compute more refined collections of probabilities. In this dissertation, the following set of probabilities has been considered:

- Trinomial:
  - p_{medal}, $p_{4th-10th}$ or worse,
  - p_{top10}, $p_{11th-20th}$ or worse.
- Tetranomial:
  - p_{top10}, $p_{11th-20th}$, $p_{21st-30th}$ or worse.
- Hexanomial:
  - p_{top5}, $p_{6th-10th}$, $p_{11th-15th}$, $p_{16th-20th}$, $p_{21st-25th}$ or worse.
- Octanomial:
  - p_{medal}, $p_{4th-6th}$, $p_{7th-9th}$, $p_{10th-12th}$, $p_{13th-15th}$, $p_{16th-18th}$, $p_{19th-21st}$ or worse.

2.2.2 Matrix form for the Luck Contribution

In *The Success Equation* [9], the author defines the $luck\ contribution$ as the ratio between the variance due to the pure luck, as winning a match or a medal it would be like winning a lottery, and the variance of the observed distribution of the real results.

Equation 8

$$luck\ contribution\ \equiv \frac{Variance\ (luck)}{Variance\ (observed)}\ .$$

However, referring to our n-nomial cases, the variance of the probability distribution is no longer a single number, but it takes the form of a matrix, known as covariance matrix:

Equation 9

$$\boldsymbol{Cov}(p_i, p_j) = \begin{pmatrix} Var(p_1) & Cov(p_1, p_2) & \cdots & Cov(p_1, p_n) \\ Cov(p_2, p_1) & Var(p_2) & \cdots & Cov(p_2, p_n) \\ \vdots & \vdots & \ddots & \vdots \\ Cov(p_n, p_1) & Cov(p_n, p_2) & \cdots & Var(p_n) \end{pmatrix}.$$

Therefore, if we want to extend the definition of the $luck\ contribution$, we need to consider operation between matrix. Thus, we define the $luck\ contribution$ on matrix form $\boldsymbol{L}$ as the multiplication of two square matrices as follow:

Equation 10

$$\boldsymbol{L} \equiv \boldsymbol{Cov}(p_{i_{luck}}, p_{j_{luck}}) \cdot \boldsymbol{Cov}(p_{i_{obs}}, p_{j_{obs}})^{-1}.$$

Where $\boldsymbol{Cov}(p_{i_{luck}}, p_{j_{luck}})$ is the covariance matrix of the n-nomial distribution related to the results due to pure luck and the $\boldsymbol{Cov}(p_{i_{obs}}, p_{j_{obs}})^{-1}$ is the inverse of the covariance matrix of the n-nomial distribution of the real observed results. If it exists, the inverse covariance matrix is also known as the concentration matrix or precision matrix.
Then, to the extent to which we can neglect the off-diagonal values, so under the hypothesis that the $Cov(p_i, p_j) \approx 0$ for each i and j, hence the $\boldsymbol{L}$ assume the form of a diagonal matrix:

Equation 11

$$\lim_{Cov(p_i,p_j)\to 0} (\boldsymbol{L}) = \begin{pmatrix} \frac{Var(p_{1_{luck}})}{Var(p_{1_{obs}})} & 0 & \cdots & 0 \\ 0 & \frac{Var(p_{2_{luck}})}{Var(p_{2_{obs}})} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{Var(p_{n_{luck}})}{Var(p_{n_{obs}})} \end{pmatrix}.$$

In a multinomial case, Equation 10 is the general and matrix case of the $luck\ contribution$ presented by Mauboussin. Then, under certain conditions, it can be approximated to Equation 11, that results to be consistent with the definition shown in Equation 8, which refers to a binomial distribution function only.

2.3 Skills-Luck continuum in Sailing

In order to esteem the position of the Olympic Sailing sport on the Skills-Luck continuum, we have first to identify which events to consider for the observation pool and for which Olympic sailing classes we intend to do so. Swiss Sailing Team required to put the focus on the Swiss elite athletes that compete (or have competed) in the following classes: RS:X, 49er, 470 M, 470 W, Laser Radial, Finn and Nacra 17. Accordingly, we collected all the results of the World-class events occurred after the 2012 Olympics, until the most recent available results. That it means a total of 54 competitions gathering 226 single events in the time window from Dec 2012 to February 2019[11]. That amount of time fully includes the previous Olympic cycle for Rio 2016 and all the available results for the present cycle heading to Tokyo 2020. The list of events includes all the World Cup Series and Finals (formerly known as Sailing World Cup), the World Championships, the Olympic Test Events and the Olympic Games of 2016.

[11] In the following chapters of this dissertation we will refer to Race Results time series that will exted to May 2019. For the computation of the Luck Contribution in Sailing, due to time restriction, we have been able to consider only the events untill and including February 2019.

However, a blind selection of all the World-class events it will appear not entirely appropriate to a sailing expert. In fact, for different reasons, some of the events are not attended by all the competitors, and the level of the competition may strongly vary due to several factors. For example, the World Cup Series and Finals are not always very attractive to the best sailors that want to peak their performance at a specific moment of the season or a specific location. In fact, ravelling the world organizing an expensive logistic is not always beneficial, and some athletes prefer to make an accurate selection of the events to attend, instead than sailing all of those.

2.3.1 Sampling methodology for Races and Athletes

To make this selection, we have looked at the event locations, the number of participants and eventually the quality of them. Therefore, using the principle of the bias-variance trade-off, we identified a set of reliable World-class events to be considered for the Luck Contribution statistical analysis for each class. The full list of the events considered and then selected is available in the Annex.

Olympic cycles	***Rio 2016 – Tokyo 2020***					***Rio 2016***	***Tokyo 2020***
Classes	*RS:X*	*49er*	*470 M*	*470 W*	*Laser Radial*	*Nacra 17*	*Finn*
$\overline{K}$	**42**	**41**	**36**	**25**	**51**	**35**	**36**
$\sigma(K)$	27	26	25	16	29	22	32
$Mo(K)$	40	40	37	23	24	17	26
$\widetilde{K}$	38	38	29	20	40	31	26
$K_{min.\ for\ signif.}$	19	19	21	17	25	17	16
$N_{tot.\ events}$	38	36	39	39	39	23	12
$N_{tot.\ signif.\ events}$	29	28	28	24	31	19	10
$N_{discarted}$	9	8	11	15	8	4	2
$\overline{N}_{signif.\ events}/year$	5	4	4	4	5	5	4
N	**12**	**11**	**11**	**10**	**12**	**12**	**6**

Table 1: descriptive statistical analysis of competitors (K) attendance and World-class relevant event offering viable results. The average, the standard deviation, the mode, and the median are shown in the top rows for each class. $K_{min.\ for\ signif.}$ is the participation threshold to consider an event viable. The $N_{tot.\ events}$ represents the total number of the World-class events collected for each class, then it followed by the partition of significant and discarded events.

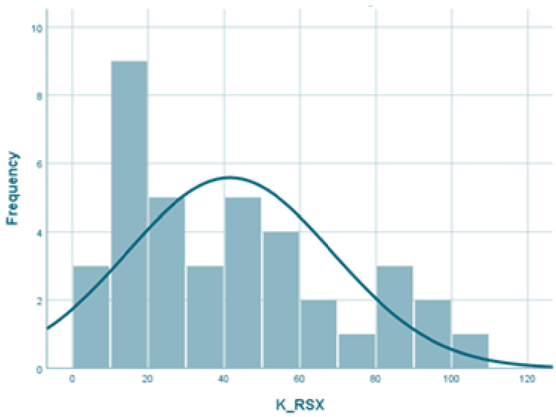


Figure 6: attendance hystogram for RS:X.

Table 1 summarizes a first analysis of the data sampling. We think relevant to explain how we estimated N, the reference number of events to keep in the account for the statistical analysis of the Luck Contribution. We have first evaluated the average number of the viable events that take place per year, then, as computing the ratio of $Var(p_{i_{luck}})$ versus $Var(p_{i_{obs}})$ requires a minimum statistical amount of events to be considered. We have chosen to evaluate the Luck Contribution throughout 2.5 seasons. We had to make an exception of the Finn, where the class is relevant for the Swiss Sailing Team only since the current Olympic cycle. The decision of considering such a period is consistent within the characteristics of the sailing sport discipline.

The top-athletes are generally committed for a full Olympic cycle, and there is not a clear tournament calendar as it is for the other team sports. In sailing, peak international events can happen at any time of the year, depending on the latitude of the event organizer, so selecting only 1 or 2 seasons we risk not to capture enough relevant events.

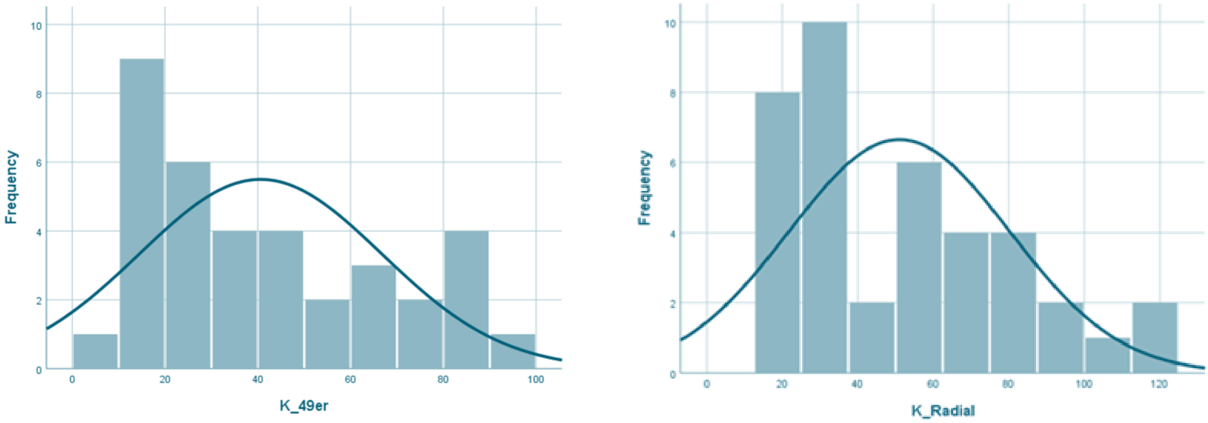


Figure 7: attendance histogram for 49er (left) and Laser Radial (right) for all the collected events.

In Figure 6 and Figure 7, the distributions of the athlete participation in the collected events are shown for three different classes. It is noticeable that events of small size are quite frequent, that because the World Cup Series, the World Cup finals, the Olympic Games and the pre-Olympic test events are closed events, where only specific eligible athletes can attend. The events with many participants are generally Open World Championships that take place in the European continent.

So far, we have found which values to use as N and $\overline{K}$ for each class. Now we need to define a reliable methodology to select the pool of athletes/teams that we intend to use to estimate the $Var(p_{i_{obs}})$. Form now onward, for the double-handed classes, we will consider only one of the two as a representative athlete for the team, so we will carry the helm as it is a common practice in sailing. This choice is not reducing the amount of information available, as the crew doubles the results information which is provided by the helm. However, to select the pool of athletes, we face a challenge that Mauboussin had not to consider. In *The Success Equation* [9], the author always refers to the teams that are within a specific tournament to identify the pool of observation, and the season tournament is effectively closed. In the case of Olympic Sailing, that approach is not possible, because, except for only a few athletes, it is not common to attend to all the events. Therefore, to select the pool of competitors to observe statistically, we studied the frequency of attendance of each athlete in each of the sailing classes that are relevant for SST. Then, we decided to collect all the sailors that attended most of the events within a certain frequency average. The threshold is fixed in order to select a sample of athletes with an average attendance that equals N_i, as it is set for each class i in the Table 1. In the Figure 9 and Figure 8, it is presented how the sampling is performed. The two figures below are representative of all the classes because we found the same repeated behaviour for the others too. Only really few sailors attended approx. 20 events from Dec 2012 to Feb 2019, but a large amount of athlete appeared at least one time to a World-class event, without coming back ever again.

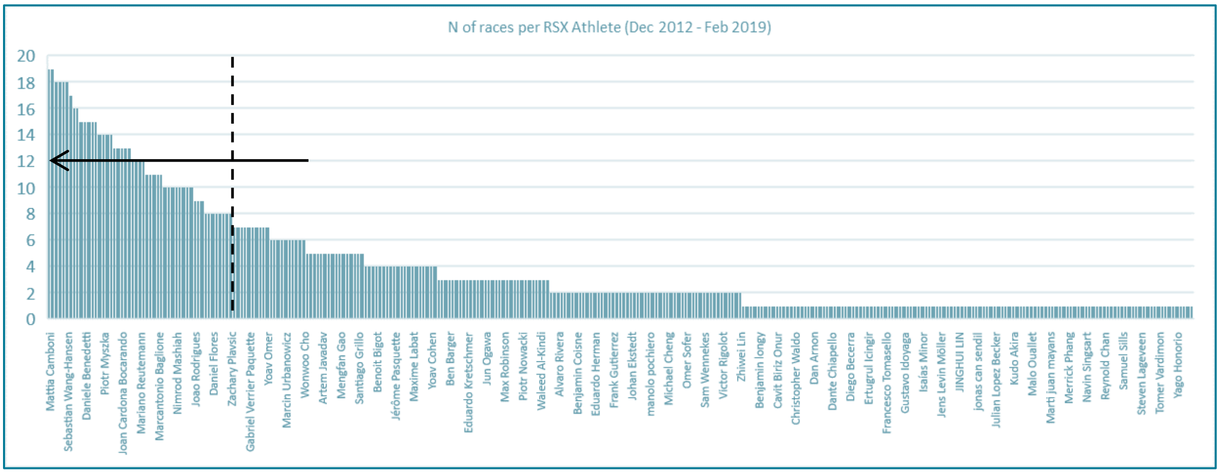


Figure 9: frequency of attendance to World-class races for each RS:X sailor. The black dashed line represent the cut-off and only the athletes on the left have been considered. The black arrows represent the average threshold equals to N that has been applied for this set of athletes.

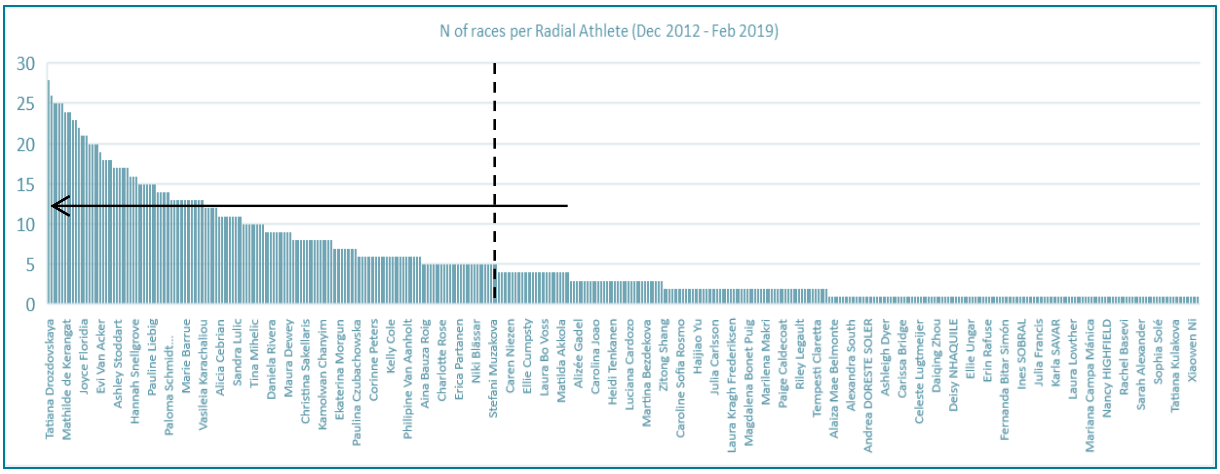


Figure 8: frequency of attendance to World-class races for each Laser Radial sailor. The black dashed line represent the cut-off and only the athletes on the left have been considered. The black arrows represent the average threshold equals to N that has been applied for this set of athletes.

Olympic cycles	***Rio 2016 – Tokyo 2020***					***Rio 2016***	***Tokyo 2020***
Classes	*RS:X*	*49er*	*470 M*	*470 W*	*Laser Radial*	*Nacra 17*	*Finn*
A_{total}	315	266	284	154	338	157	162
$\bar{N}_{attendance}$	12	11	11	10	12	12	6
$A_{selected}$	**51**	**94**	**83**	**68**	**110**	**39**	**37**

Table 2: athlete attending a World-class event at least once, then filtered (to enter the pool) by an average number of the event attended.

The information contained in Table 2 shows the results of the sampling methodology we used to select the pool of athletes to consider for the evaluation of $Var(p_{i_{obs}})$. The complete list of the selected athletes is available in the annex. The sample includes 482 athletes (counting only helms of double-handled boats and each athlete of a single-handled or windsurf) out of a total amount of 1676. With this process of selection, we have a representative sample for our statistical analysis, and for each class, it contains many Olympic medallists, but it collects, as well, many sailors that did not have achieved any type of remarkable result in World-class events.

2.3.2 Estimating the Luck Contribution

In Table 3 and Table 4, the random aleatory probabilities μ_{luck} are computed using Equation 4, where x_i indicates the number of places available in the ranking for each probability listed in the first column and $\bar{K}$ is the average number of participants for the given class at a World-class event already shown in Table 1. The mean values of distributions μ_{obs} are computed filtering the real observed results frequencies in the sample of all the athletes for each class, which are normalized by N. With the comparison of μ_{luck} and μ_{obs} presented in the Table 3 and Table 4, we control if the random probability is actually centred with the mean value of the real data distribution.

Classes	***RS:X***		***49er***		***470 M***		***470 W***	
$\bar{K}$	42		41		36		25	
N	12		11		11		10	
$A_{selected}$	51		94		83		68	
μ_{luck} vs. μ_{obs}	$\frac{x_i}{\bar{K}}$	$\langle\frac{n_i}{N}\rangle$	$\frac{x_i}{\bar{K}}$	$\langle\frac{n_i}{N}\rangle$	$\frac{x_i}{\bar{K}}$	$\langle\frac{n_i}{N}\rangle$	$\frac{x_i}{\bar{K}}$	$\langle\frac{n_i}{N}\rangle$
p_{medal}	0.07	0.10	0.07	0.08	0.08	0.09	0.12	0.11
$p_{4th-6th}$	0.07	0.10	0.07	0.08	0.07	0.09	0.07	0.11
$p_{7th-9th}$	0.07	0.10	0.07	0.08	0.07	0.09	0.07	0.10
$p_{10th-12th}$	0.07	0.10	0.07	0.08	0.07	0.09	0.07	0.10
$p_{13th-15th}$	0.07	0.09	0.07	0.07	0.07	0.08	0.07	0.10
$p_{16th-18th}$	0.07	0.08	0.07	0.07	0.07	0.08	0.07	0.09
$p_{19th-21st}$	0.07	0.06	0.07	0.07	0.07	0.07	0.07	0.08
p_{top5}	0.12	0.17	0.12	0.13	0.14	0.15	0.20	0.18
$p_{6th-10th}$	0.12	0.20	0.12	0.13	0.14	0.14	0.20	0.17
$p_{11th-15th}$	0.12	0.12	0.12	0.15	0.14	0.14	0.20	0.17
$p_{16th-20th}$	0.12	0.12	0.12	0.12	0.14	0.13	0.20	0.14
$p_{21st-25th}$	0.12	0.13	0.12	0.10	0.14	0.12	0.20	0.11
$p_{4th-10th}$	0.17	0.23	0.17	0.18	0.19	0.20	0.28	0.24
p_{top10}	0.24	0.33	0.24	0.26	0.28	0.29	0.40	0.35
$p_{11th-20th}$	0.24	0.27	0.24	0.25	0.28	0.31	0.40	0.31
$p_{21st-30th}$	0.24	0.18	0.24	0.19	0.28	0.21	0.20	0.19

Table 3: random aleatory probability related to the pure luck computed using $\bar{K}$ is compared with the mean value distribution for RS:X, 49er, and 470 Men and Women results

Classes	Laser Radial		Nacra 17		Finn	
$\overline{K}$	51		35		36	
N	12		12		6	
$A_{selected}$	110		39		37	
μ_{luck} vs. μ_{obs}	$\frac{x_i}{\overline{K}}$	$\langle\frac{n_i}{N}\rangle$	$\frac{x_i}{\overline{K}}$	$\langle\frac{n_i}{N}\rangle$	$\frac{x_i}{\overline{K}}$	$\langle\frac{n_i}{N}\rangle$
p_{medal}	0.06	0.07	0.09	0.12	0.08	0.12
$p_{4th-6th}$	0.07	0.07	0.07	0.12	0.07	0.12
$p_{7th-9th}$	0.07	0.07	0.07	0.10	0.07	0.11
$p_{10th-12th}$	0.07	0.07	0.07	0.10	0.07	0.10
$p_{13th-15th}$	0.07	0.06	0.07	0.09	0.07	0.09
$p_{16th-18th}$	0.07	0.06	0.07	0.08	0.07	0.10
$p_{19th-21st}$	0.07	0.06	0.07	0.07	0.07	0.07
p_{top5}	0.10	0.12	0.14	0.19	0.14	0.20
$p_{6th-10th}$	0.10	0.11	0.14	0.18	0.14	0.18
$p_{11th-15th}$	0.10	0.11	0.14	0.16	0.14	0.17
$p_{16th-20th}$	0.10	0.11	0.14	0.13	0.14	0.14
$p_{21st-25th}$	0.10	0.10	0.14	0.08	0.14	0.09
$p_{4th-10th}$	0.14	0.16	0.20	0.26	0.19	0.26
p_{top10}	0.20	0.23	0.29	0.37	0.28	0.38
$p_{11th-20th}$	0.20	0.21	0.29	0.29	0.28	0.31
$p_{21st-30th}$	0.20	0.18	0.29	0.16	0.28	0.13

Table 4: random aleatory probability related to the pure luck computed using $\overline{K}$ is compared with the mean value distribution for Laser Radial, Nacra 17 and Finn results.

Now, to verify that the random distribution centred on μ_{luck} can be used as a reference to evaluate the $\mathrm{Var}(p_{i_{luck}})$, we need to verify that μ_{luck} properly approximate to μ_{obs}. From this comparison, we can notice that the theoretical values are not always matching the observed values. So, it means that $\overline{K}$ is not a representative value to define the aleatory probabilities. Therefore, due to this discrepancy, to perform a correct evaluation of the Luck Contribution in Olympic Sailing, we have to redefine the probabilities p_i using the mean value of the distributions μ_{obs} as follow:

Equation 12

$$p_i = \langle\frac{n_i}{N}\rangle = \mu_{obs_i} .$$

The variance and covariance of the distributions due only to pure luck will be then so computed:

Equation 13

$$\mathrm{Var}(p_{i_{luck}}) = p_i(1-p_i)N = \langle\frac{n_i}{N}\rangle\left(1-\langle\frac{n_i}{N}\rangle\right)N;$$

Equation 14

$$\mathrm{Cov}(p_{i_{luck}}, p_{j_{luck}}) = -\frac{p_i\, p_j}{N} = \frac{\langle\frac{n_i}{N}\rangle\,\langle\frac{n_j}{N}\rangle}{N}.$$

At that stage, we have all the elements for the trinomial and multinomial Luck Contribution estimation finally. Regarding the trinomial case, we analyzed two sets of probabilities: p_{medal}, $p_{4th-10th}$ or worse, and p_{top10}, $p_{11th-20th}$ or worse.

Equation 15

$$\boldsymbol{L}_{\boldsymbol{Class_i}}(p_{medal}, p_{4th-10th}) = \begin{cases} \boldsymbol{L}_{\boldsymbol{RS:X}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 31\% & -14\% \\ -27\% & 32\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 22\% & 0\% \\ 0\% & 32\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{49er}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 29\% & -12\% \\ -25\% & 29\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 20\% & 0\% \\ 0\% & 20\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{470\,M}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 15\% & -8\% \\ -13\% & 24\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 11\% & 0\% \\ 0\% & 19\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{470\,F}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 21\% & -10\% \\ -18\% & 23\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 15\% & 0\% \\ 0\% & 17\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Radial}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 29\% & -10\% \\ -20\% & 27\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 12\% & 0\% \\ 0\% & 18\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Nacra\,17}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 22\% & -10\% \\ -17\% & 26\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 18\% & 0\% \\ 0\% & 21\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Finn}}(p_{medal}, p_{4th-10th}) = \begin{pmatrix} 60\% & -28\% \\ -46\% & 75\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 49\% & 0\% \\ 0\% & 62\% \end{pmatrix} \end{cases}$$

Equation 16

$$\boldsymbol{L}_{\boldsymbol{Class_i}}(p_{top10}, p_{11th-20th}) = \begin{cases} \boldsymbol{L}_{\boldsymbol{RS:X}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 13\% & -20\% \\ -6\% & 42\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 12\% & 0\% \\ 0\% & 42\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{49er}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 14\% & -17\% \\ -9\% & 36\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 12\% & 0\% \\ 0\% & 33\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{470\,M}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 13\% & -15\% \\ -10\% & 25\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 9\% & 0\% \\ 0\% & 20\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{470\,F}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 10\% & -17\% \\ -6\% & 33\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 9\% & 0\% \\ 0\% & 32\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Radial}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 13\% & -16\% \\ -10\% & 33\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 9\% & 0\% \\ 0\% & 27\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Nacra\,17}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 12\% & -30\% \\ -7\% & 56\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 11\% & 0\% \\ 0\% & 55\% \end{pmatrix} \\ \boldsymbol{L}_{\boldsymbol{Finn}}(p_{top10}, p_{11th-20th}) = \begin{pmatrix} 28\% & -17\% \\ -7\% & 45\% \end{pmatrix} \xrightarrow[]{\lim\limits_{Cov(p_i,p_j)\to 0}} \begin{pmatrix} 31\% & 0\% \\ 0\% & 47\% \end{pmatrix} \end{cases}$$

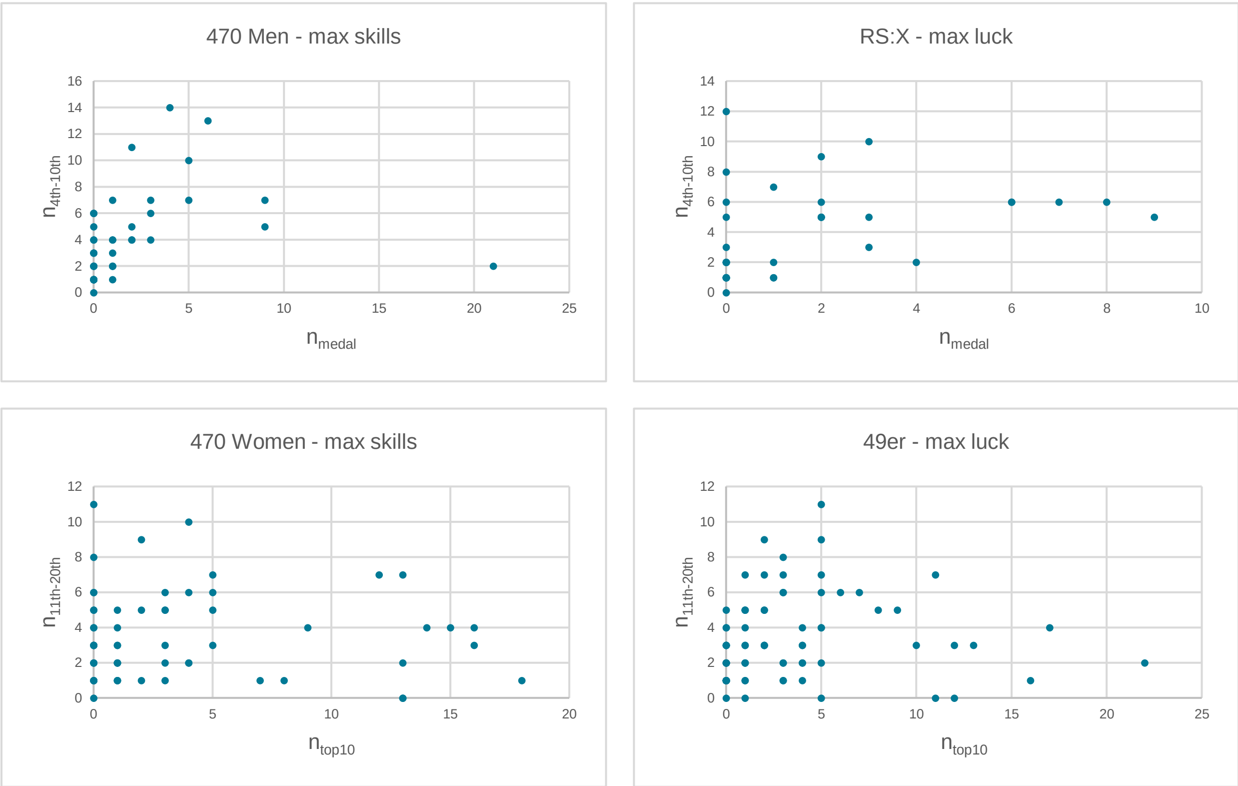


Figure 10: study of the correlation between the observed values for n_i which correspond to the results obtained by the athletes during the events. The two upper plots correspond to the trinomial distribution p_{medal}, $p_{4th-10th}$ or worse and the two lower plots to the p_{top10}, $p_{11th-20th}$ or worse. In both cases, it's possible to see that many data lay on the vertical axis. These data correspond respectively to the athletes that have achieved a top 10 results, but not a medal, and then those athletes that have been in the top 20, but never in the top 10. On the horizontal axis, only few data points are available. In the upper case, these would be athletes that are only winning medals, but this is not the case for 470 Men and RS:X. In the lower row, we see some data laying on the horizontal axis, these are the athletes that have been ranked only in the top 10. The data in the origin of the axis represent all the athletes that are worse than any of the other above-mentioned cases. Then, the two right graphs show data that are more spread in respect of the two on the left, this is in line with a larger contribution of the luck in the results.

Interpretation

Looking at the results shown in Equation 15 and Equation 16, we can highlight the following findings.
First, in both cases, the $\boldsymbol{L_{Finn}}$ estimation is over the double than any other class. This estimation may occur because, for the Finn class, the number of events considered is smaller and so statistically less significant than the others. In this regard, we do not have to forget that the data collected for the Finn class are referred only to the Tokyo 2020 Olympic cycle, which is currently only halfway.
Second, $\boldsymbol{L_{Nacra\,17}}$ refers to data collected over a full Olympic cycle (Rio 2016) and shows values which are reasonably in line with the five classes where we have results collected over 2 Olympic cycles. This fact would let us assume that a four-year period produces already a reasonable estimation of the Luck Contribution in sailing.
Third, if we compare the $\boldsymbol{L_{Class_i}}$ for $(p_{top10}, p_{11th-20th})$ with the one estimated for $(p_{medal}, p_{4th-10th})$, we notice that the case in which we consider the top 10 and then the second 10 boat ranked, the contribution of the luck is always smaller. As shown in Equation 13, the $\mathrm{Var}(p_{i_{luck}})$ depends by $p_{i_{luck}}$ and the smaller is the probability, the smaller is $\mathrm{Var}(p_{i_{luck}})$. Then, for a fixed observed sample, the more the $\mathrm{Var}(p_{i_{luck}})$ is becoming similar to $\mathrm{Var}(p_{i_{obs}})$, the propagated error becomes the larger.
Fourth, keep comparing the two trinomial cases $(p_{top10}, p_{11th-20th})$ and $(p_{medal}, p_{4th-10th})$, we can see (except for the 49er and Radial class) that the contribution of the luck is always smaller for the top ranking. This fact leads us to assume that an increasing amount of skills are required to be on the top of the ranking, despite the complexity of the sport and the aleatoriness of the marine conditions. In 49er and Radial, the extreme level of competitiveness may contribute to not differentiate the skills level within the top 10.

Last, the roles that the $\mathrm{Cov}(p_i, p_j)$ entries play in the matrix $\boldsymbol{L_{Class_i}}$ is not investigated in this dissertation. What we can notice from Equation 15 and Equation 16 is that, neglecting the $\mathrm{Cov}(p_i, p_j)$, the estimation of the Luck Contribution results to be always smaller. So, for this study, where we intend to evaluate the contribution of luck in the discipline to predict later the opportunity of achieving a targeted result starting from a given situation, a minimal evaluation is therefore conservative but appropriate.

The interest of the Swiss Sailing Team is to assess the minimal contribution of luck in a competition result, this because the interest is to esteem how better can appear an athlete during a lucky World-class event. For performance and result-driven sports federation, knowing the minimal Luck Contribution is an element to set appropriate targets and to identify the best possible conservative scenario. Conversely, we could decide to evaluate the maximal Luck Contribution, but the behaviour of a sports manager would not reflect that. For sports people, the principle of the "5P" (Proper Planning Prevents Poor Performance and all the other declinations) is dogma, and the attitude is not to play the roulette.
Therefore, we assume valid to simplify the multinomial approach, by considering only the elements on the diagonal of the $\boldsymbol{Cov}(p_i, p_j)$ matrix, which corresponds to neglect the contribution of the $\mathrm{Cov}(p_i, p_j)$. This methodology leads to a minimal estimation of the luck contribution for the tetra-, hexa- and octanomial cases. The results obtained with Equation 11 are summarized in the Tables below.

Prob.	$\boldsymbol{p_{top10}}$	$\boldsymbol{p_{11th-20th}}$	$\boldsymbol{p_{21st-30th}}$
RSX	12%	42%	55%
49er	12%	33%	51%
470M	9%	20%	51%
470F	9%	32%	60%
Radial	9%	27%	42%
Nacra17	12%	55%	45%

Table 5: here reported all the elements on the diagonal of each $\boldsymbol{L_i}$ matrix for tetranomial distribution. The percentages have been calculated as presented in Equation 11, where all the off-diagonal $\mathrm{Cov}(p_i, p_j)$ have been neglected.

Prob.	$\boldsymbol{p_{top5}}$	$\boldsymbol{p_{6th-10th}}$	$\boldsymbol{p_{11th-15th}}$	$\boldsymbol{p_{16th-20th}}$	$\boldsymbol{p_{21st-25th}}$
RSX	18%	42%	52%	55%	45%
49er	17%	30%	38%	58%	72%
470M	10%	30%	34%	49%	79%
470F	11%	27%	50%	45%	70%
Radial	10%	27%	48%	43%	70%
Nacra17	16%	32%	46%	106%	54%

Table 6: here reported all the elements on the diagonal of each $\boldsymbol{L_i}$ matrix for hexanomial distribution. The percentages have been calculated as presented in Equation 11, where all the off-diagonal $\mathrm{Cov}(p_i, p_j)$ have been neglected.

Prob.	p_{medal}	$p_{4th-6th}$	$p_{7th-9th}$	$p_{10th-12th}$	$p_{13th-15th}$	$p_{16th-18th}$	$p_{19th-21st}$
RSX	22%	44%	40%	89%	82%	67%	80%
49er	20%	28%	52%	54%	56%	71%	69%
470M	11%	31%	43%	41%	42%	54%	86%
470F	15%	29%	46%	39%	73%	49%	69%
Radial	12%	28%	41%	52%	62%	66%	53%
Nacra17	17%	34%	43%	67%	69%	87%	113%

Table 7: here reported all the elements on the diagonal of each $\boldsymbol{L_i}$ matrix for octanomial distribution. The percentages have been calculated as presented in Equation 11, where all the off-diagonal $\mathrm{Cov}(p_i, p_j)$ have been neglected.

In Table 5, Table 6, and Table 7, we can remark again that the smaller is the probability analyzed, the more significant the role of the luck appears. For example, if we want to be ranked in an interval of only 3 places instead of a range of 5 or 10 places, it is possible to understand how more luck can be involved, now that we have three different multinomial approaches to compare. It can be noted that we decided not to bring forward the Finn class in this evaluation because already at the first stage the statistic sample was too small to hold in terms of reliability of the statistical analysis. Now, with this further analysis, it appears that the Nacra 17 class, which carries data related only to the past Olympic cycle, start to show some contradiction. So, if for the trinomial approach, it seemed that the data were enough, here the smaller number of total events considered shows its limits. However, it is consistent through all the classes, the trend that the higher is the position in the ranking the lower is the contribution of the luck.

Preliminary conclusions

The goal of this chapter was to define where to position Olympic Sailing in the Skills-Luck continuum. First, we had to generalize the approach of Mauboussin to a multinomial matrix format. Then we identified a methodology to collect our sample of events, results, and athlete to analyze. Moreover, last, we presented the Luck Contribution for different sets of probabilities. The outcome of the results shows that the role of the luck in the sailing sport can be appropriately evaluated only if the sample of the available results is big enough. Then, depending on the set of probability used in the multinomial distribution, the percentage of Luck Contribution may vary with an inverted proportionality to the size of the probability. Mauboussin considers only 50-50 probabilities; in our cases, the larger theoretical probability considered is about 0.3 or 30%. However, focusing the attention on the five classes where we have the data from Dec. 2012 to Feb 2019, we can consistently notice that to be in the top 10, the minimal luck contribution settles between 9% and 10%. Overall, for the top 3 positions, the highest luck contribution is 22% in the RS:X. So we can generalize this trend, concluding that the Olympic Sailing sport has a minimal Luck Contribution within a range from 10% to 20%. That would rank this discipline on the skilled end side of the continuum. In comparison with other professional sport disciplines, Olympic Sailing has a Luck Contribution like National Basketball Association (NBA), and it is less influenced by randomness than many others like Premier League, Major League Baseball, NFL or NHL.

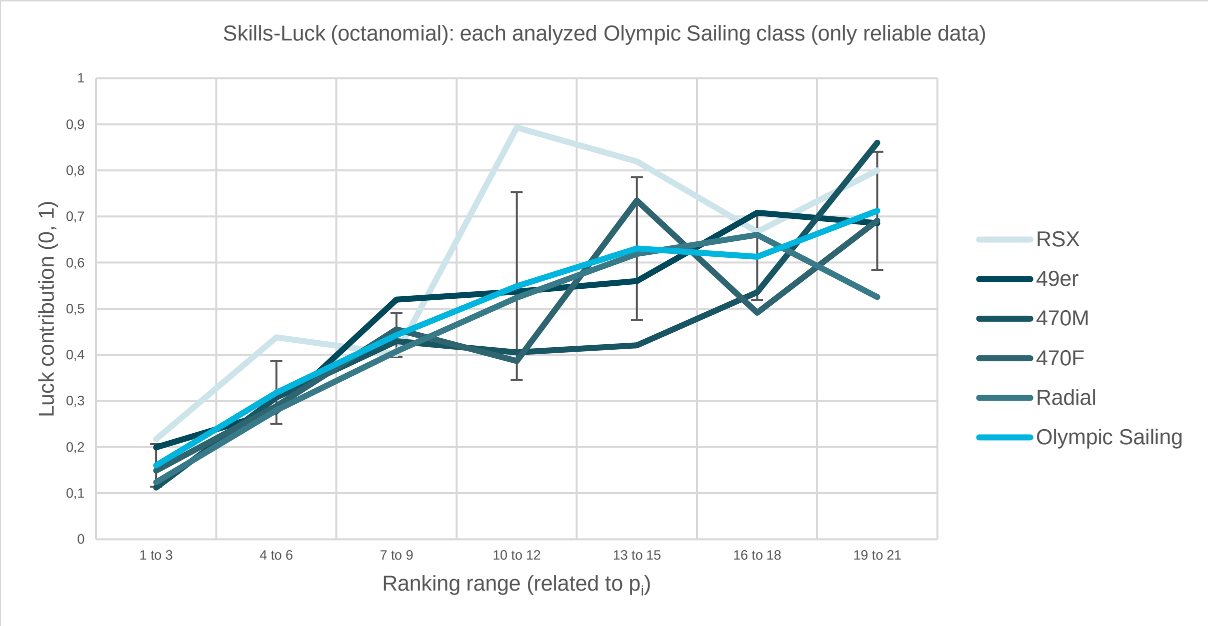


Figure 11: graphical representation of all the elements on the diagonal of each $\boldsymbol{L_i}$ matrix, that can be seen as the minimal Luck Contribution for each set of 3 places in the ranking. The graph clearly shows that the Luck Contribution is at its minimum for the highest position in the ranking, so more skills are required to be closer to the medals. The light blue line shows the average for five of the seven analyzed classes, Finn and Nacra 17 have been discarded during the analysis process. The error bars represent the standard deviation of the average. The achievement of an Olympic medal requires a Luck Contribution within a range from 10% to 20%.

3 Race Results and Performance

In this chapter, we will analyze the trend of the Race Results achieved by the Swiss Sailing Team elite athletes from January 2013 until now, May 2019[12]. We aim to give a thorough interpretation of the trend of the results in competition, including the conclusions concerning the Luck Contribution presented in Chapter 2. Then we will explore the Swiss Sailing Team Performance Development Process; this is an internal online form that has been introduced in 2016 as a self-assessment and analysis tool for the elite and junior Swiss athletes. At the end of this Chapter, we will use the available data to build a predicting model to offer a managerial tool for improving over the time the Race Results of the Sailing National Team as a whole. The complete set of results are reported in the Annex.

3.1 Modelling the Luck Contribution

In 2.3, we concluded that the luck contributes to winning a medal for a range of 10% to 20% on the final results of an Olympic Sailing World-Class event. Also, we saw that the percentage is inversely proportional to the number of places that we considered for the intervals of the multinomial distribution. Based on these conclusions, we intend to model a contribution of luck that can be inferred to any of the ranking places. The Luck Contribution is a value on a continuum between 0 and 1, as it can be 0% if the sport is entirely skill based or 100% if the game is totally aleatory like a lottery draw. Therefore, we need to identify an interpolating function that can generally respect this range within the interval of ranking places we intend to investigate.

From Figure 11 of Chapter 2, we see a trend that shows the Lack Contribution decreasing with the ranking, so the more skilled a sailor is, the less affected by luck the athlete will be. At the same time, it is not possible to assume that the Luck Contribution increases linearly with the ranking because soon the Luck Contribution will overtake 1 and the Sailing Sport would become merely a lottery, which it has trivially denied by a reality check approach. As the Skills-Luck continuum methodology proposed by Mauboussin is not yet developed in scientific literature, we have to assume to model the Luck Contribution in the function of the Ranking. In our case, we are assuming the following behaviour:

Equation 17

$$Luck\ Contribution = \alpha + \beta\ Log(Rank).$$

This approach gives us the possibility to fit accurately the data already presented in Figure 11 and to remain with the constraints mentioned here above. In the previous section 2.3, we focused on three multinomial cases, and here we apply the modelling to all the 3 cases, one it will be valid for the top rankings (ref. Table 7), and it will represent the maximal contribution of luck (later named Max). Then we will have other two cases, one intermediate (later named Mid – ref. Table 6), to model the Luck Contribution within the range from Top10 to Top20 and then another that can be extended to the range of results beyond the 20th place (later named Min – ref. Table 5). Figure 12 shows the fitting to the data of the three different modelling approaches.

[12] In Chapter 2, we mentioned a period from December 2012 to February 2019. Here we are considering only the results for the Swiss sailors and none of them attended the World Class event in Melbourne in December 2012, so we started from January 2013. Then, during the elaboration of this dissertation, it took place the World Cup Series in Genoa during the month of April 2019. Therefore, the time series of the results for the Swiss Sailors ends in May 2019.

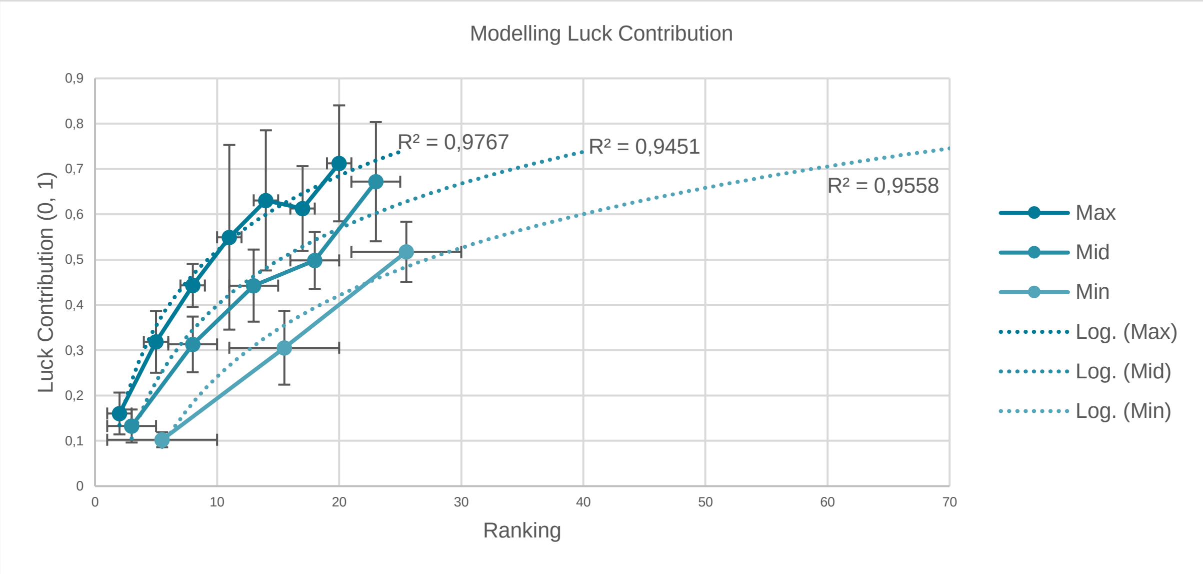


Figure 12: based on the findings of Chapter 2, resumed in Table 5, Table 6 and Table 7 and then shown in Figure 11, here we represent three models for the Luck Contribution as a function of the place in the Ranking. Each model is valid within a different range of ranking. The Max considers intervals of 3 places (represented by horizontal error bars), and it is assumed valid up to the 25th place. The Mid models the intervals of 5 places, and it is assumed valid up to the 40th place. Then, the Min covers intervals of 10 places, the validity is assumed from the 5th place to the 70th. Vertical error bars represent the standard deviation of the relative sample, based on the data presented in 2.3.

3.2 Race Results as Learning Curves

Now that we have set an assumption for the Luck Contribution in the function of the ranking, we can start to shift the focus on the Race Results of the elite Swiss athletes. In fact, in this subchapter, we intend to investigate the time series of the results in the competitions of each single athletes and identify a reasonable way to understand the trend. This behaviour will be then the ground to build the predicting model.

As we previously stated, the Olympic Sailing Sport is a skill-based sport, and the previous discussion helped to understand this concept. Therefore, we expect that, over an interval of time, an athlete, that has appropriately worked to improve his/her skills, should experience an improvement in the results. Within the fluctuation due to the non-controllable variables, that assumption holds if the other competitors, so the external environment to compete against, have improved little less (or if a competitors' turnover kept constant the average skills of the sailing fleet). In fact, for an athlete, to see the results to get better is a matter of rate of improvements, which has to be higher than the average.

Equation 18

$$Rate\ of\ Improvement_{personal} = \frac{Rank(t_0) - Rank(t_1)}{(t_1 - t_0)} > Rate\ of\ Improvement_{fleet}$$

Concerning the literature The Learning Curve and Competition [31] and Toward a Theory of Continuous Improvement and the Learning Curve [10], whenever there is a process of improvement with successive refinements, we can assume a law of diminishing returns, because it will generally be harder to improve further. In this dissertation, we are looking at the results of elite Swiss sailors, which are on the young side of the age distribution percentiles of the sailing Olympic competitors. However, they have more than a decennial sailing experience at a high level and at least 5-years long experience in an Olympic class. Therefore, we can expect that they are not yet at their learning plateau, but simultaneously that it will be not that simple to keep improving at a high rate.

Assuming a law of diminishing returns for the time-dependent evolution of the race results, it gives us the possibility to interpret the trend of the Racing Results with a power law of the following form:

Equation 19

$$Rank(t) = a * t^{-k} + \varepsilon ;$$

Where ε is the Race Result volatility. So, by using Equation 19 as the interpolating function, three examples follow. The first (Figure 13) is concerning an athlete with about 10-years of experience on his Olympic Class. The second (Figure 14) is a team that started the Olympic Campaign for Rio 2016 only in 2014, after a remarkable junior career in other classes. Then, the third (Figure 15) example is about a team of newcomers in the Olympic World-Class scene after a long career as juniors in the same sailing class, now willing to attend for the first time the Olympic Games in Tokyo 2020.

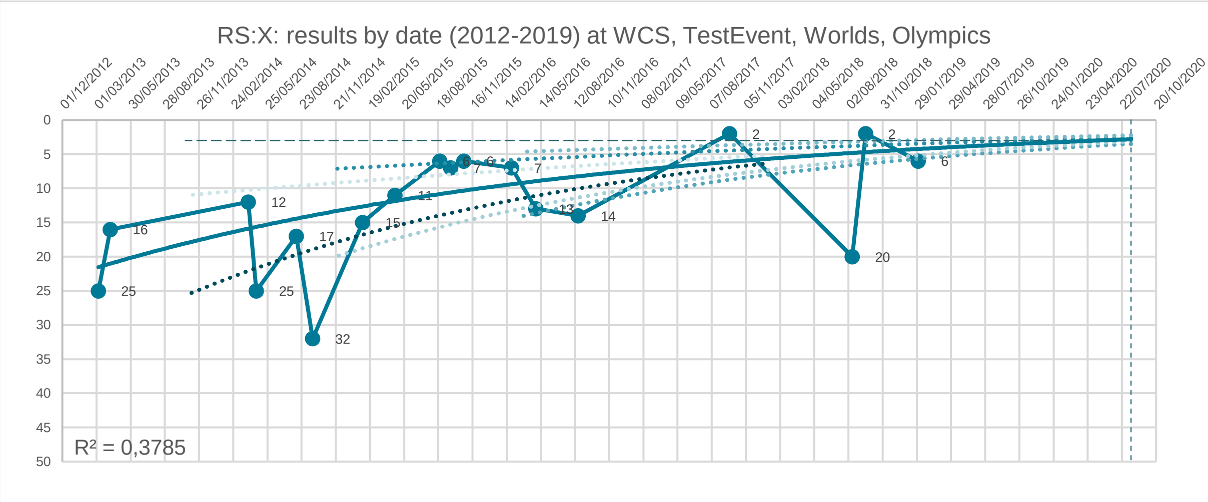


Figure 13: race results of RS:X Swiss athlete, the horizontal dashed line represents the bronze medal target result. The vertical dashed line is the date of the Tokyo 2020 Olympic games. The bold power law line (Equation 19) interpolates the time series of the results. The three dotted lines above the trendline represent the Good luck contribution, respectively corresponding (from outer to inner) to the Max, the Mid and the Min Luck Contribution modelling. The three dotted lines below the trendline represent the Bad luck contribution, respectively corresponding (outer to inner) to the Max, the Mid and the Min Luck Contribution modelling.

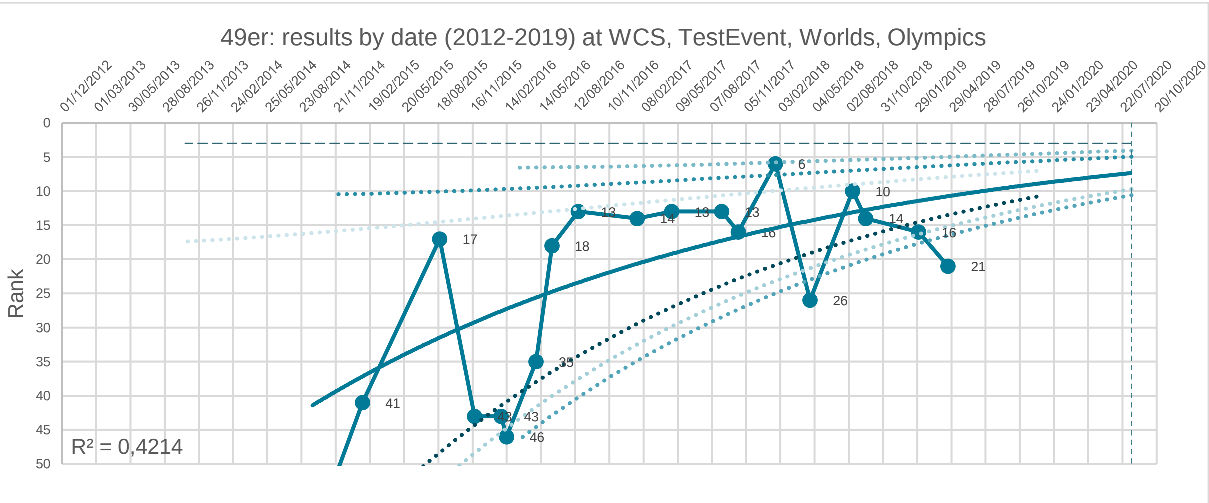


Figure 14: race results of the 49er Swiss team, the horizontal dashed line represents the bronze medal target result. The vertical dashed line is the date of the Tokyo 2020 Olympic games. The bold power law line (Equation 19) interpolates the time series of the results. The three dotted lines above the trendline represent the Good luck contribution, respectively corresponding (from outer to inner) to the Max, the Mid and the Min Luck Contribution modelling. The three dotted lines below the trendline represent the Bad luck contribution, respectively corresponding (outer to inner) to the Max, the Mid and the Min Luck Contribution modelling.

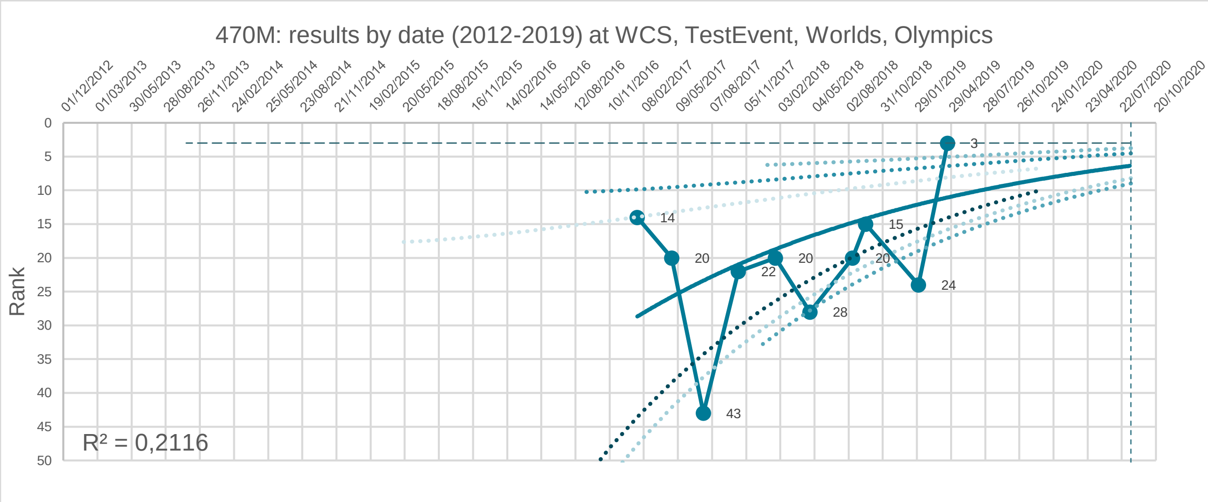


Figure 15: race results of 470M Swiss Team, the horizontal dashed line represents the bronze medal target result. The vertical dashed line is the date of the Tokyo 2020 Olympic games. The bold power law line (Equation 19) interpolates the time series of the results. The three dotted lines above the trendline represent the Good luck contribution, respectively corresponding (from outer to inner) to the Max, the Mid and the Min Luck Contribution modelling. The three dotted lines below the trendline represent the Bad luck contribution, respectively corresponding (outer to inner) to the Max, the Mid and the Min Luck Contribution modelling.

Interpretation

From Figure 13, Figure 14, and Figure 15, we can intuitively notice that the learning curve differs for each sailor or team. Also, it depends on the experience collected and on the range of the obtained results. Therefore, we can soon understand that the learning curve is not static over time, but it evolves. The higher in the rank, the harder will be the improvement. Within the data collected for this dissertation, we had the opportunity to analyze the time series of 14 different Swiss Sailing Team members, sailing on 9 different boats of 6 different sailing classes. In two cases we have observed results trendlines that reached a plateau, in one of the two cases, the plateau was reached in the proximity of the bronze medal result target line and, in the other case, it was far from that target.
In other two cases, we have that strong junior teams, that entered the World-Class Series recently, are showing steeper learning curve, as they can presumably transfer part of their previous experience and in the meanwhile learn the new technical skills that the new category of age requires.
Also, the trendline based on the power law presented in Equation 19, can predict the achievement of the bronze medal result target. This prediction would tell us that one of the athletes in the three examples above is expected to achieve a medal within the next Olympic time horizon. Then, even if improving faster, the other two (49er and 470M) start from a position in the ranking that is too far from the top to reach the Top3 result target within August 2020. However, from the statistical point of view, the R^2 values are small to predict the next results with a high level of confidence. That is due to the significant volatility of the Race Results that we will discuss in a detailed manner in Chapter 4. Anyhow, from a managerial point of view, treating the time series of the results as a learning curve is very useful to understand the improvement rate of each boat in the Swiss team.

Here we want to focus on the Luck Contribution, so if the modelling assumption is holding, a large portion of the volatility, it could be graphically explained by the contribution of the luck.
Besides, observing the available data, we understand that the power law fitting function is characterizing each athlete and his/her presumable evolving trend. In fact, the interpolating curve may slightly change with every new result. That it happens because, on one side, the improvement rate of each athlete is influenced by several factors, which we will analyze later. Moreover, on the other side, the average rate of improvement of the fleet can increase or decrease too. Therefore, we can reformulate the Equation 19, with a power law where the parameters a and k are time dependent and the contribution of the luck (as presented in Chapter 2) is explicitly expressed as part of the volatility term. So, a more general form is:

Equation 20

$$Rank(t) = a(t) * t^{-k(t)} + \varepsilon_{Luck} + \dot{\varepsilon}.$$

However, for this dissertation, this dynamic version of the power law for the Race Results is too complex to be correctly handled with the available data.

Interpretation

The learning curve that characterizes each athlete should be monitored continuously or at least periodically (every 6 months or 1 year maximum). Then, the prediction on the long term it can give a hint of what the athlete can achieve, even if it remains influenced by each new result, mainly if the level of volatility is high.

In order to compare the success in competition of the different Swiss sailor, we can perform a linearization of Equation 19. This process would allow us to compare, on a Log-Log scale, the rate of improvement of each athlete. Therefore, neglecting the temporarily the term ε, the Equation 19 becomes:

Equation 21

$$Log(Rank) = Log(a) + k * Log(t).$$

Using this expression, we can perform quantitative analysis for the Race Result of each of the elite Swiss sailors (Figure 16).

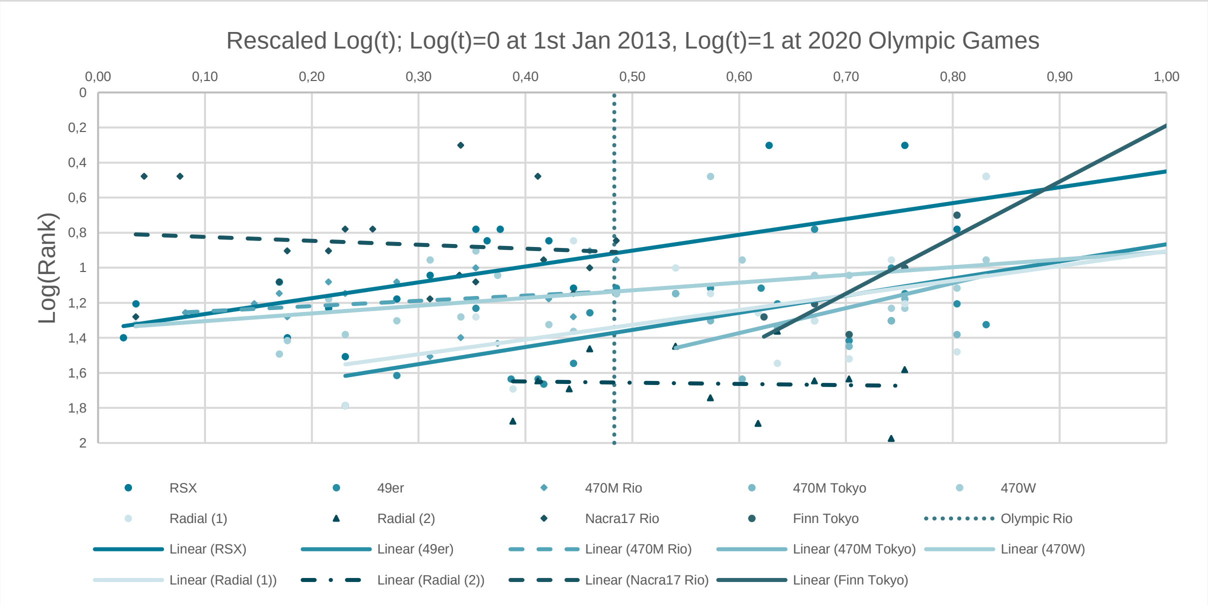


Figure 16: 9 different Swiss boats are analyzed here. The dotted vertical line represents the time of the Rio 2016 Olympics. Dashed lines represent the linear interpolation for Log(Rank) of the boats that attended to the Rio 2016 Olympics only, and stopped after it. The solid lines represent the linear interpolation for Log(Rank) of the teams that are trying to qualify for Tokyo 2020. Some of them (RSX, 49er, 470W) attended to Rio 2016. Conversely, the dash-dotted line represents an elite athlete that is no longer part of the SST. Lines with downward slope mean that the results are degrading over time, upward slopes represent an improvement in the results. Athletes that entered the Olympic scene later tend to have a steeper line, but we have to account that they are not yet at a mature stage of their learning curve, which can slow down over time as in Equation 20.

With the information condensed in Figure 16, we can offer a synthesis of the analysis, presented in Table 8, for the Swiss sailors that are competing now for their participation to (and ultimately their result) at the next Olympic Games.

Class	Current predicted rank (May 2019)	Latest Result (Jan-Apr 2019)	Delta	Current Rate of improvement	Relative speed of improvement	Potential Tokyo 2020
RSX	4	6	-2	0,00432	Slow	Medal - Top 3
49er	11	21	-10	0,01293	Moderate	Diploma - Top 8
470M	10	3	7	0,02382	Fast	Diploma - Top 8
470F	10	9	1	0,00413	Slowest	Diploma - Top 8
Radial	11	3	8	0,01087	Moderate	Diploma - Top 8
Finn	5	6	-1	0,06412	Fastest	Medal - Top 3
SST Average	**8,5**	**8**	**0,5**	**0,02003**	**Fast**	**Top 6**

Table 8: synthesis of Race Result analytics. The current predicted rank is the value obtained by the linear regression performed on the data set for each Swiss boat running for Tokyo2020. Then the predicted value is compared with the latest available results. The rate of improvement is computed as defined in Equation 18, on a time window of 1000 days, from the time of 2016 Olympics until now. The relative speed of improvement is a qualitative interpretation of the rate. Finally, the potential is the projection into the future, assuming that the power law (learning curve) is constant in time.

With Table 8, we offer a condensed snapshot of the overall result trend picture. First, even if there are some individual fluctuations, the delta between the latest results and the predicted results is pretty well represented as team average. Then, we can assert that currently, each team has a positive rate of improvement, some improving faster other less. Finally, looking at the potential, a couple could achieve the medal result target. Later in 4.2.1, we will offer a tool to understand the reasons for the deltas that are reported in Table 8.

Preliminary conclusion

From the managerial point of view, these intermediate results offer already very interesting insights, for example, it is possible to understand if the rate of improvement is good enough to reach the desired targets, and it can be possible to define shorter-term targets to validate the learning curve. Besides, the prediction of the results based on an individualized learning curve could help to assign SMART[13] Results Targets. Otherwise, it is possible to use the relative speed of improvement to reward the sailors for their achievement, without being trapped in the volatility of each result, which can lead to the wrong conclusions. Eventually, this type of analysis repeated periodically; it would give the possibility to the management to measure the acceleration in the improvement, which would be a relevant quantity to understand and model the athlete’s learning curve evolution, as proposed in Equation 20.

3.3 Predicting model for Race Results

Until now, we have debated only about the results. Doing that, we have looked at the contribution of the luck, and then we have fitted the data with a power law learning curve, and we have looked at some properties of the linearized model. From now onwards, we intend to analyze, interpret and draw some conclusions for the managerial purpose about the factors that can cause and contribute to the success of the sailing team.

[13] Specific, Measurable, Achievable, Relevant, Time-bound

3.3.1 Performance Development Process and Race Results

Since before the 2016 Olympic, the Teamchef of Swiss Sailing Team, Ph.D. Thomas Reulein introduced a Performance Development Process form. This form is a self-assessment and analysis tool for the elite and junior Swiss athletes. The systematic use of this tool has been implemented only since the begin of the current Olympic cycle. The SST Performance Development Process is available online via the TeamDataLog platform (a screenshot of the form is available in the Annex), which is used by the Swiss Sailing Federation as a tool for Regional and National activity. The form is structured in 7 sections, presented in the following order:

- Technique (starting, speed up&down, manoeuvres, rounding, …);
- Tactics / Strategy (start, legs, wind strategy, attack/defence, risk-control, …);
- Physical Preparation (endurance, power, flexibility, coordination, …);
- Mental Preparation (energy, emotion-control, toughness, fighting, confidence, …);
- Equipment (tuning boat & rig, optimization equipment, …);
- Know How (rules, weather, currents, …);
- Communication (between Helm and Crew or with the Coach).

For each of these 7 factors, the responder (one form per boat) has to:

- Define his/her level to the world champion, from 0% to 100% fit;
- Define (or tag) the most critical 3 targets the sailor needs to improve for that specific factor;
- Mutually prioritize the factors on a scale from 1 to 7, each factor needs to have a different priority;
- Comment the answer when it needs an explanation.

The Performance Development Process needs to be completed at least a couple of time a year, in phase with the planning of the meso-cycle training periods. Some teams/athletes prefer to use it even more often. That the availability of the data since 2016:

- 470M, Radial, and Finn: 8 forms;
- RSX: 7 forms;
- 49er: 5 forms;
- 470F: 4 forms;

As the type of boats that we are treating in this dissertation are both, single-handed and double-handed, we are forced to neglect the aspect of Communication, because that is actually defined as discretionary for the single-handed sailors and it has not consistently answered by all the responders. Therefore, from now, we will use only the first 6 factors. In addition, we have to assume that the information collected in the Performance Development Process forms are valid and reliable. Then, due to the scarcity of data, for the following analysis, we have to consider the Swiss Sailing Team as a whole and not anymore performing the analysis by boat. The methodology used in the following dissertation is assumed to be valid even when applied to each athlete, and so we will do in 4.2.2.
Now, we want to study if it is possible to infer a principle of causality from the Performance Development Process (PDP) to the Race Results. So, we are assuming that the Race Results depend from the 6 factors of the PDP as it is for the output of a production function in respect of its input.

Equation 22

$$Rank \approx \alpha \prod_{i=1}^{6} F_i^{\beta_i}$$

Where F_i are the values of the gap to the world champion of the first six factors of the PDP (Technique, Tactic / Strategy, Physic Preparation, Mental Preparation, Equipment, and Know-How). Hence, assuming that the F_i are like the learning processes and then obey the same diminishing return law as the Race Result, we can apply a process of linearization. That is like the one we performed in the previous section, so for brevity, we do not repeat the details. Then, we can rewrite Equation 22 as it follows:

Equation 23

$$Log(Rank) \approx \alpha + \sum_{i=1}^{6} \beta_i * Log(F_i)$$

Therefore, to study the causality from the PDP to the Race Results, we will perform first a correlation study between the Rank and the Factors and then a multiple linear regression. This statistical approach brings us from Equation 23 to the following, which should represent each Race Result j of the SST elite sailors career since 2016, within the tolerance of an error $\varepsilon_j = \varepsilon_{Luck} + \dot{\varepsilon}$:

Equation 24

$$R_j^{(\lambda)} \sim \alpha + \sum_{i=1}^{6} \beta_i * F_{i,j}^{(\lambda)} + \varepsilon_j \, ;$$

where

Equation 25

$$R_j^{(\lambda)} = Log\left(Rank_j\right) = Log(a) + k * Log\left(t_j\right) ;$$

and

Equation 26

$$F_{i,j}^{(\lambda)} = Log\left(F_{i,j}\right) = \alpha_i' + \beta_i' * Log(t_j) + \varepsilon_j' \, ;$$

such that

Equation 27

$$t_j \colon R_j^{(\lambda)}, \boldsymbol{F}_j^{(\lambda)} \Rightarrow \bar{\varepsilon}_j = \left(\bar{R}_j\left(\bar{\alpha}_j, \overline{\boldsymbol{\beta}_j}\right) - R_j^{(\lambda)}\right).$$

The bar over the letters represents the sample average. Now, before performing the correlation study and the multiple linear regression, we have to solve a common problem of asynchronism between the Race Result and the PDPs. If we intend to build a predicting model for the results in competition, we have to synchronize the factors of the PDP to the times j at which racing events $R_j^{(\lambda)}$ took place. Assuming the fixed regressor design, we interpolated the $F_{i,j}^{(\lambda)}$ for each $t_j^{(\lambda)} = Log(t_j)$ using Equation 26 with:

Equation 28

$$\alpha_i' = \overline{F_{i,j}^{(\lambda)}} - \beta_i' * \overline{t_j^{(\lambda)}};$$

and

Equation 29

$$\beta_i' = \frac{\sum_j \left(t_j^{(\lambda)} - \overline{t_j^{(\lambda)}}\right)\left(F_{i,j}^{(\lambda)} - \overline{F_{i,j}^{(\lambda)}}\right)}{\sum_j \left(t_j^{(\lambda)} - \overline{t_j^{(\lambda)}}\right)^2}.$$

Where the values $\overline{t_j^{(\lambda)}}$ and $\overline{F_{i,j}^{(\lambda)}}$ are respectively the sample averages of the known $t_j^{(\lambda)}$ values and known $\overline{F_{i,j}^{(\lambda)}}$ values.

As previously mentioned, firstly we analyzed the cross-correlations, with attention to the correlation between $R_j^{(\lambda)}$ and each one of the other factors $F_{i,j}^{(\lambda)}$.

From Table 9, we can soon observe that the correlations are not high, but two factors, Technique and Mental, are more correlated with the Race Results than the other four. On the other hand, the low level of correlation can be explained with the volatility that we already observed in the collected data of the World-Class events. Then, we cannot forget that the PDPs are data based on self-assessment, which we assumed reliable and valid, but those are not exempted from errors and fluctuation that the term ε_j' captures in Equation 26. Furthermore, the lack of synchronization between the Race Results and the PDP factors introduce an additional factor of approximation.

Correlation	***Log(Rank)***
Log(Technique)	0,1460
Log(TactStrat)	0,0416
Log(Fitness)	0,0310
Log(Mental)	0,3265
Log(Equipment)	0,0643
Log(KnowHow)	0,0952

Table 9: Correlation between series of $R_j^{(\lambda)}$ and each of the $F_{i,j}^{(\lambda)}$.

However, those the only available data which can be analyzed to study managerial insights, so we decided to proceed with the multiple linear regression approach. Therefore we performed the first round of analysis, keeping in account all the six factors as predictors, but the analysis of the variance (ANOVA) of the model showed a $p_{6-factors} = 0{,}319$, which is a p-value too large to consider our hypothesis statistically acceptable. Hence, we considered other options, such as considering only the variables that are most correlated with the Race Results. As a result of this systematic alternative approach, which had the scope to find a model with $p < 0{,}05$, we identified the following hypothesis as statistically significant:

Equation 30

$$R_j^{(\lambda)} = \alpha + \beta_1 * F_{1,j}^{(\lambda)} + \beta_2 * F_{2,j}^{(\lambda)} + \varepsilon_j$$

Where Factor 1 is the Mental preparation and Factor 2 is the Technique. This Equation 30 is a particular case of Equation 24, where the other four factors do not appear anymore. The statistical analysis of the model proposed in Equation 30 has been studied with SPSS, and it returns the analytics shown in Table 10.

Model	**R**	**R^2**	**$p_{technique+mental}$**	**α**	**β_1**	**β_2**
Equation 30	0,340	0,166	0,052	-0,415	0,780	0,277

Table 10: results of the statistical analysis performed with SPSS for the hypothesis presented in Equation 30.

The data used to study the statistical significance of the model presented in Equation 30 are the collection of the full set of Race Results of the Swiss Sailing Team athletes. Therefore this model is representing how the Race Results of the whole team are predicted by the Mental and Technique factors of the PDP. With a more extensive set of data for each athlete, that now is not available, it would be possible to perform the same analysis individually instead that for the whole group.
If we move our attention to the R^2 value, we can notice that it can be considered rather low in comparison with good regression models in general. Nevertheless, we have already previously insisted on the role of pure luck, which is modelled in the Equation 17 and it introduces a noise factor of about 10% to 20% within the top places and increasing going down in the ranking. In addition, here the term $\varepsilon_j = \varepsilon_{Luck} + \dot{\varepsilon}$ can be interpreted as in Figure 17.

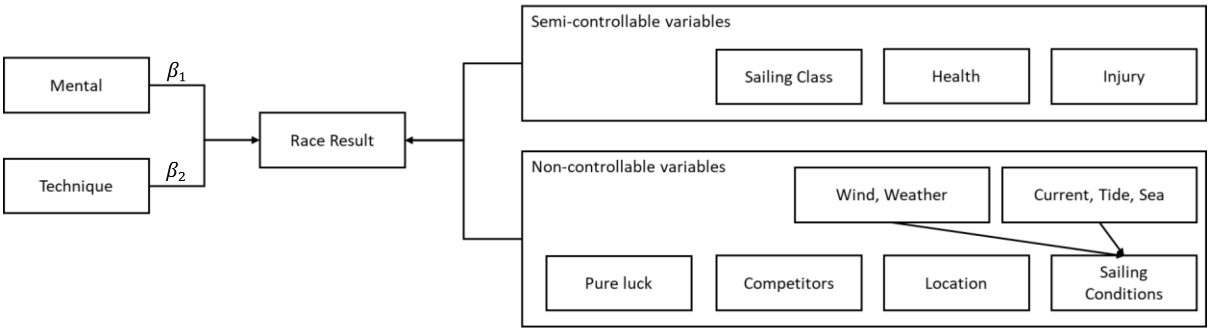


Figure 17: visual diagram explaining the elements of Equation 30. At the centre we have Race Result, that is the term that we intend to predict. On the left-hand side, the Mental and Technique skills, that we can control and improve. On the right-hand side, we regrouped all the terms that are sources of uncertainty, and this is represented in the ε_j term of the equation.

Therefore, it should not surprise that we can control only a fraction of the whole complex system. Then, with a more extensive database, gathering all the information on the right-hand side of the diagram in Figure 17, we could probably predict more accurately the Race Result. This additional elaboration could be a future development of this current research.

Preliminary conclusion

From Table 10, we can see that the p-value is on the edge of the statistical significance, and therefore, we accept this model for the continuation of the present dissertation. Then we can notice that β_1 contributes about three times than β_2. Which it means that at the Olympic level, the mental preparation presents a more significant impact than the sailing technique itself. However, this message shall not be misunderstood. At the elite level, the technical skills are highly comparable amongst the competitors, and therefore with the coefficients obtained by this model, we are detecting that the mental strength (and in general the mental preparation) is a factor that influences the results in World-Class competitions more than the sailing technique. Somehow this result should be not surprising, but at the same time, it shows that the Swiss Sailing Team is mature enough to shift the focus from the development of additional technical skills to the development of better mental skills. It is trivial to say that it is not about stopping to improve technically, but it is about shifting the spotlight on the factor that will contribute the most to the improvement of the results, for this given athlete portfolio.

We have to stress that we still consider the model proposed in Equation 24 as a general case of Equation 30. Therefore, if the analysis of a new athlete portfolio is intended, a new analysis of the correlation has to be performed, and then a systematic multiple linear regression study has to be performed. For a different team, with different skills, the factors could be therefore different.

3.3.2 Interdependences of the Performance Development Process factors

So, the question that arises now is about how the other four factors contribute to the success of the team. In fact, the model of Equation 30 does not exclude the implicit contribution of the other factors. Hence, we are interested in investigating further on that matter, so to address this topic, we start from the study of the cross-correlation within the factors of the PDP.

Cross-Correl.	*Log(Technique)*	*Log(TactStrat)*	*Log(Fitness)*	*Log(Mental)*	*Log(Equipment)*
Log(TactStrat)	0,7150				
Log(Fitness)	0,4866	0,5511			
Log(Mental)	0,4995	0,5169	0,3853		
Log(Equipment)	0,2875	0,3419	0,4747	0,1673	
Log(KnowHow)	0,4644	0,4629	0,4142	0,1293	0,4924

Table 11: Cross-correlations within the 6 factors if the Performance Development Process.

From Table 11, we notice that the correlations between the different factors are rather strong, particularly for some combinations of variables. Therefore, we decided to approach the modelling of a causal relationship between the different factors with a multiple linear regression method, as previously performed between the Race Results and the PDP factors. In this case, all the factors are directly part of the PDP, and intrinsically synchronized, so we do not need to make any additional assumption. Hence, similarly to Equation 24, we intend to study a system of equations of the following form:

Equation 31

$$F_j^{(\lambda)} \sim \alpha + \sum_{i=1}^{n} \beta_i * F_{i,j}^{(\lambda)} + \varepsilon_j, \qquad \forall\, i \neq j.$$

In the diagram of Figure 17, we displayed that Mental Preparation and Sailing Technique are the two factors that can predict with a sufficient level of statistical significance the Race Results, even if the R^2 is limited by the influence of the other exogenous factors. Because of that, to offer a model that could be used for managerial purposes, we decided to study the multiple regressions avoiding direct feedback loops. In other words, if, for example, Mental Preparation is strongly predicted by one of the other factors, like Fitness, when we will define the regressors for Fitness, we will neglect the Mental Preparation, to identify the others relevant factors.

Consequently, we performed the multiple linear regression analysis via SPSS for 6 models that would represent the system of inter-causality between the 6 factors of the Performance Development Process. In Table 12, we summarized the statistical results of such analysis.

Multiple linear models	**R**	**R^2**	**p-value**	**Principal Regressors**	**Neglected Regressor**
$F_{Mental}^{(\lambda)} = \alpha + \sum_{i=1}^{5} \beta_i * F_i^{(\lambda)}$	0,633	0,401	0,003	Fitness	-
$F_{Technique}^{(\lambda)} = \alpha + \sum_{i=1}^{5} \beta_i * F_i^{(\lambda)}$	0,753	0,569	0,000	TactStrat	-
$F_{TactStrat}^{(\lambda)} = \alpha + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)}$	0,697	0,485	0,000	KnowHow	Technique
$F_{Fitness}^{(\lambda)} = \alpha + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)}$	0,488	0,238	0,044	Equipment	Mental
$F_{KnowHow}^{(\lambda)} = \alpha + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)}$	0,549	0,302	0,012	Technique	TactStrat
$F_{Equipment}^{(\lambda)} = \alpha + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)}$	0,601	0,361	0,003	Mental, TactStrat	Equipment

Table 12: summary of the most relevant statistical parameters for the 6 multiple linear models. In all cases, the p-value is smaller than 5%. Therefore the model is statistically significant. The Principal Regressors are the variables that primarily contribute to the prediction of the dependent variable of the model. The neglected regressors are the variables which have been discarded because acting a primary feedback loop.

From Table 12, we can notice that the set of models, which are all statistically significant, present values of R^2 largely more representative that the model predicting the Race Results. This result could have been facilitated by the synchronicity of all the variables, a condition that was not present previously.

Now, that we have studied the cross-correlation and the multilinear regression for all the factors of the PDP, we can move forward to a thorough predicting model for Race Results of the World-Class events in the Olympic Sailing domain. In fact, now we have a deeper understanding of how all the factors of the Performance Development Process contribute directly and indirectly to the Race Results. The diagram of the interdependencies is presented in Figure 18.

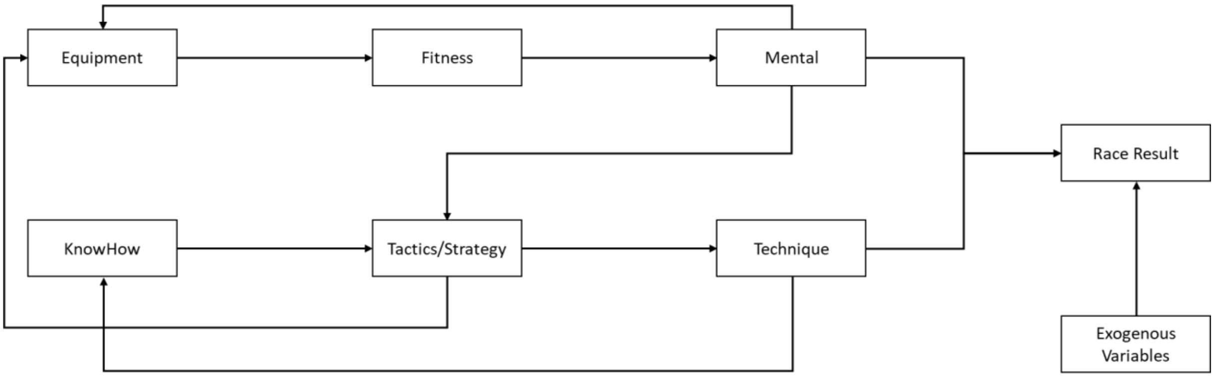


Figure 18: Diagram of the principal interdependence of the Performance Development Process factors and the Race Results. The arrows represent the primary causal relations; second order causal relationships have been neglected for the sake of the clarity of the diagrams.

Interpretation

The insights of Figure 18 are relevant from the managerial point of view. In fact, from the diagram, it is possible to visualize and understand how the different factors are interacting and influencing each other. Nevertheless, it is essential to remind that the causal relationships drawn on the diagram, do not explain the totality of the variance of the data. Therefore, other not detected influences add noise to the system. In addition, this model represents the interconnections between all the factors for the totality of the Swiss Sailing Team, and it is not individualized for each athlete.

Once represented in mathematical form, the predicting model for the Race Results assume the form of the following systems of equations. In Table 13, we reported the full set of coefficients.

Equation 32

$$
Model_{SST} = \begin{cases}
R^{(\lambda)} = -0{,}415 + 0{,}780 * F_{Mental}^{(\lambda)} + 0{,}277 * F_{Technique}^{(\lambda)} + \varepsilon_{Rank} \\
F_{Mental}^{(\lambda)} = 0{,}534 + 0{,}266 * F_{Fitness}^{(\lambda)} + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)} + \varepsilon_{Mental} \\
F_{Technique}^{(\lambda)} = -0{,}017 + 0{,}565 * F_{TactStrat}^{(\lambda)} + \sum_{i=1}^{4} \beta_i * F_i^{(\lambda)} + \varepsilon_{Technique} \\
F_{TactStrat}^{(\lambda)} = 0{,}323 + 0{,}343 * F_{KnowHow}^{(\lambda)} + \sum_{i=1}^{3} \beta_i * F_i^{(\lambda)} + \varepsilon_{KnowHow} \\
F_{Fitness}^{(\lambda)} = 0{,}575 + 0{,}405 * F_{Equipment}^{(\lambda)} + \sum_{i=1}^{3} \beta_i * F_i^{(\lambda)} + \varepsilon_{Fitness} \\
F_{KnowHow}^{(\lambda)} = 0{,}866 + 0{,}444 * F_{Technique}^{(\lambda)} + \sum_{i=1}^{3} \beta_i * F_i^{(\lambda)} + \varepsilon_{KnowHow} \\
F_{Equipment}^{(\lambda)} = -0{,}217 + 0{,}475 * F_{TactStrat}^{(\lambda)} + 0{,}272 * F_{Mental}^{(\lambda)} + \sum_{i=1}^{3} \beta_i * F_i^{(\lambda)} + \varepsilon_{Equipment}
\end{cases}
$$

Coefficients	$F^{(\lambda)}_{Mental}$	$F^{(\lambda)}_{Technique}$	$F^{(\lambda)}_{TactStrat}$	$F^{(\lambda)}_{Fitness}$	$F^{(\lambda)}_{KnowHow}$	$F^{(\lambda)}_{Equipment}$
α	0,534	-0,017	0,323	0,575	0,866	-0,217
β_{Mental}	-	0,198	0,254	-	-0,177	0,272
$\beta_{Technique}$	0,290	-	-	0,037	0,444	0,123
$\beta_{TactStrat}$	0,243	0,565	-	0,192	-	0,475
$\beta_{Fitness}$	0,266	-0,040	-0,002	-	0,014	-
$\beta_{KnowHow}$	-0,227	0,209	0,343	-0,104	-	0,217
$\beta_{Eqipment}$	0,063	0,059	0,188	0,405	0,158	-

Table 13: coefficients of the multi-linear models for the Performance Development Process prediction.

3.3.3 Assumptions Verifications and General Considerations

In section 3.3.1, we assumed that the data of the Performance Development Process are valid and reliable. We based our hypothesis on the fact that the sailors and the coaches that make the assessment are highly experienced, and we expect them to know well what it is the target level to reach to become a World-Class series medallist. Nevertheless, someone could argue that the information collected with the PDP is biased and not systematically assessed. To prevent this kind of conjectures, we decided to try to validate the assessment process.

Out of the 6 parameters that we kept in the account, Mental preparation, Technique, Tactic / Strategy, Equipment and Know How are variables vast and general, interconnected and hard to measure with an absolute metric. That is not the case for Physic Preparation, which can be monitored with physical tests. Therefore, we decided to proof the quality of that specific factor. Doing that, we assume the possibility to infer the findings to the other factors. In fact, if the respondent does it for the Fitness, he/she should be able to answer validly and reliably for all the factors of the PDP.

Swiss Sailing Team benefits of the partnership with the Hôpital La Tour of Geneva, which is a Swiss Olympic labelled clinic, and it regularly performs the Physical Test on the elite Swiss sailors. The clinic is testing both endurance and strength, with two standardized testing processes. To proof the validity and the reliability of the Fitness factor, as previously done, we compute first the correlation between the data of self-assessed evaluation form with each of the parameters measured in the Physical Test (shown in Table 14) for the whole Swiss Sailing Team elite sailors. To overcome the problem of the synchronicity, we are again assuming a fixed regressor design, and therefore we perform a linear interpolation of the Physical Test data to achieve the synchronization with the Fitness factor of the PDP.

Cross-cor	*s(ventral)*	*s(lateral)*	*s(dorsal)*	*Repetitions*	*Kg*	*<W>(30s)*	*W/Kg*	*m(30s)*	*m(4min)*
Fitness	0,0157	-0,4295	0,0547	-0,3446	-0,4268	-0,4503	-0,4212	-0,4111	-0,3666

Table 14: cross-correlation between the self-assessment of Physical Preparation and the measured parameters are here presented. The parameters with ventral, lateral and dorsal into brackets refer to Swiss Olympic Strength Test protocol [37]. Repetitions and Kg refer to the number of pulls at the bar, and the total lifted weight (repetitions times athlete's weight). <W> is the 30 seconds average power in Watt produced at the rowing machine, and W/Kg is the ratio between the power output and the athlete's weight. The last two variables are the highest distance in meter performed in 30 s and the total distance covered in 4 min.

For brevity, we do not repeat all the methodology, but in a few words, we performed another multiple linear regression to estimate how well the Physical Tests describe the Fitness factor of the PDP. For the sake of a thorough analysis, we tested 3 cases, the first considering only the strength tests as regressors of the dependent variable, then we repeated it for endurance only and finally with both. In Table 15, the output is summarized.

Model	R	R^2	p-value
Strength	0,425	0,180	0,033
Endurance	0,489	0,239	0,017
Both combined	0,593	0,351	0,037

Table 15: Summary of the most relevant statistical parameters of the multiple linear regressions of the PDP Fitness factors with the physical strength test, the physical endurance tests and the combination of the two.

Using this validation method, we can conclude that the model that combine the two sets of parameters as regressors for the Fitness factor of the PDP is statistically significant and it explains the 35% of the variance. In our opinion, if we consider the scarcity of the data, the asynchronicity issue and the fact that the Physical Test themselves are affected by fluctuations because those are measuring human parameters of different subjects, we can conclude that our assumption of validity and reliability of the PDP is checked as valid.

Preliminary conclusion

In this chapter, we treated the factors of the Performance Development Process as crucial references to predict the Race Results (Figure 18). Then we stated that not only endogenous learning/improvement processes contribute to the success, but many other exogenous variables are playing an important role (Figure 17). We stated that the predicting model summarized in Equation 32 is statistically significant for all the equations of the system, but we reported as well that some of these equations could explain only a limited proportion of the dependent variable. Two were the challenges in our opinion that affected the model; on the one hand the small amount of available data, that reduced the statistical significance, and, on the other hand, the asynchronicity that most of the data where presenting.

Therefore, to improve the model, we strongly recommend increasing the frequency of the PDPs and performing the self-assessment as a *post-mortem* analysis after each relevant World-Class event. That change in the process would help to produce more data for each athlete and to explain better the reasons for the success in the competitions. In literature are available several examples about how to perform this kind analysis, but we would like to mention and recommend the *Impartial division of a dollar* [38], written by de Clippel, Moulin and Tideman. In this article, different methods are presented, and we reckon that it would it gives good insight to improve the validity and reliability of the PDP. In addition, to increase the volume of data, we think that it could be possible to keep in consideration not only the World-Class events but to include at least the European circuit because it reasonably well represents the best-in-class competitors. When the management and the athletes would follow the recommendation mentioned above, the numbers of the Race Results to treat it would be approximately doubled in number, and the PDPs would be synchronized, and we would have three times the forms available now.

With more data, it would be then possible to analyze and then to optimize the priorities for each sailor, instead than for the Swiss Sailing Team as a whole. It would be then possible to perform mixed effect models and develop more complex models, including the measure of the effect of the success itself inside the equations, as a reinforcing feedback loop.

Similarly, for the learning curves of each athlete, this predicting model of the Race Results based on the data derived from the PDPs is not static. For managerial purposes, we recommend performing the analysis on the data at least 2 times a year: before-season (early spring) and post-season (mid-autumn). This process can be adapted and performed for the Youth Team too. The diagram obtained will contribute to the decision making by helping with the prioritization and the allocation of the resources to the most influencing factors.

From the Equation 32 and the Figure 18, we could understand that the Mental Preparation and the Technique are the two most important priorities, then Physical Preparation and Tactic / Strategy follow and eventually Know How and Equipment come. In 3.3.1, we stated that, while answering to the PDP form, the respondent has to state the priorities amongst the different factors. Now we can compare our findings with a descriptive statistical analysis of the prioritization made by the Swiss Sailing Team elite sailors (Table 16).

PDP priority	Technics	TactStrat	Fitness	Mental	Equipment	KnowHow
μ_{priority}	2,0	2,8	3,1	3,6	4,6	5,2
σ_{priority}	1,280	1,512	1,519	1,541	1,367	0,912

Table 16: a descriptive statistical analysis of the self-assessed prioritization of the SST elite sailors. μ_{priority} is the mean of the priority distribution (1 to 6) and σ_{priority} is the related standard deviation.

So, we can see that the elite Swiss sailors and their coaches are somewhat accurate to assess the priorities, except Mental Preparation. In fact, it is quite evident this mismatch, as Mental Preparation should result to be now their first priority. On the other hand, this is a descriptive statistical analysis over two and a half years. Therefore, it does not show if recently the responded started to bring higher in priority the Mental Preparation. Moreover, it would be essential to keep monitoring the dynamic of these self-assessed priorities, which are subjective for each athlete and not the same as for the whole Team.

The last insight that we can offer for this part of the dissertation is concerning Equation 22. In fact, in the first part of this chapter, we assumed that the Race Results behave like a product function depending on different factors. Afterwards, we linearized the system and studied it via multiple linear regression. We understood that currently, only Mental Preparation and Technique are significantly contributing to the Race Results. This scenario can lead us to rewrite Equation 22 in the form of a Cobb-Douglas Production Function [32].

Equation 33

$$Rank \approx \alpha * F_{Mental}^{\beta_1} * F_{Technique}^{\beta_2}$$

Now, using the coefficient presented in the first line of Equation 32, we can notice that $\beta_1 + \beta_2 = 1.057$. So, as the sum of the two exponents (statistically derived) is currently slightly above 1, we can say that the production function of Equation 33 has an increasing return to scale. For further analysis, it could be interesting to understand first if that is always the case and then how the management can benefit from this property.

4 Team Success Analysis

In this chapter, we will first combine the findings of the previous sections to assess the Risk and Return. The aim is to formulate a framework for the optimization of the SST Athlete Portfolio. To do so, we will explore parallelism with the Financial Market, applying an optimization tool developed for the modern portfolio theory. Then we will discuss the Olympic Project Reviews, an SST internal and multi-criteria assessment process. After that, we will use the finding of the previous sections to elaborate a prediction. Only at the end of the chapter, we will be in a condition to define a Multi-criteria Objective Function for SST, and we will analyze some relevant scenarios.

4.1 Risk and Return assessment

In Figure 16, we have shown a Log-Log scale graphs for the Race Results time series of each Swiss elite sailor. Thanks to that analysis, we have been able to characterize each of them with their mean value of the distribution and volatility. Now we want to look at the whole portfolio of athletes as a financial portfolio of assets. In order to do so, we can offer a risk-return graph by plotting the standard deviation of the Race Results distribution for each boat in the SST Elite versus its mean of the distribution. This visualization follows the classical approach for an efficient portfolio optimization by minimizing the variance and maximizing the return for a given asset portfolio and a given risk-free rate. What for the financial market is considered as the volatility of the price of an asset, here it represents the volatility of the Race Results, which is a peculiar characteristic of each athlete or boat kind. Also, to continue the parallelism between the financial market and the athlete portfolio, we computed the Sharpe Ratio [12] for the elite members of the Swiss Sailing Team, which is a return-to-variability ratio. Therefore, the Sharpe Ratio is a method to compare the performance of an investment, in our case, an athlete by adjusting for its risk, and it is defined for each athlete as:

Equation 34

$$S_i = \frac{\mu_{Log(Rank)_i}}{\sigma_{Log(Rank)_i}}.$$

Using the Sharpe Ratio, we intend to give the first insight into the contribution that an athlete offers to the average team success. While following the parallelism with the Financial Market, this ratio helps to rank the assets for their mean return weighted on their risk. For sailors, a high Sharpe Ratio shall inform about the quality of the results weighted on the stability of their performance in competition. To properly do so, we first have to consider that specific ratio is originally a tool for assets evaluation, so the higher the price, the more valuable is the asset and therefore, the higher the mean performance. However, when we look at the Race Results, the best performance is given by the highest place in the ranking, which is represented by a smaller number. Therefore, to apply in a meaningful way the Equation 34 to our pool of athletes, we had first to compute the $\mu_{Log(Rank)_i}$ and then introduce a new indicator so defined:

Equation 35

$$\mu^*{}_{Log(Rank)_i} = R - \mu_{Log(Rank)_i};$$

with the constant $R = 2 > \max(\mu_{RaceResult_i})$. From Equation 35, it follows our definition for a modified Sharpe Ratio that accounts for rankings with “Low System Points.”

Equation 36

$$S_i^* \equiv \frac{\mu^*_{Log(Rank)_i}}{\sigma_{Log(Rank)_i}}$$

From now, we will use this form for the following discussion. So using the computed $\mu_{Log(Rank)_i}$ and $\sigma_{Log(Rank)_i}$, we performed the two graphs of Figure 19. There we compared two Olympic cycles. The choice of organizing the analysis on Olympic cycles holds on the idea to compare only assets that are or were active "on the market" at the same time. The size of the bubbles corresponds to the modified Sharpe Ratio proposed in Equation 36; the values are shown in Table 17.

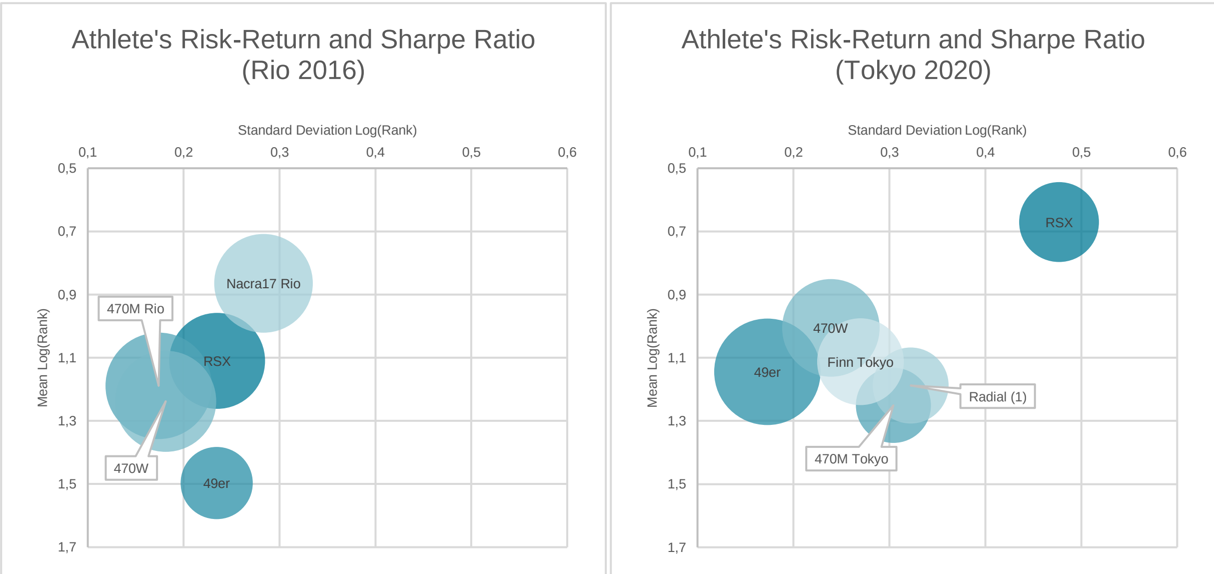


Figure 19: risk-return charts for the SST athlete portfolios. On the left chart, the athlete portfolio for the 2013-2016 Rio Olympic cycle. On the right chart, the athlete portfolio for the 2017-2020 Tokyo Olympic cycle. For the right chart, at moment of the dissertation editing, the availability of the data ended with May 2019. The size of the bubbles represents the Sharpe Ratio.

Class	S_i^* Rio 2016	S_i^* Tokyo 2020 (May 2019)
RSX	3,79	2,79
49er	2,15	4,95
470M Rio	4,66	-
470M Tokyo	-	2,46
470W	4,20	4,16
Radial (1)	-	2,52
Nacra 17 Rio	4,01	-
Finn Tokyo	-	3,29

Table 17: modified Sharpe Ratios for each athlete/class. The Ratio has been computed for each Olympic cycle.

Before approaching the interpretation of the data presented in Figure 19 and Table 17, we intend to look a bit deeper in the dynamic of the standard deviation and why or how it changed between the previous cycle and the current one. We can notice that all the 3 classes (RSX, 49er, 470W) that were in Rio 2016 and now expecting to compete in Tokyo 2020 show an improvement in the results, but their standard deviation evolved differently. For the RSX, the risk largely increased with the increase of the performance, for the 49er decreased and for the 470W increased only by little. Therefore, using all the Race Results available data for the two Olympic cycles, we can graphically show the evolution of the position of each SST team in the risk-return space, from Dec 2012 till now, May 2019. To perform this analysis of the Olympic cycle-dependence of the standard deviation and the mean, we considered the results at the World-Class events for all the Swiss sailors that have been part of the Elite Team (seasons 2012-2019), even if they did not qualify to Rio 2016. In Figure 20, we present the graphical result of that analysis.

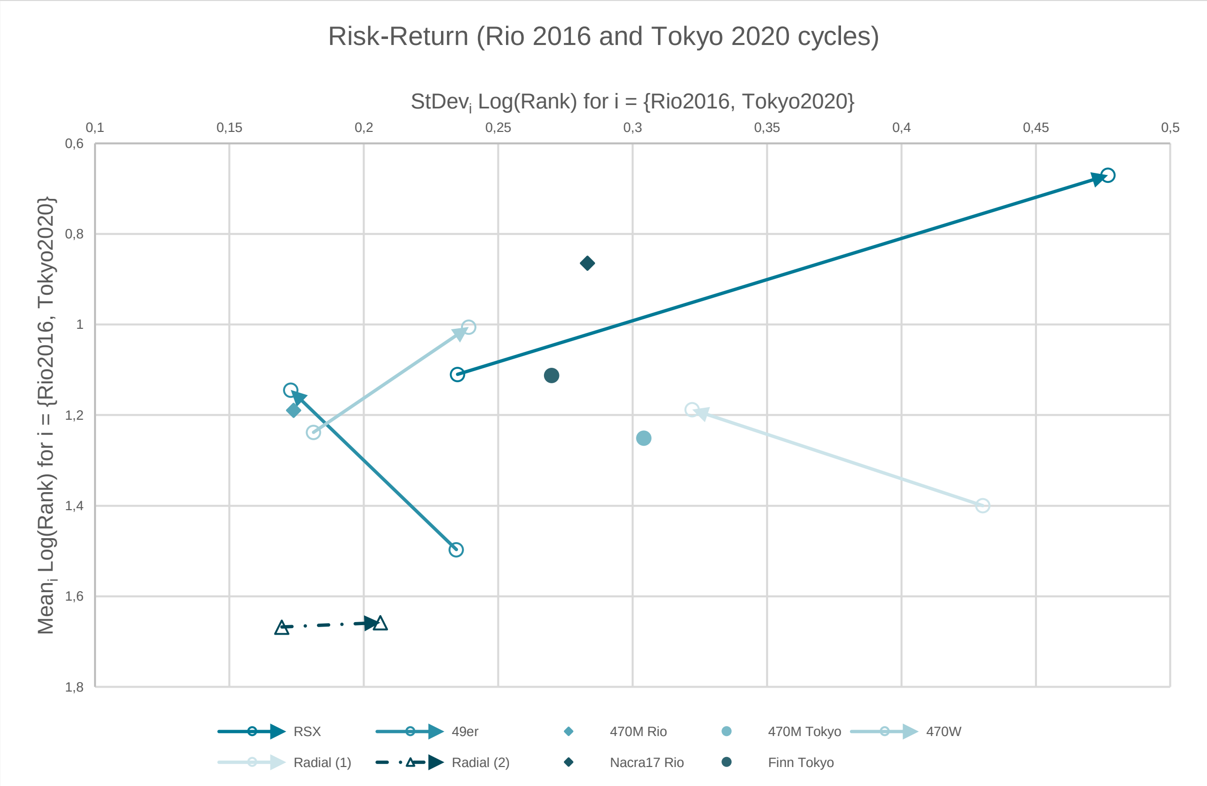


Figure 20: the cycle-dependent position of each athlete/class in the risk-return space. To be noted that all athletes improved their performance in the subsequent cycle (the arrows indicated the time direction), that is in accordance with the theory of the learning curves presented in section 3.2. On the other hand, the standard deviations follow a different evolution.

As is it visible in Figure 20, for some of the sailors, we are not in the condition to compute the risk and return position for each of the two cycles. This fact is simply due to lack of data, that because the youngest teams were not competing at the World-Class event in the past and then some of the oldest quitted the Olympic scene after 2016. Nevertheless, we would like to formulate a hypothesis concerning the trend of the risk evolution over time. The scope of this attempt is to offer better insight for the management to understand whether the athletes are carrying a hidden increase of risk into the team configuration, or they are contributing to mitigating it.

To do so, we will use the data that World Sailing, the International Sailing Federation, has recently published in spring 2019. The report [39] from the Technical Department is a descriptive statistical analysis of the physical characteristic (weight and height) of the athletes that attended the World Sailing 2018 World Championship in Aarhus, Denmark. Therefore, we thought to compare this data with the weight and height of each of the SST Elite athletes. Then to verify if there is any correlation between the gap and the trend of the standard deviation of $Log(Rank)_i$.

As we have been able to perform this comparison only for few athletes (RSX, 49er, 470W and Radial), we are not claiming for a statistical significance, but rather for a well-correlated trend indicator. To do so, we computed the following two gaps:

Equation 37

$$\Delta m_i = \mu_{weight_i} - m_i;$$
$$\Delta h_i = \mu_{height_i} - h_i.$$

Where i indicates the Class, m_i and h_i stand for the mass weight and the height of the Swiss athlete for the given Class and μ_i are respectively the mean of the weight and height distribution for that specific Class. Then we studied the correlation between the values obtained with Equation 37 and the standard deviations, and we obtained the results presented in Table 18.

Correlation	$\boldsymbol{\sigma_{Log(Rank)_{Tokyo}}}$	$\boldsymbol{\Delta\sigma_{Log(Rank)} = \sigma_{Log(Rank)_{Tokyo}} - \sigma_{Log(Rank)_{Rio}}}$
Δm_i	0,691	0,988
Δh_i	0,856	0,913

Table 18: correlation between data obtained from Equation 37 and the risks. In the central column, the correlations between Δm_i and Δh_i with the risk factors carried by each athlete with a computed $\sigma_{Log(Rank)}$ for the Tokyo 2020 Olympic cycle. In the right column the correlations between Δm_i and Δh_i and the variation of the risk factors computed for each athlete with attendance to World-Class events for both cycles.

Encouraged by this strong correlations, even if the number of data is meagre, we performed a multi-linear regression to predict both the values $\sigma_{Log(Rank)_{Tokyo}}$, and $\Delta\sigma_{Log(Rank)}$ using the Δm_i and Δh_i as regressors. Table 19 shows the results.

Model	Multiple R	p-value	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{\Delta m}}$	$\boldsymbol{\beta_{\Delta h}}$
$\sigma_{Log(Rank)_{Tokyo}}$	0,900	0,082	0,207	-0,025	0,042
$\Delta\sigma_{Log(Rank)}$	0,993	0,115	-0,079	0,055	-0,012

Table 19: statistical values and coefficients for the multi-linear regression models for the estimation of the risk and risk variation in the function of weight and height of the athletes. In particular, the second case refers to the relation between the gap of weight Δm_i and height Δh_i from the mean of distribution for each class and the change of the standard deviation of the $Log(Rank)$ of SST athletes between two cycle,

Interpretation

The more the weight and height of the sailors, or the teams (helm and crew) for the double-handled boats, differ from the mean of the respective distribution, the higher the risk ($\sigma_{Log(Rank)}$). That it means that an athlete with large Δm_i and Δh_i, while improving his/her mean of results distribution over time, will experience an increase of variation of the results too. So, the outstanding results will be probably reached when the sailing condition particularly favours his/her body characteristics. On the other hand, a team which has very low Δm_i and Δh_i, it will see that the variation in the Race Results will show a decreasing trend, and the results will be more consistent once achieved, but probably it will need more time to emerge.

This above is our hypothesis, but the argumentation, to be validated, it would require a more extensive statistical analysis, acquiring detailed physical data of other competitors, which are not available to us. However, we think that it gives the flavour of why the risk can increase or decrease. Someone could argue that weight and height are not the only reason, but so far, that is the only quantitative analysis we can offer.

As a general recommendation, if we assume that the ultimate target of a sports federation is to collect top results, both strategies (minimizing the risk or taking the risk) could bring to the success, but within a different time horizon or wind condition scenarios. That is like an investment portfolio; it depends on the interests and needs of the investor. Looking at the Swiss Sailing Team, we must account that the pool of athletes is not large and, at least in the past and the current cycle, there has not been the possibility to select the sailors because of their physical characteristics. That is maybe the case for other nations, with a larger athlete's reservoir.

In Table 20, we assess the relative risk status and trend for the case of the Swiss Elite Sailing Team.

	RSX	49er	470M Tokyo	470W	Radial	Finn Tokyo
Risk status	Highest	Lowest	Mid-High	Mid-Low	High	Moderate
Risk trend	Increasing	Decreasing	Decreasing	Increasing	Decreasing	Increasing

Table 20: risk status and trend of the SST Elite 2019, this summary has been elaborated using the data of Figure 20 and Table 19.

So at the present state, SST almost is forced to follow a mixed portfolio strategy, with some high-risk asset and some others with a decreasing trend. So, it is more about dealing with the risk and returns status than to drive a short-term decision for this Olympic campaign. However, we reckon that it is relevant to estimate the current portfolio situation and look for possible optimal configuration.

Then, when we are discussing risk mitigation and risk minimization, we have obviously to take in consideration the covariance matrix of our assets, because that would give us the possibility to estimate the overall risk of our portfolio in the function of the weights we allocate to each asset. For this first estimation, we decided to allocate the weights evenly ($\sum w_i = 1,\ w_i = 1/6$), because we can only have or not have an athlete in the team, so a fraction it would be meaningless. The athlete's covariance matrix, presented in Table 21, leads to the calculation of the risk of the whole SST Athlete portfolio via Equation 38.

Equation 38

$$\sigma_{SST}^2 = \sum_i \sum_j w_i w_j Cov(i,j)$$

Cov	RSX	49er	470M Tokyo	470W	Radial (1)	Finn Tokyo
RSX	0,2273	-0,0247	-0,0227	0,0298	-0,0490	-0,0700
49er	-0,0247	0,0299	-0,0123	-0,0029	-0,0008	0,0022
470M Tokyo	-0,0227	-0,0123	0,0925	0,0015	0,0801	0,0189
470W	0,0298	-0,0029	0,0015	0,0571	0,0076	-0,0164
Radial (1)	-0,0490	-0,0008	0,0801	0,0076	0,1038	-0,0028
Finn Tokyo	-0,0700	0,0022	0,0189	-0,0164	-0,0028	0,0728

Table 21: SST Elite 2019 covariance matrix for the Tokyo 2020 Olympic cycle (Dec 2012, May 2019).

Then, by calculating the square root of Equation 38, we can obtain the portfolio return volatility, which is in our case the risk that SST is taking by managing the current athlete portfolio, for a given expected return.

Measure	Formula	SST Portfolio	Min in SST	Max in SST
Risk / Volatility	$\sqrt{\sigma_{SST}^2}$	0,1131	0,1728	0,4768
Expected Return	$R_{SST}^{(\lambda)} = \sum w_i \mu_{Log(Rank)_i}$	1,0618	0,6703	1,2506
Exp. Rank + Risk[14]	$R_{SST} = 10^{R_{SST}^{(\lambda)}} \pm 10^{\sigma_{SST}}$	11th ± 1 rank	4th ± 1 rank	18th ± 3 ranks

Table 22: in the first raw, the SST portfolio risk estimation is compared with the max and minimum risks within the athletes set. In the second raw, the expected average return in Log scale (computed with evenly allocated weights) is compared with the two extremes of the $\mu_{Log(Rank)_i}$ set, as we are dealing with Race Results, the lowest the better. In the third raw, the average return in Log scale has been projected to the traditional ranking to have a better understanding of the return.

The SST portfolio with evenly allocated weight w_i presents an expected return that is the average[15] of the $\mu_{Log(Rank)_i}$ set and the risk is below the amount of risk carried by the team/athlete with the lowest $\sigma_{Log(Rank)_i}$. This fact is due to the properties of the covariance matrix. In finance, the well-diversified portfolios are known to often offer a lower risk for a higher expected return than a single asset, particularly when the stocks are poorly intercorrelated in the market.
Usually, a set of about 20 well-diversified stocks are enough to hit the bedrock risk, also known as idiosyncratic risk of the financial market.

Looking at the Olympic Sailing sport, there are 10 different Olympic medals to win, and the largest National Federations can support at list a couple of teams for each of 10 disciplines. As is it visible in Table 21, the results of the athletes are partially correlated (and Equation 32 shows that too), so we can assume that a big National Federation is dealing with a lower risk than SST, which with small resources (human and financial) is competing for the same goal.

Another way to tackle the problem is to assume that the weights w_i are representing the contribution that each athlete is offering to the team. This contribution could be then mapped in a rewarding system from the Federation to the athlete. In the case above, SST is investing in each of the asset (athlete/team) because they are part of the team. Now, if we decouple the team membership (which is granted by the Kaderreglement) from the meaning of the weights, we could run an optimization where the w_i are free parameters to be optimized for minimizing the risk or maximizing the Sharpe Ratio of the whole portfolio. So, assuming alternatively one of these two Objective Functions, we obtain Table 23, where the results of the portfolio optimization are presented.

Objective	Improvement	Optimized	$\boldsymbol{R_{SST}^{(\lambda)}}$	$\boldsymbol{w_{RSX}}$	$\boldsymbol{w_{49er}}$	$\boldsymbol{w_{470M}}$	$\boldsymbol{w_{470W}}$	$\boldsymbol{w_{Radial}}$	$\boldsymbol{w_{Finn}}$
Min σ_{SST}	- 42%	0,0795	1,0516	16,16%	**33,93%**	<u>0,00%</u>	9,98%	13,95%	25,97%
Max S_{SST}^*	+ 31%	11,9613	1,0462	17,19%	**32,68%**	<u>0,00%</u>	10,11%	13,56%	26,46**%**

Table 23: results of the portfolio optimization. The first raw concerns the minimization of the portfolio volatility (σ_{SST}), the second the maximization of the Sharpe Ratio of the portfolio ($S_{SST}^* = \frac{\sum \mu_{Log(Rank)_i}^*}{\sigma_{SST}}$). In both cases, the weights for the different assets result to be close in the order of 1% or less. In both optimized scenarios, the support to the 470M team should be extinct. The fourth column represents the expected return of the portfolio, which it has only marginally improved in comparison with the value presented in Table 22.

[14] The Expected Rank and Risk are meant to be a re-mapping in the linear domain of the results found in the Log-Log scale. The purpose is to offer to a reader that is not familiar with the values of the logarithmic scale the flavour of the correspondent positions in the ranking. Nevertheless, those are not the mean and the standard deviation of the data distribution in the linear space.

[15] The average for the team of $\mu_{Log(Rank)_i}$ differs from the average presented in Table 8. In that case, it was the average of the Current Predicted Rank at May 2019 and the average of the Predicted Rank extrapolated for the future time of the Olympic Games in 2020.

Preliminary conclusions

This pure mathematical optimization for the two above mentioned objective function is probably too naïve to capture all the shades that bring a sports federation to the success; however, it brings in quantitative information that before was not available by just merely looking at the results of athletes. At the same time, a careful observer can collect some essential insides for the managers. First, a rewarding system could be developed in function of a quantitative portfolio optimization analysis. For example, it would be a way to support the athletes for their reciprocal beneficial contribution to team success and not only for their pure results. Besides, the personal modified Sharpe Ratio could be compared with the same ratio as the whole team. The same process could be done for the risk. The weights could be used as a proportional financial contribution as a bonus on top of a fixed lump-sum that comes for the SST membership status.

In the next sections of this chapter, we will focus more on the Olympic Project Review and a more sophisticated Objective Function, but for now, we can eventually argue more on Figure 19 and Table 17. In this section, we started by positioning the Swiss elite athletes in a risk-return space and computing for each of them a modified Share Ratio S_i^*. Now we know that those values are, on one side related to the history of their results ($\mu_{Log(Rank)_i}$), on the other hand, we have formulated an hypothesis about the trend of the risk in the function of weight and height. Then, we presented how it is possible to build an athlete portfolio with different risk-return characteristics and how to minimize the risk with the differentiation of the assets. For the Swiss Sailing Team, that cannot have access to more than the available assets, active management with incentives can be introduced. Once again, we remind the importance to see this approach as a dynamic analysis, because the values presented here are in continuous evolution. Similar to the Stock Market, but on a slower time scale.

Even if we have assessed a hypothesis for the trend of the risk, the limit of this analysis could be found in the use of $\mu_{Log(Rank)_i}$ as a critical value for the performance. We could argue that a peak performance should be something that goes beyond and above the mean of the distribution. That because a medal is in some cases the product of consistent long work in combination with a positive (good) Luck Contribution. That it means that it can be an outlier, far from the mean. An outstanding and lucky performance which the effect of the regression to the mean would hide soon, because of the mean of the distribution that shifts slowly. To make an effort for capturing some better future information, we can assume that the performance evolves following a learning curve, so instead of using a rewarding retrospective approach, we can try to formulate indicators that can offer a prospective reward [15].

To do so, we want to propose the same type of graphical representation as offered in Figure 19, but instead of using $\mu_{Log(Rank)_i}$, we substitute that value respectively with the $Rate\ of\ Improvement_i$ shown in Equation 18 and the values $Log(Rank)_i$ of Equation 21 predicted for $t = 1$, which correspond to August 2020, when the next Olympic Games will take place. The results are shown in Figure 21.

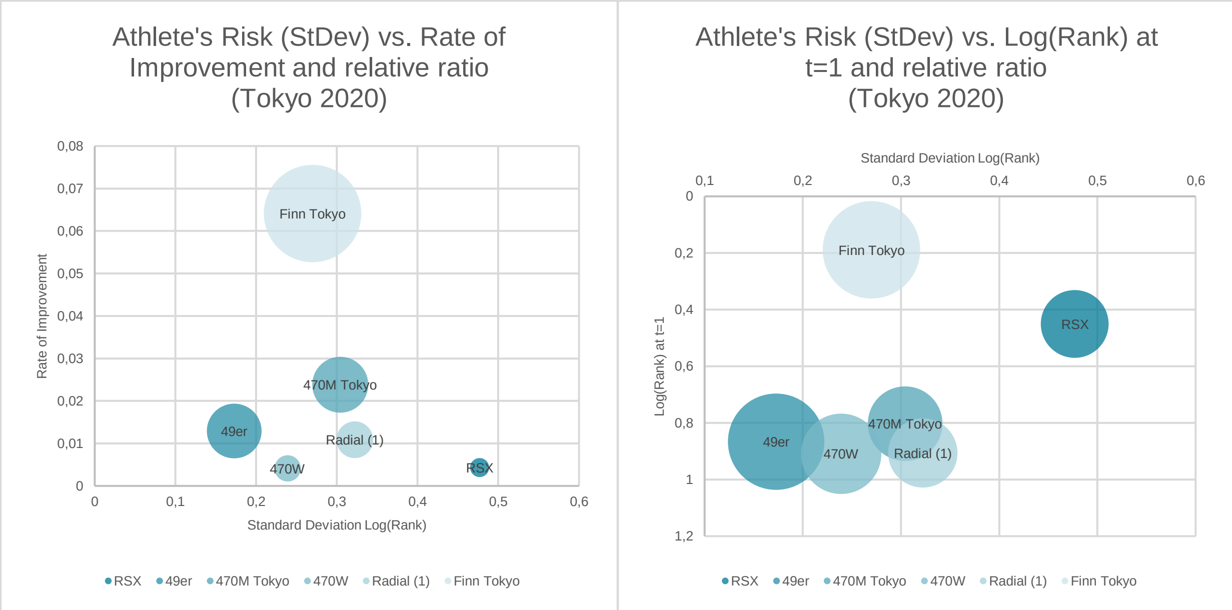


Figure 21: these two graphs are a fist attempt for introducing a prospective reward approach. Based on the assumptions and analysis elaborated in Chapter 3, we have modified the risk vs. return space into a risk vs. rate-of-improvement (left) and a risk vs. potential-achievement at a given date. Where in Figure 19 the bubbles were representing the modified Sharpe Ratio of Equation 36, here these represent the ratio between the value on y-axis vs. the standard deviation. The difference between these two figures and the right chart of Figure 19 are evident, but only for the risk-return return space we can ground our observation on a parallelism with the mean-variance portfolio analysis. Only when more data will be available in the next years, the management we will be in condition to evaluate the goodness of these two charts, for the moment these are holding on the assumption presented in this dissertation. Something evident, that deserves to be commented is the predominance of the Finn athlete in these charts. That athlete is really new in that class and he is improving fast because, we think, he has a solid proved experience. However, in these charts there is anything saying about the possibility that he has to hold such improvement rate, which it could allow him to fight for a medal in August 2020. As of other analysis, even this one needs to be considered dynamically.

4.2 SST Olympic Project Review and prediction

The Olympic Project Review is a periodical assessment of the status of the project that takes place once a year, generally in October. It is based on a multi-criteria evaluation method, which includes the previously presented Performance Development Process. Similarly to the PDP, the OPR has been introduced by Ph.D. Thomas Reulein and successively refined with the contribution of the other members of the SST Selection Committee (Thomas Rüegge and Pierre-Yves Jorand). Thoroughly the Olympic Project Review includes the following items.

- Quantitative and qualitative analysis of the training and racing activities. The analysis is performed directly by TeamDataLog, the planning and reporting software in use at SST. This summary analysis includes general and detailed indicators, depending on the time scale of interest. At the level of the Olympic Project Review, only macro indicators are kept in consideration, such as:
    - The average of the daily on-water training time;
    - The total amount of days on water;
    - Proportions between training, racing and peak event days;

  These indicators are compared with target values based on the decennial experience of the management. Also, a comparison with the information concerning the training programs of the other competitors, or other National Federations is performed.
- A comparison between the Result Target Settings defined ahead of the season and the real Results Achieved in the season.
- A success factors evaluation. The items in this section, to be evaluated on a 10 points scale, are predefined by the SST management and include:

- The volume of time on the water: is the total time appropriate for the target to reach, the sailing class and the corollary activities of the athletes?
- Private funding: on top of what provided by SST, is the financial situation of the team or athlete good enough to complement the support of the federation?
- Additional expertise: how broad and useful is the network of complementary expertise (individual sport psychologist, nutritionist, physical preparation, equipment and gears, etc.) that the team or athlete is accessing? Moreover, how much is that beneficial?
- Project management: how well done and smooth is the management (personal organization, coordination with SST, sponsors, and experts, etc.) of the personal Olympic Project?
- Health and injuries: how good are the medical prevention and how any occurred injury impacted on the season? The fewer the injuries, and the better the prevention, the higher the score.
- Training sparring: how many and of which standing are the sparring partners?
- Number of competitors: how large and tough is the fleet? Is a class with many sailors at the top level? Moreover, how realistic is the chance to achieve targets and qualification?

- A Performance Development Process, like presented in 3.3.1.
- A Coaching Evaluation, which is a tool for the sailor to assess the performance of his/her coach. The following items are assessed on a 10 points scale: athlete-coach relationship, match of coach skills with sailor's need, methodology and systematic work, quality and accuracy of TeamDataLog documentation, training skills, coaching skills, coaching under pressure at the peak events and last the communication skills of the coach.
- An overall agreed conclusion.
- The Result Target Settings for the following season.

For this dissertation, we had access only to the Project Olympic Reviews (OPRs) of autumn 2018, that because the SST management has updated this document after the Olympics 2016 and the revision of October 2017 was done with the old form still.
Our purpose in this section is to analyze some significative aspects of the OPR in order to perform a predicted OPR that the Selection Committee can use as a reference while evaluating the athletes. Then, in the next section, we intend to formulate a thorough Objective Function for the final athlete portfolio optimization.
As mentioned, the amount of data related to the project review is slim, as we have only one form for each athlete or team. However, in Chapter 3, we have extensively investigated the Race Results as learning curves with marginal returns, and we developed several multi-linear models to predict the Race Results. This achievement will be here useful for developing a predicted OPR for each athlete or team. To do so, firstly, we investigated the cross-correlation between the most relevant items of the available OPRs, and we obtained Table 24.

	Total sailed days	***On-water training days***	***Racing days***	***Success Factors***	***Perf. Dev. Process***	***Result Target***	***Achieved Results***
Success Factors	0,4080	0,5569	-0,6190	1	-0,0288	0,0916	0,0949
Perf. Dev. Process	0,0845	0,1767	-0,5762	-0,0288	1	-0,6940	-0,5078
Result Targets	-0,3453	-0,3972	0,3120	0,0916	-0,6940	1	0,7699
Achieved Results	-0,4118	-0,5027	0,4677	0,0949	-0,5078	0,7699	1
Coaching Evaluation	-0,3339	-0,5146	0,8838	-0,4442	-0,8313	0,6699	0,6315

Table 24: cross-correlation table between the most relevant items. To present a better synthesis, we decided not to display the full table of correlations, so, for brevity, we neglected the cross-correlation between the total, the training and the racing days, because those are not relevant.

To compute the values that have been used to perform the cross-correlation table, we calculated, for each athlete's form, an arithmetical average of the sub-items contained in the heading of the first column of Table 24.

Interpretation

From the results in Table 24 (reading by rows), we can sort the following insights.
The more time they spend afloat and for training, the higher the scores of the success factors, on the contrary, the more the racing days, the lowest the score for these. The averages of Success Factors are almost not correlated with the PDPs and the Results, either targeted or achieved.
The PDPs are slightly correlated with the number of on-water training days and negatively correlated with the racing day. That it would mean that the more days they are racing, the less the PDP factors are improving. One could argue that, with a fixed amount of available time, there should be an optimum between the time to spend in competition and while training. In this case, it would look that too much time is spent in competition. Once we look at the Result Target and the Achieved Target, we find a negative correlation again. That is expected, because as we have seen in the previous chapter, the closer a sailor is to the top, the smaller is the number targeted and higher the achieved position in the ranking.
The Result Targets are negatively correlated to the total sailed time and the training time. That is because, the more they sail, the higher their targets get. On the contrary, here again, the number of racing days, do not correlate in favour of increasing the Result Target. Then the Result Targets are strongly correlated with the Achieved Results.
The Achieved Results are presenting correlation to the other factors similar to the Result Targets, that trivially consequences to the high correlation that links the two. Besides, we can remark that, except the PDPs, the Achieved Results are better correlated than the Result Targets.
The Coaching Evaluation is presenting high scores when the number of the racing day is the highest and when the Result Targets and Achieved Results are the least ambitious. Then it negatively correlates with the total amount of days afloat and the training time. That would give the idea that a coach is generally well appreciated while coaching a race or a peak event, but it loses the scores over a long period, such during a long training season. What is rather surprising is that the coaching evaluation is strongly and negatively correlated to the PDPs. That it would mean that the higher are the scores of the coach, the lowest are the scores of the PDP. That could be explained with the sailors' expectation. An experienced and successful sailor would probably expect a high performance by his/her coach, and then it would be probably tighter with the evaluation. In addition, we have to mention another important detail, which is not visible from Table 24: the turnover of the coaches (interruption of coach-athlete relation) is not correlated to the Coaching Evaluation. That would lead to the conclusion that Coaching Evaluation item is not reliable.

Preliminary conclusion

This detailed interpretation of the cross-correlations, while keeping in mind the reliable evidence offered by the Achieved Results, we can state that the OPR present two items that seem not be significative for the review of the Olympic Project. These are the Success Factors and Coaching Evaluation. However, the limit of this interpretation lies in the meagre number of OPRs that we had the opportunity to analyze, but we strongly recommend investigating further when more information will be available.

4.2.1 Result Target Achievement interpretation

As previously mentioned, one of the items of the OPR is the comparison between the Result Target Settings defined ahead of the season and the real Results Achieved in the season. In general, this process is rather simple; in fact, it is just about checking if the achieved result is smaller or higher than the targeted.

Equation 39

$$Result\ Target\ Achievement = \begin{cases} if\ Rank_{achieved} \leq Rank_{targeted} \Rightarrow Target\ Achieved \\ if\ Rank_{achieved} > Rank_{targeted} \Rightarrow Target\ NOT\ Achieved \end{cases}$$

Now, after the dissertation of sections 2.3, 3.1 and following, we have enough elements to enrich this process, introducing a prediction. That prediction can be based on the individual learning curve (computed with Equation 21) of each athlete plus a buffer (Equation 17). This buffer accounts for the Luck Contribution, hence allowing for a better understanding of the Result Target Achievement.

	Events	RSX	49er	470M	470W	Radial	Finn
Target Results 2018	Miami	<u>10</u>	**10**	<u>15</u>	**13**	<u>15</u>	<u>12</u>
	Hyeres	**10**	<u>10</u>	<u>15</u>	**13**	<u>10</u>	<u>12</u>
	Worlds	<u>10</u>	**10**	**20**	<u>15</u>	**15**	<u>15</u>
	Enoshima	**10**	<u>10</u>	**15**	<u>13</u>	<u>10</u>	**12**
Results Achieved 2018	Miami	18	6	20	11	20	16
	Hyeres	10	26	28	11	33	24
	Worlds	20	10	20	17	9	RET
	Enoshima	2	14	15	17	16	10
Predicted Results 2018 + Luck	Miami	<u>6 ± 2</u>	**15 ± 5-9**	**19 ± 8-13**	**11 ± 3-6**	**15 ± 5-9**	**17 ± 7-11**
	Hyeres	<u>5 ± 1-2</u>	<u>14 ± 5-8</u>	**17 ± 7-11**	**11 ± 3-6**	<u>14 ± 5-8</u>	<u>14 ± 5-8</u>
	Worlds	<u>5 ± 1-2</u>	**13 ± 4-8**	**15 ± 5-9**	**11 ± 3-6**	**13 ± 4-8**	<u>10 ± 2-5</u>
	Enoshima	**5 ± 1-2**	**12 ± 3-7**	**14 ± 4-8**	<u>10 ± 2-5</u>	**13 ± 4-8**	**9 ± 2-4**

Table 25: table of 2018 Target Results, Results Achieved and Predicted using the Learning Curves and the model for the Luck Contribution presented respectively in sections 3.1 and 3.2. In bolt are highlighted the Predicted Result or the Target Result achieved in this season. The underlining highlights the Target or the Predicted Results not achieved.

From Table 25, we can see that Equation 39 lead to a rather pessimistic interpretation of the season because it would bring to the conclusion that 14 of 24 targets have been not reached by the sailors. Moreover, here, for a complete understanding of the target setting process, we have to mention that are the athletes in agreement with their coaches (and the project leader) that define their Result Targets. So the objectives are not top-down, even if SST sets the minimum standard to be part of the B-Kader or the National Team. Instead, when we used the Learning Curves to predict the target of the season, the Result Target is computed on the personal result trend based on a diminishing return law, we can see the achievements under a new light. In fact, by setting the target with Equation 21 plus the positive or negative contribution of luck (the range is due to the possibility to apply different models: Max, Mid, Min presented in Figure 12), we see that only 8 of the 24 targets have not been achieved. Besides, we could mention that the sailor with the highest risk (Table 20) is the one who achieved the least of the target, but at the same time, the only medal of the 2018 season.

Preliminary conclusion

Thereby, we recommend adopting a new method for assessing the Result Targets, namely computing the coefficients of the Learning Curve and then forecast the result for the next season. On top of it, we recommend adding the Luck Contribution as a model in function of the ranking position. The reasoning of the recommendation is not due to the more optimistic outcome of the “reality check” that derives by applying Equation 39. On the contrary, here we want to offer an objective way to forecast future Result Target by relying on consistent assumptions and not only on a “gut-feeling” and “experienced-based” interpretation of the possible future scenarios. That because it seems that the Result Targets so defined are too aleatory and may lead to a misperception of the SST team improvements, which are solid instead. To support this recommendation, we want to propose a more sophisticated version of Equation 39, in the following algorithmic format.

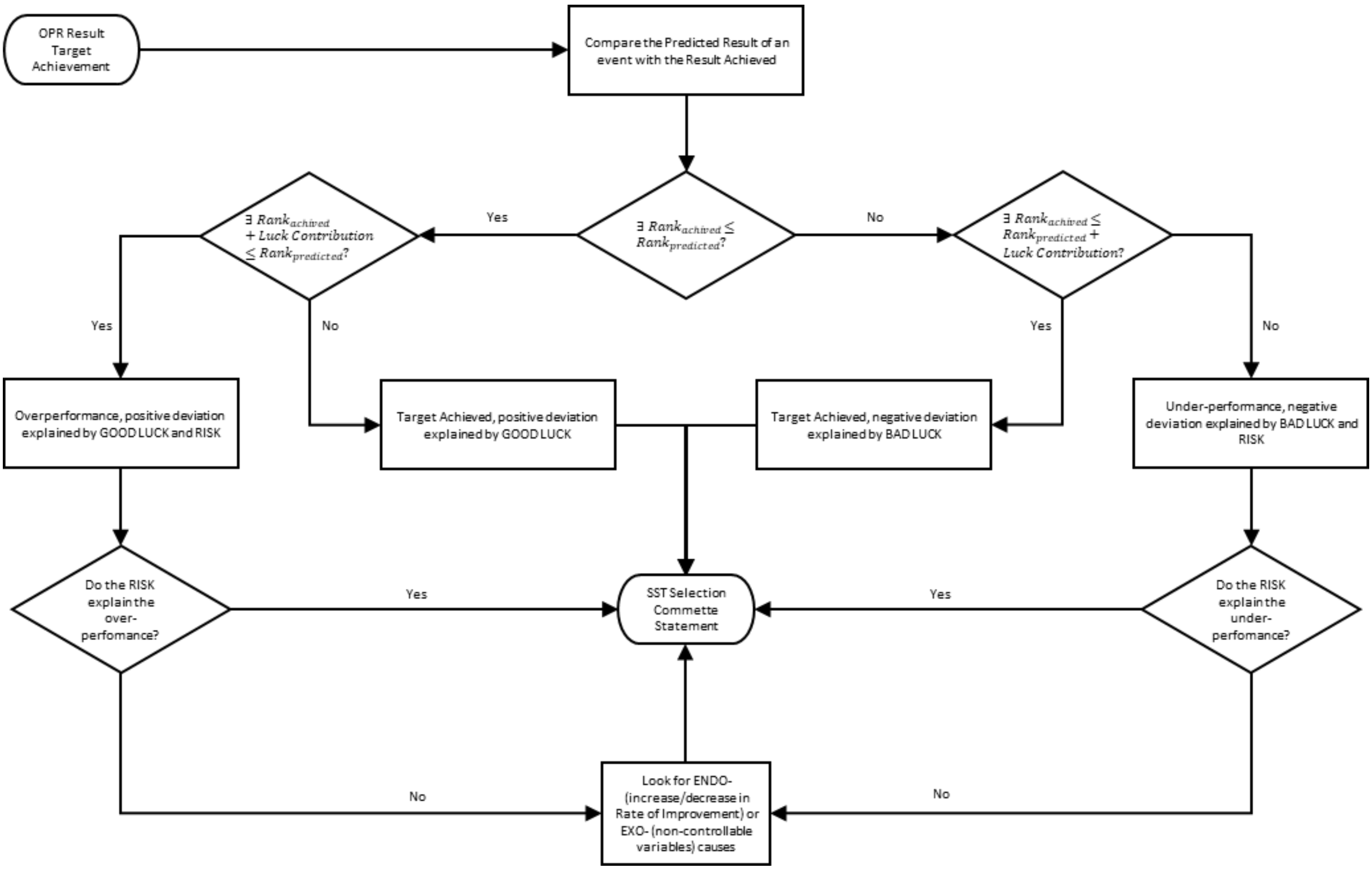


Figure 22: an algorithm for the interpretation of the results. We advise integrating into the OPR this process for the evaluation of the Result Target Achievement. The use of this algorithm can be implemented in combination with the Predicted Results by Learning Curves approach (Equation 20) and the Luck Contribution models (Equation 17). The risk is computed as $\sigma_{Log(Rank)_i}$.

The approach presented in Figure 22 offers to the SST Selection Committee the possibility to have a deeper understanding of the Results Achieved by the athletes. Then, in combination with the diagram of Figure 18 and the PDP data, it would be possible to assess the origin of the over- or under-performance. So deeply understand if the achievement was triggered mainly by endogenous or exogenous factors.

	Events	RSX	49er	470M	470W	Radial	Finn
Target Results 2019	Miami	**12**	8	15	8	12	**10**
	Genova	-	10	**15**	8	**10**	-
	Worlds	18	5	15	Nat. Quota	10	10
	Olympic Test Event	5	8	10	8	8	10
	Enoshima	10	5	15	8	10	10
Results Achieved 2019	Miami	6	16	24	13	30	5
	Genova	-	21	3	9	3	-
Predicted Results 2019 + Luck	Miami	**4 ± 1-2**	**11 ± 3-6**	12 ± 3-7	**10 ± 2-5**	12 ± 3-7	**7 ± 2-3**
	Genova	-	11 ± 3-6	***11 ± 3-6***	**10 ± 2-5**	***11 ± 3-6***	-
	Worlds	4 ± 1-2	9 ± 2-4	10 ± 2-5	9 ± 2-4	10 ± 2-5	4 ± 1-2
	Olympic Test Event	4 ± 1-2	9 ± 2-4	10 ± 2-5	9 ± 2-4	10 ± 2-5	4 ± 1-2
	Enoshima	4 ± 1-2	9 ± 2-4	9 ± 2-4	9 ± 2-4	10 ± 2-5	3 ± 1-2

Table 26: table of 2019 Target Results, Results Achieved (only the one already accomplished) and Predicted using the Learning Curves and the model for the Luck Contribution presented respectively in sections 3.1 and 3.2. In bolt are highlighted the Predicted Result or the Target Result achieved in this season. In bold and italic, we show the Predicted Results achieved by keeping into account the Luck Contribution plus the Risk, that can contribute positively or negatively (ref. Figure 22). The underlining highlights the Target or the Predicted Results not achieved. Half-way of the 2019 season, the predictive methods are better to predict the results that will be achieved than the sailors and their coaches.

Here in Table 26, we offer the most updated available outlook on 2019. Once again, it is visible that the individual result target setting defined by the athletes during the OPR process in autumn 2018 looks more based on an “educated guess” than on a real improving path. Conversely, the results predicted with the learning curves plus the luck contribution show an incremental improving trend within a specific range given by the aleatory nature of Olympic Sailing.

Interpretation

So, by measuring the gap between the Target Results and the Predicted Results, the management can predict if a decrease in the Rate of Improvement shall be expected. In fact, if the athlete is setting the goals systematically below what the Learning Curve would predict, then, even if the target has been nominally achieved, we have to reassess the long-term targets, because the new learning curve interpolating the new Race Result time series will lay below the previous one. Indeed, predicting a lower long-term result. Summing up what we have discussed so far about the OPR Result Target setting and achievement, we have offered a completed interpretation and available prediction, which is going beyond what was achievable with Equation 39. Now we have: first, a method to objectively set the targets as a projection of the past improvement and results, then a tool to interpret the achievements thoroughly and last an indicator of the trend for the future improvement tendency.

4.2.2 Long-term Results and Performance prediction

The Performance Development Process has been a central subject of Chapter 3, and here, we acknowledge that it has a role in the OPR. Furthermore, in the previous chapter, we have studied in a detailed manner the proprieties of the PDP, and we have assumed that each of the six factors that contribute the Race Results is evolving following a law of diminishing return that it can be described by a power law function. Equation 32 describes how these factors interact in a multi-linear regression model, and the diagram of Figure 18 shows the main interdependencies qualitatively. So, by extrapolating the values of the PDP factors for a future time, we are in a condition to assess, using both methods (the Equation 20 and Equation 21 or Equation 32), what to expect by the time of the next Olympics in August 2020. We already partially did that (Table 8) using simply Equation 20, but here we intend to extend the analysis by using all the tools developed in this dissertation.

Tokyo 2020	**Model at $t = 1$**	**RSX**	**49er**	**470M**	**470F**	**Radial**	**Finn**
	Predicted Rank	7 ± 3	9 ± 2	14 ± 12	12 ± 5	22 ± 13	10 ± 7
Predicted PDP: gap to World Champion in %	Technique	23 ± 7	26 ± 5	11 ± 3	22 ± 2	61 ± 2	31 ± 0
	TactStrat	19 ± 6	25 ± 5	32 ± 31	24 ± 5	62 ± 9	33 ± 5
	Fitness	11 ± 5	24 ± 3	59 ± 39	18 ± 5	43 ± 13	23 ± 0
	Mental	19 ± 4	20 ± 4	59 ± 44	34 ± 14	60 ± 14	30 ± 5
	Equipment	12 ± 2	25 ± 6	57 ± 48	16 ± 6	53 ± 7	31 ± 4
	KnowHow	19 ± 11	42 ± 5	38 ± 14	29 ± 8	51 ± 10	40 ± 7

Table 27: combined prediction at $t = 1$ (time of 2020 Olympic Games). The prediction has been performed combining the extrapolation at $t = 1$ obtained by the Learning Curve regression and the multi-linear model for Race Results in the function of the six factors of the PDP. The presented value of the prediction is the average of the models, and the interval of accuracy is computed as the mid-range of the predicted values. All values have been first computed in the Log-Log scale (linear) and after reversed in the system of reference used by SST (law of diminishing return).

Table 27, in combination with Table 8, Table 17 and Table 20, shows in a glance all the available predicting power collected in this dissertation. Probably one of the first remarks that someone could argue is that some of the values present a vast range. Then we need to remind that the amount of PDP available for each athlete (or team) is often minimal. Where in Table 27, the values show a wide range, then it means that the values stored in the PDPs are rough.

Interpretation

That could be explained in different ways. First, it could be that the athlete is not experienced enough to assess the level in comparison to the World Champion. A second option could be that the athlete is rather conservative or ambitious concerning certain factors, but it may neglect the interdependencies between them, which we highlighted in 3.3.2. A third option could see an athlete, which is focusing on one specific aspect of the PDP, to increase (instead of closing) the gap in other factors. That could be explained by the limited time available to train and consequently improve.
A good example could be an athlete that has to increase his/her body weight to get closer to the mean of the fleet. To achieve that improvement in the Fitness factor, the sailor has to invest much time in the gym, that it can jeopardize the time he/she can dedicate to stay afloat. That it would result in a decrease of the Technique and/or TactStrat factor. If this would be the case, the range of uncertainty in Table 27 has to increase. Besides, what we shall not forget is that the learning process is generally seen as an up-warding improvement process, but it can be flat or even downward sloped when not enough resources are spent for it.

In this section, we presented the Olympic Project Reviews, and we provided an interpretation of the cross-correlation of its constituent items, identifying that some of the indicators are probably not reliable or at least not correlated to the results in competition. Then we performed a thorough Result Target Achievement interpretation, and last we computed the long-term prediction of Race Result for the next Olympic, including the gap to the World Champion for each of the Performance Development Process factors. Now the SST management and the Selection Committee, while using those new Keep Performance Indicators (KPIs) can extend the overview with a more extensive set of information that can nourish and widen the level of understanding of the athlete portfolio.

4.3 Objective Function and Scenarios Optimization

In Table 23, we have shown the results of our first attempt of portfolio optimization, and we commented on the limitation of this approach. In fact, optimizing by minimizing the risk or maximizing the Sharpe Ratio of the portfolio is not a thorough process for a sport of performance, even if it can offer useful insights. Therefore, in this section, we intend to propose a complete formulation of an Objective Function which shall capture the whole complexity of the Olympic Sailing sport.

The ultimate strategic target of the Swiss Sailing Team is to win an Olympic Medal, that is the "Holy Grail" to reach. The achievement of this goal is not happening in the vacuum, and it cannot be reached at any cost. There are several constraints which are influencing the reaching of the target. To mention two that are considered some of the most relevant: finances and amount of athletes are limited. In comparison with major National Sailing Federation, on one end, Switzerland has proportionally scarce financial resources, on the other end, even forecasting limitless funding, the number of athletes is limited in size. That small size, as we have seen in 4.1, influences the portfolio composition and therefore the success of the team.
Swiss Sailing Team is proactively cooperating with the stakeholders and sports organizations such as Swiss Olympic, BASPO (Swiss Federal Office of Sport), Swiss Sailing Clubs and sponsors to maximize the financial resources. However, the possibility to increase or maintain the overall budget is an argument that goes beyond this dissertation, and regulations bind it. Therefore, for this work, we will assume the financial resources as fix constraints.
Another crucial strategic element is the Youth Development. The Youth Team is, at the same time, a resource for the long-term success of the team and a constraint for the short-term financial resources dedicated to the Elite Team. What is trivial to say is that without the Youth Team, there would not be an Elite Team in the long-term. Therefore a fraction of the total amount of financial resources must be allocated to the Youth Development. The size of this fraction and the overall Youth Concept [30], the strategic plan that defines how to provide enough athlete to the Elite Team, could be discussed. However, to limit the level of complexity of the Objective Function in this dissertation, we assume that the Youth Department nourish the Elite Team at a fixed rate and that is corresponding with the number of Elite sailors that SST can sustainably support.

Once stated these preliminary conditions, we can qualitatively describe the Objective Function that shall be used to optimize the SST Athlete Portfolio. As it could be now expected, such function is based on multiple criteria. In agreement with the SST management, we identified ten control parameters, five which can be defined as classic Keep Performance Indicators and other five that are stemming from this dissertation. The classic KPIs were already traditionally used by the Federation's manager. So this new SST Multi-criteria Objective Function focuses on:

- Nation Quota achievement and personal qualification to Olympic Games: to be in a condition to achieve any results to the Olympic Games, an athlete or a team has first to qualify the nation and then to satisfy the selection criteria defined by the National Olympic Authority. In general, this accomplishment is considered as part of the process and is not strictly determinant for the final result at the games. So it does not matter if the qualification happened early or last minute[16]. Surely it has to happen if we want to have an athlete attending the Olympics. This KPI is digital; it is 1 when the Nation Quota is obtained, it is 0 when not.
- Medal Achievement at World-Class events: the achievement of one or more medals at the World Championship, the World Cup Series and at a Continental Championships is generally considered as a proof of the potential of an athlete. Based on a retrospective assessment, the

[16] We could not find any statistical evidence of that assumption, but that reflect the opinion of the SST management.

assumption lies in the idea that, if an athlete achieves that level once, it can potentially do it again during another peak event. This KPI is discrete, starting from zero, each medal collected by the athlete counts as one additional integer unit.

- Olympic Games Experience: many athletes, coming from different disciplines and sports, say the same, the participation at the Olympic Game is mindblowing. The amount of feelings and emotions can be overwhelming — the stress and expectations skyrocket. Sportsmen and sportswomen say that "being under pressure is a privilege," but not everyone is able to deal with that. Therefore, a sailor with a previous Olympic experience knows what to expect and possibly learnt how to deal with it. So a previous attendance contributes generally positively to success. As for the medals, this KPI is discrete, starting from zero, each Olympic experience by the athlete counts as one additional integer unit.
- SST Membership Status: as previously mentioned, in Switzerland, an elite sailor can be in the C-Kader, the B-Kader, the National Team or the *Olympiakader*. This achievement is reached by satisfying criteria that are published on the SST website. Without entering the details of the system, the criteria are set to select the sailors that are already above a level which is meant to be the minimum acceptable to reach the medals in a reasonable amount of time (one or two Olympic cycles). This KPI assigns zero points to the C-Kaders, one point to the B-Kaders, two points to the National Team members and four to the *Olympiakader*. The main difference between these status consists of the number of coaching days offered by SST.
- Project Review Success Factors: even though this item of the OPR is not correlated to the Race Results, it remains a useful indicator for the overall health of the Olympic Project. In 4.2, we described it in details. This KPI is taken as the average of the items that compose it. It can assume positive continuous values between 0 and 10. In the current case, the averages span between 6 and 7.6.
- Past Rate of Improvement: plugging Equation 20 into Equation 18, we build the first new KPI. The rate of improvement computed from the begin of the Olympic cycle over a well defined period, in this case, 1000 days, offers a retrospective evaluation about how quickly a sailor can climb the ranking and improve his/her level. The values of the KPI for the SST athletes are shown in Table 8. These are positive when there is an improvement, negative when there is a worsening and close to zero with stagnation.
- Potential Tokyo 2020: with the results shown in Table 8 computed with Equation 20, we build the second new KPI.

  Equation 40

  $$KPI_{Potential_i} = \left(10^{Log(a_i)+k_i*Log(t=1)}\right)^{-1}.$$

  This KPI assumes values in the continuum between 1 and 0. The higher the value, the greater the potential of the sailor.
- Multi-linear Race Result Prediction: using Equation 32, we compute the next KPI as it follows:

  Equation 41

  $$KPI_{MLPrediction_i} = \left(10^{\left[-0{,}415+0{,}780*F_{Mental_i}^{(\lambda)}+\,0{,}277*F_{Technique_i}^{(\lambda)}\right]_{t=1}}\right)^{-1}.$$

  This indicator accounts for the prediction of the Race Results based on the PDP extrapolated at $t = 1$, so the time of the next Olympic games. This KPI assumes values in the continuum between 1 and 0. The higher the value, the greater the potential of the sailor[17].

[17] We decided to consider both, Potential Tokyo 2020 and Multi-Linear Race Result Prediction because these are two different method to predict the results and we don't have enough elements to identify if one of the two is more or less reliable than the other.

- Margin of Future Improvement: given a fixed number of events j, we compute for each athlete i the gap between the predicted results with Equation 20 and the Target Result declared in the OPR. The gaps are then averaged to obtain a value for each sailor.

  Equation 42

  $$KPI_{Margin_i} = \langle Predicted\ Result_{i,j} - Target\ Result_{i,j} \rangle_j.$$

  This value can be computed each season, and the KPI is assumed to be continuous. Scores close to 0 identify teams that expect to reach targets in line with the prediction. Negative scores highlight sailors that target results below their expected rate of improvement. Positive values account for athletes that expect to progress faster than their expected rate of improvement.
- Risk Mitigation: this last of the new KPI that we introduced for the SST Athlete Portfolio Optimization, and it accounts for the risk. Deriving it from section 4.1, we have:

  Equation 43

  $$KPI_{Risk_i} = \sigma^{-1}_{Log(Rank)_i}.$$

  So the smaller is the risk carried by the athlete, the higher is the indicator.

Then, in order to consider the whole set of KPIs together, each KPI has been normalized within the interval $KPI_i = [0, 1]$ to obtain Table 28.

10 KPIs	**RSX**	**49er**	**470M**	**470F**	**Radial**	**Finn**
Nation Quota	0,00	1,00	0,00	0,00	1,00	0,00
Medals	1,00	0,00	0,50	0,50	0,50	0,00
OG Experience	1,00	1,00	0,00	1,00	0,00	0,00
SST Status	1,00	1,00	0,50	1,00	1,00	1,00
Success Factors	0,98	0,89	1,00	0,79	0,89	0,85
Rate of Impro.	0,07	0,20	0,37	0,06	0,17	1,00
Potential 2020	0,67	0,29	0,33	0,25	0,25	1,00
ML Prediction	1,00	0,90	0,50	0,64	0,31	0,64
Margin of Impro.	0,00	1,00	0,18	0,86	0,74	0,21
Risk Mitigation	0,36	1,00	0,57	0,72	0,54	0,64

Table 28: summary of the 10 KPIs considered relevant for the Athlete Portfolio optimization. For each variable, the value related to each athlete or team assumes a value between 0 and 1.

For a better understanding of the indicators, we have mapped Table 28 into qualitative scales. For the first 5 KPIs, the conversion has been rather simple. For the second five, the new and quantitative KPIs, we mapped the values on a five-level Likert-type scale, from Very Low to Very High. The qualitative mapping is shown in Table 29.

10 KPIs	RSX	49er	470M	470F	Radial	Finn
Nation Quota	No	Yes	No	No	Yes	No
Medals	2	No	1	1	1	No
OG Experience	Yes	Yes	No	Yes	No	No
SST Status	NT	NT	B-K	NT	NT	NT
Success Factors	Very High	Very High	Very High	High	Very High	Very High
Rate of Impro.	Very Low	Low	Low	Very Low	Very Low	Very High
Potential 2020	High	Low	Low	Low	Low	Very High
ML Prediction	Very High	Very High	Moderate	High	Low	High
Margin of Impro.	Very Low	Very High	Very Low	Very High	High	Low
Risk Mitigation	Low	Very High	Moderate	High	Moderate	High

Table 29: the normalized KPIs of Table 28 have been mapped into a qualitative scale.

With Figure 23, we offer a visualization of the data in Table 28. A careful look at the chart can reveal the differences between the teams. The six elite Swiss teams running an Olympic Project with SST show different strength and weaknesses and contribute differently to the overall success of the team.

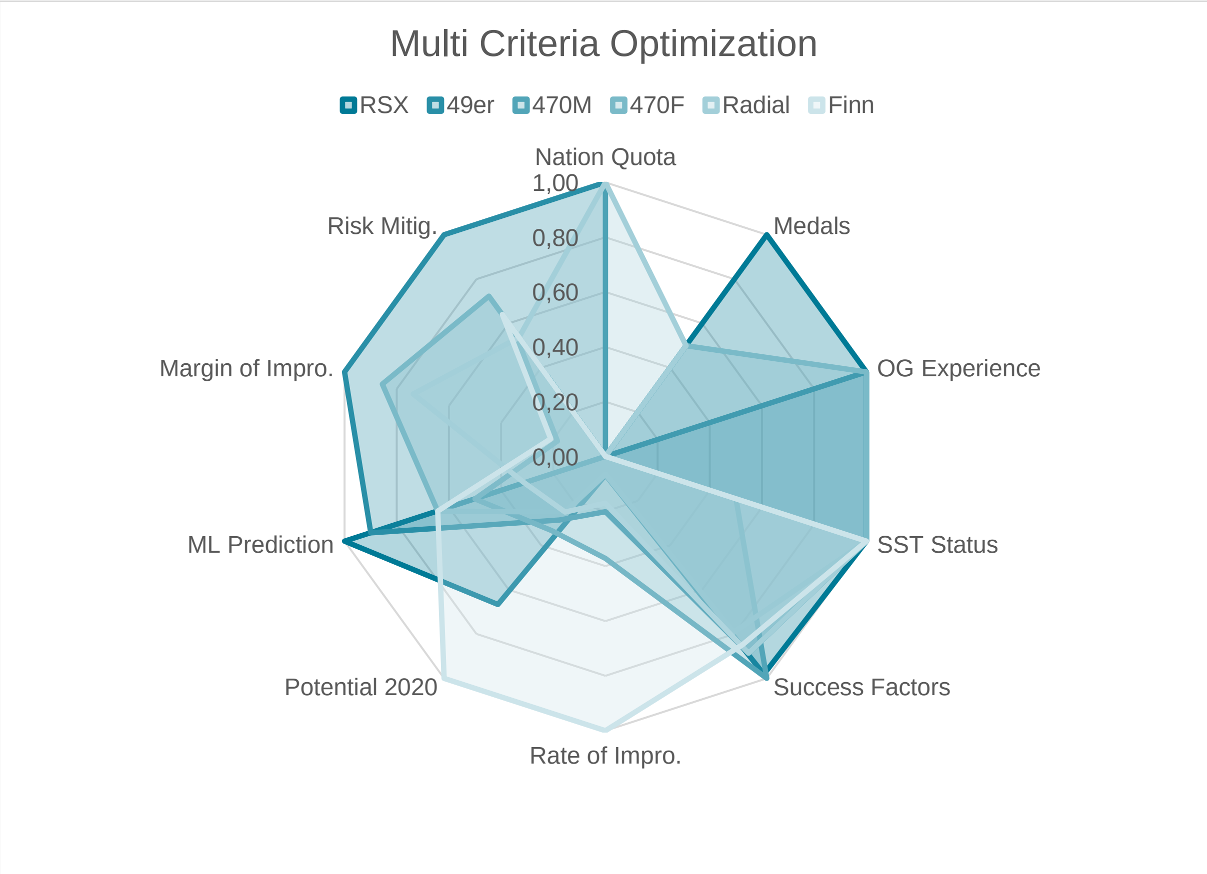


Figure 23: the Multi-Criteria Optimization KPIs are shown on this chart for each sailor/team of SST. The data displayed correspond to Table 28. The present visualization highlights the substantial differences between the Elite sailors.

Preliminary conclusion

To optimize the SST Athlete Portfolio, we should maximize this Objective Function. Then, after this optimization process, we could understand which the athletes are that contribute the most to the success of the National Team. As already mentioned, the ultimate target is to reach an Olympic Medal; however, it is disputable how to use the different KPIs to achieve it. Moreover, we have to accept the fact that we do not know much about the mathematical formulation of this complex Objective Function. On that topic, we exchanged and discussed with the SST management, but, unfortunately, for them, it is not possible to clearly weight and/or prioritize the 10 KPIs, or to define a clear mathematical relationship between the different KPIs. In fact, the approach presented in this dissertation is, for SST (and in our knowledge for any National Sailing Federation), an entirely new way of seeing the athletes. However, we can present the following formulation and tentative approximation for this complex Objective Function to optimize:

Equation 44

$$OF_{SST}\left(KPI_{i,j}\right) = f\left[KPI_{i,j}(t)\right] \approx \sum_{i,j} \omega_j KPI_{i,j} \,.$$

Where j refers to the KPIs and i refers to the sailors. So, for small t, in the order of a sailing season, we are assuming that the Objective Function is approximate with a linear combination of the $KPI_{i,j}$ with weights ω_j. Hence, we accept to leave the general form of $OF_{SST}\left(KPI_{i,j}\right)$ unknown, because there are not sufficient elements to determine how the different $KPI_{i,j}$ are interconnected. The best approach we could offer to study such interconnection we have presented it in 3.3 and 4.1, by developing the Multi-Linear Model for the Race Results and studying the Risk-Return optimization using the covariance matrix, but that not enough to close Equation 44 and define the relative constraints.

Therefore, to approach the optimization of the Objective Function, we decided to formulate some reasonable scenario discussed with the SST management. Then we computed, similarly as we did in Table 23, the contribution of each athlete/boat to the success of the whole SST team. The contribution to the success will be then measured as the athlete's percentage weight in $OF_{SST}\left(KPI_{i,j}\right)$, given by:

Equation 45

$$w_i = \frac{\sum_i \omega_j KPI_{i,j}}{\sum_{i,j} \omega_j KPI_{i,j}} = [0, 1] \,.$$

To design the different scenarios, we decided to do a parametric analysis by allocating digital values, zero or one, to the different ω_j. To offer the maximum of the information to the management, we have then studied 6 scenarios: the first and more general scenario (Combined) keeps in consideration all the 10 factors with the same weight. This scenario stands as a reference for a comparative analysis between the scenarios with different combinations of ω_j. Then we computed a second scenario (Classic) with $\omega_j = 1$ only for the following KPIs: Nation Quota, Medals, OG Experience, SST Status, Success Factors, and $\omega_j = 0$ for all the others. Conversely, the third scenario (New only) allocates $\omega_j = 1$ only to Rate of Improvement, Potential 2020, ML Prediction, Margin of Improvement and Risk Mitigation, and $\omega_j = 0$ for all the classic KPIs. Then to study how the new KPIs are interacting, we analyzed a scenario (Improvement) based on the factors that measure how quick an athlete is expected to increase his/her performance, independently by the current position in the ranking. To do so, we allocated $\omega_j = 1$ for $KPI_{RateOfImprovement_i}$ and KPI_{Margin_i} and $\omega_j = 0$ for all the others. The fifth scenario (Predicted Result) allocates $\omega_j = 1$ to $KPI_{Potential_i}$ and $KPI_{MLPrediction_i}$ and $\omega_j = 0$ for all the others, so it accounts for the results that the sailors can achieve in the future and it depends on where they stand at present. Last, we approached a Risk Mitigation scenario, where we look only at KPI_{Risk_i}, with $\omega_j = 0$ for each $j \neq KPI_{Risk_i}$. This last scenario leads to a different result than what we presented in 4.1 because it is obtained with a different methodology. In the following table, we summarize the results of this study.

Scenario	**KPIs**	w_{RSX}	w_{49er}	w_{470M}	w_{470W}	w_{Radial}	w_{Finn}
Combined	All ten	17,95%	**21,48%**	<u>11,68%</u>	17,21%	15,91%	15,78%
Classic	First fives	**21,64%**	**21,13%**	<u>10,87%</u>	17,90%	18,41%	<u>10,05%</u>
New only	Second fives	<u>13,55%</u>	**21,89%**	<u>12,65%</u>	16,39%	<u>12,95%</u>	**22,58%**
Improvement	$KPI_{RateOfImprovement_i}$ KPI_{Margin_i}	<u>1,39%</u>	**24,72%**	11,43%	18,92%	18,64%	**24,90%**
Predicted result	$KPI_{Potential_i}$ $KPI_{MLPrediction_i}$	**24,58%**	17,48%	12,29%	13,17%	<u>8,26%</u>	**24,22%**
Risk Mitig.	KPI_{Risk_i}	<u>9,46%</u>	**26,11%**	14,83%	18,88%	14,00%	16,72%

Table 30: the Athlete Portfolio Optimization scenario analysis is presented in this table. By computing the percentual contribution of each team based on a specified set of KPIs, we can identify the strength and the weaknesses of each team member. With the bold digits, we highlighted the highest contributions for each row, and with underlined digits the lowest. The 49er contributes most of the majority of the scenarios. RSX and Finn could be top or least contributors depending on the KPIs accounted. 470M and Radial are often contributing the least. 470W is always settling in the middle of the spectrum.

5 Conclusions and Outlook

Exploring a well-known domain with new eyes

In recent decades, the sport of performance as a whole has seen a definite increase in professionalism. Olympic Sailing is one of those sports where professionalism, in particular for coaching and management, developed a little later. When we are looking at the education of the sailing coaches and the federation managers, we can see that most of them collected their experience in the field. As confirmation of this assumption, we can assert that the coaching education system in continental Europe is mainly based on checking the personal knowledge and competencies instead than transferring it. That is probably due to the complexity of the subject and the lack of knowledge concerning the proper methodology to reach the ultimate goal of winning a medal a the Olympic Games.

Whit this thesis, we explored a well-known domain for the Swiss Sailing Team using tools which are generally applied to other areas, like Financial Market, Management or Economy in general. During this journey, we discovered that the data are still too few to always reach a solid conclusion, but on the other hand, we highlighted a set of new insights that can be used for future decision. To obtain these results, we had to build a framework and a methodology that can be applied and extended to other sailors or generalized and used for other sports disciplines.

A long journey for the good of the team

One of the needs of the Swiss Sailing Team is always to invest and operate to obtain a real and immediate benefit for the athletes. This approach is required because the resources are often used to the highest degree of efficiency, and a long-term investment may not bring to a useful result if, in the meanwhile, the athletes cannot be sufficiently supported. With this dissertation, we are contributing to this immediate benefit, by identifying new Keep Performance Indicators that can be used by the management to assess the status, the targets and the priorities of the whole team and each sailor.

Summarising, in this thesis, we have first identified the position of Olympic Sailing on the Skill-Luck continuum (Figure 11) introduced by Mauboussin [9] and proposed a model for the Luck Contribution in the function of the position in the Ranking (Equation 17). Then we have studied how the Race Results evolve (Equation 21), by assuming a law of diminishing returns [31] [10] for the trend of the Learning Curves used for data interpolation. This analysis conducted to the first possibility to predict the Potential Result for each sailor at the Olympic Game of Tokyo in 2020 (Table 8). After, having the opportunity to access to the Performance Development Processes of the Swiss Elite Team, we dived into the complexity of the sailing sport discipline searching for the interconnections between the factors and how those are contributing to the achievement of a result in a competition (Equation 32, Figure 17, Figure 18, Table 13). Therefore, in Chapter 3, we had the opportunity to treat the factors of the Performance Development Process as terms of a Production Function [32] and to conclude that Technique and Mental preparation contribute to the Race Result with an increasing return to scale (Equation 33). In Chapter 4, we investigated the success, and we have studied the team with two methods. First, we claimed for parallelism with the Financial Market, treating the athletes as assets carrying an expected return and a risk (Figure 19). Doing so, we have formulated a hypothesis (Table 19) for the trend over time of the standard deviation related to the results of each athlete. Holding on this parallelism, we have performed two optimizations [13], targeting two simple Objective Functions (Table 22); the minimization of the Risk and the maximization of the Sharpe Ratio [12] of the SST Athlete Portfolio. For the second method, we began approaching the study of the Olympic Project Reviews. So, to offer the best interpretation of the state of the projects, we used the previous findings to elaborate full predictions for the seasonal Result Target (Table 25, Table 26) and the long-term Result and Performance evolution (Table 27). This in-depth analysis of the Olympic Project Review finally leads to the qualitative formulation of a complex Objective Function, for which we used five new Keep Performance Indicators developed during this dissertation (Table 29). Then, due to the lack of a mathematical formulation (Equation 44), to optimize the Objective Function, we got inspired by the multi-criteria decision analysis [14] process. Therefore have studied different scenarios and computed the percentage contribution of each athlete (Equation 45, Table 30).

Olympic Sailing: a skill-based sport discipline

When in the introduction, we mentioned Gould and his book *The Full House* [21], we brought up the example of baseball. In that case, the continuous improvement of the professional players led to a plateau of the statistical indicators for the quality of the players. So it becomes progressively harder to be an outlier. Now, referring to the results of Chapter 2, we can conclude that Olympic Sailing is not yet experiencing this situation. Looking at the diminishing trend of the Luck Contribution in the function of the ranking position, we can confirm that the sailors on the top of the ranking have more skills than the one behind. The contribution of luck is only marginal for the top position, so it is not possible for a sailor to claim for a prominent role of bad or good luck. However, noticing an increment in professionalism in the sailing sport, we can expect that in the future the situation may evolve differently. As a signal for that, we can remind that the 49er and Radial class are the only Olympic Sailing disciplines showing the equal contribution of luck for being a medal winner or just in the medal race, but finishing out of the podium. That results are in line with the reality of the sailing sport; the Laser Radial is the most popular within women (in total 338 athletes attended at least a World Cup event since Dec 2012), and 49er is currently extremely competitive with many sailors that are active in other professional circuits too, like the GC32 and the well known America's Cup.

The challenge of a continuous improvement

While formulating the assumption that the time series of the Race Results can be interpolated by a function that respects the law of diminishing return, we accepted that each elite sailor has to fight increasingly harder to improve the same amount. In this dissertation, we discussed only marginally the rate of improvement of the other competitors, and we decided to focus only on the results of the Swiss sailors. What we can conclude is that not all the athletes can reach a medal in a limited amount of time comparable with an Olympic cycle. An expert can argue that it is trivial, but what we offered with our analysis is a prediction of when that should happen in the time. As we focused only on the Swiss athletes, we had not a large sample to validate the accuracy of the prediction statistically, but as requested by SST, we did a reality check for the past Olympics. So considering all the World-Class event data available for the Swiss sailors who attended Rio 2016, we used our approach to predict the results at the past Olympic Games. In Figure 24, we report this successful qualitative validation of the model.

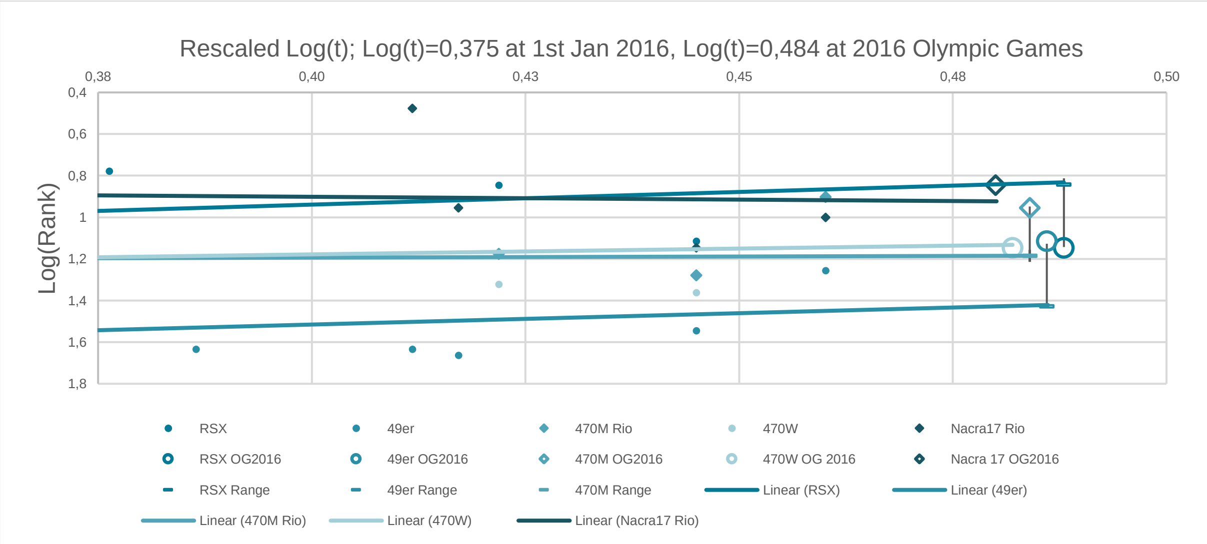


Figure 24: analysis of the result prediction for the Swiss sailors at the past Olympics (Rio 2016). Nacra 17 and 470W are precisely predicted within the range of one ranking position. The 49er and the 470M benefitted of a positive luck influence, and the prediction was still accurate within the tolerance range given to the luck contribution. The RSX suffered the influence of bad luck instead. However, applying the algorithm presented in Figure 22, the result is still on the edge of the range of negative luck and risk (standard deviation of the results for that specific athlete) combined.

Including the prediction and real results presented in Table 26, we can conclude that, with an anticipation of 2 to 3 months from the predicted event, the approach presented in this dissertation forecasted correctly (within the range of uncertainty) 12 results of the 15 that we considered.
Further development of this thesis can focus on a more vast sample of sailors and attempt to provide a statistical significance for the predictions. For example, this work could be performed to anticipate the results of other national teams at the next Olympic Games. Also, to increase the number of events to account in the sample, so avoiding to consider only the World-Class events, a more sophisticated method of selection could be implemented. For example, we could rank the quality of an event by finding a correlation between the competitors attending the event and their individual result. That method, or a similar one, should allow finding the most significant and relevant events, independently by their label or name.

Seeking for the peak performance

In this dissertation, we interpolated the Race Results with a power law function. That method, in the linear or Log-Log space, offered us the possibility to perform prediction by extrapolation. However, this approach cannot explain the noise of the results. Therefore we allocated to this noise the role of the risk that each athlete is carrying within his/her performance. In the diagram of Figure 17, we have shown that many uncontrollable factors play a role in the achievement of a result. So an approach could be to collect more information and offer a more accurate prediction by offering more inputs to the model. For example, we could predict how is an athlete that is consistently winning with a particular configuration of marine conditions, or in a specific location. However, from the managerial perspective, such type of model could be only partially useful, that because a National Federation cannot control the location or the weather condition.
Moreover, as we have stated in 1.1.1, there is no correlation between the locations or weather condition of the Olympic qualifier events and what can be expected at the Olympic Games. So we have the impression that increasing the sources of data would not improve the decision-making process of a team manager. On the other hand, there might be other endogenous factors that can influence the performance of an athlete, like the one we have seen analyzing the Performance Development Processes. With the experiences collected during this dissertation, as a conclusion, we would like to formulate a hypothesis for future elaboration. In particular, observing the Race Result data, we can observe oscillatory behaviour that moves around the interpolating function (Figure 25).

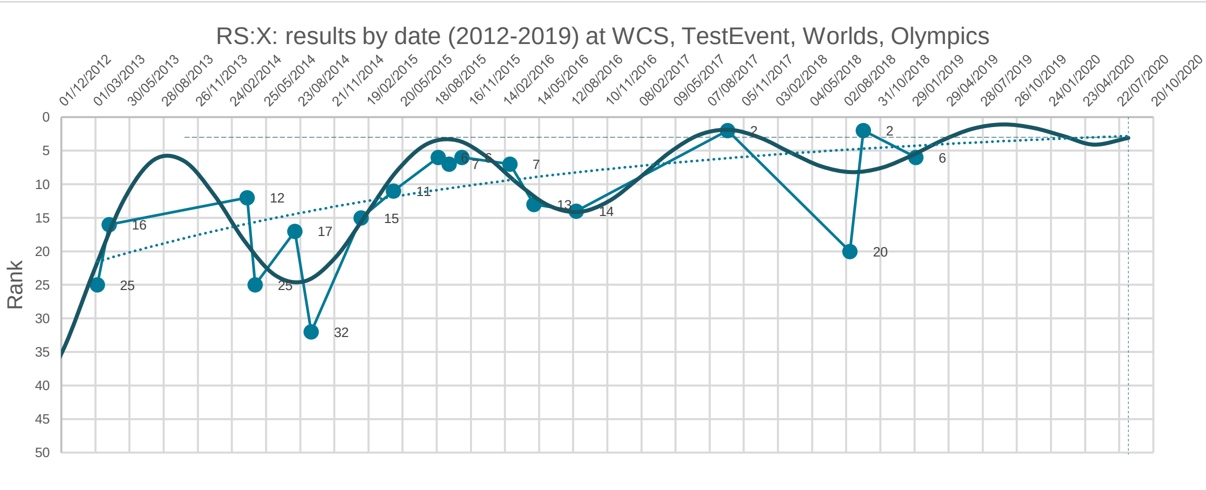


Figure 25: in a bold, thick line, an illustrative and qualitative oscillatory data interpolation of the time series of Race Result for RSX is presented. The dotted line represents the interpolation function used during this dissertation. The dashed lines are respectively the medal threshold for the horizontal and the time of the 2020 Olympic Games for the vertical. The thinner continuous line connects the real data.

This particular type of oscillatory interpolation function could respond to an equation of the following form:

Equation 46

$$Rank(t) = a(t) * t^{-k(t)} + \frac{A(t)\cos[a'(t) * (t - \varphi(t)]}{(a(t) * t^{-k(t)})^{f(\sigma_i)}} + \varepsilon_{Luck} + \ddot{\varepsilon}$$

Where the exponent $f(\sigma_i) \lesseqgtr 0$ can assume positive or negative values in function of the risk of the athlete, as formulated in 4.1. Then $\ddot{\varepsilon}$ is what it remains of the error term previously resented. To be validated, this hypothesis requires a statistical analysis that goes beyond the limits of this work. However, in the case that would hold, then it could be possible to predict the peak performance in the function the endogenous components of the performance (here identified with the factors of the PDPs) — leaving to the exogenous agents, as the wind conditions, only a marginal influence on the peak performance.

The possibility to understand in an increasingly refined way the role of the endogenous factors it is crucial for the preparation of the team because the management can control those with the tools developed in this dissertation.

Improving the team as a whole

In most of the sport disciplines that are fully professionalized, the data analysis is increasingly gaining in importance. In sailing, the researches focus mainly on equipment development or in physical preparation. So, in general, the approach in sailing is to improve each aspect independently. Only particular sporadic examples, like America's Cup, are probably able to develop a systemic and integrated [40] approach to development, but the knowledge is kept confidential.

In this dissertation, thanks to the availability of the Performance Development Processes, we have been able to elaborate a system of equations (Equation 32) that describe how the endogenous components of the performance are interacting within each other. This model is now a tool for the immediate benefit of the Swiss Sailing Team, and the diagram of Figure 18 it can guide the management for the decisions to take in the next future. However, we have to acknowledge that the current management seems to have a good perception of the priorities of its team. Independently from this study, that has lasted over the past three months, the Teamchef of Swiss Sailing Team has decided *ante tempore* to focus on the mental preparation the skill development of the Elite team during the present season. That is surprisingly entirely in line with what the model developed in this work is advising to do.

So, even if we are satisfied with the result that we obtained using the multi-linear regression approach, we are aware of the limitations. The model has been build over a limited amount of data, and we had to go through the challenge offered by the asynchronicity between the information stored in the Performance Development Processes and the Race Results. To improve the model, we recommend the Swiss Sailing Team management to link to each race a *post-mortem* analysis based on the same factors. This solution would offer a more significant amount of data to analyze and consequently, the possibility to have a more refined model. In particular, it would be possible to perform the multi-linear regression for each athlete, instead of the whole sailing team only. With a diagram of the skills interdependencies of each athlete and a more refined tool to identify the peak of the performance, the Swiss Sailing Team management could benefit from an even more refined and integrated approach than what we achieved in this work.

A self-fulfilling prophecy

Swiss Sailing Team is striving to become a winning team. Over the past two Olympic cycles, the mindset of the team evolved. With different methods, the Swiss Sailing Team is working to leave behind the *clichés* that would label a nation without any sea as a non-competitive sailing team. Swiss sailors proved several times that they could be excellent, winning Worlds titles and medals. Now, the current elite team is working hard to achieve its Result Target.

The action of setting Result Target itself is part of this process of improvement, and correctly doing that is not trivial. Setting targets too high that the athlete may fail, it can bring to a demotivating spiral, because the expectations increase and the results are not coming. On the other hand, effortless results targets are not pushing up enough the performance and lead to an unrealistic impression to be in a condition to reach an ultimate result that is too far from the range of reachability.
While studying the Olympic Project Reviews, we have set up a Result Target setting framework and Race Result analysis, which improve the current processes of the SST. Using the predicting model developed in this study, we offer the possibility to set a target in line with the current improvement trend of the athlete. On one side, that approach gives the athlete the possibility to know that he/she can achieve that result if he keeps improving at the same rate. So if he/she accomplishes all the milestones (the Predicted Results), he will be in a condition to target the ultimate predicted goal. On the other side, if the athlete, or the management, is not satisfied with the current rate of improvement, because, for example, is too slow, then it would be possible to define how the rate has to improve to reach the desired target within the given time constraints. Looking at Table 25 and Table 26, we are convinced that the "educated guess" used until now as *modus operandi* to set the targets it might become soon obsolete. The use of the algorithm shown in Figure 22 will complete the feedback loop process, helping the SST Selection Committee, the management, the sailors and the coaches to understand the value of the achievements.

Winning is a risky job

Every National Sailing Federation is competing for the same goal, and if we categorize the teams by size, the Swiss Team is rather small in comparison to the major players like the teams from Great Britain, Australia, Spain, France, and Brazil (to quote some of those). The big teams generally have more financial resources than the small ones, but even more important, they have more sailors, which means a broader pool of youth and elite athletes from which to choose and to maximize their potential.
While using the parallelism with the Financial Market, we analyzed the Swiss athletes as an asset portfolio, and so we explored the risk and expected returns of the members of the team. From this investigation, we understood that the Swiss Federation's managers have to deal with a mixed portfolio, with some risky assets, because the volatility of their Race Result is big, and some others that have a lower average performance, but more stable results in competition.
This financial way to see the team and the computation of a Sharpe Ratio [12] for each of the athletes, it has been done for the first time during this dissertation. We do not know yet how significant will be the contribution of this approach, but it gives the possibility to the SST to set up and run a continuous observatory based on the methodology here presented. The knowledge of the characteristics of its asset is indeed strategically crucial for the decision-making process and team goal settings. A proactive manager should be able to exploit the remunerative and risky assets at the right time while mitigating the risk and protecting the overall return of the portfolio with more stable assets. That dynamic would lead to having a constant improvement with some peak performances.
In the end, to offer some other perspectives, we combined the risk of each athlete with some Keep Performance Indicators developed in this work for SST. We explored these other ways to offer a more thorough and prospective point of view.

Optimizing for the good of the team success

Following the parallelism with the Financial Market, we approached the team optimization using the mean-variance analysis at first. This method, even if it may look rough when applied to athletes, showed that the 49er team is contributing the most to the team success when the success is measured as risk-return optimum (Table 23). The Finn sailor is the second and the RSX windsurfer the third. In section 4.1, we presented the limitation of such an approach, and so we moved forward with the qualitative definition of the Objective Function. Combining the researches and the analysis that we performed during this work, in agreement with the Swiss Sailing Team, we have identified 10 Keep Performance Indicators that define the success of the team. The ten factors are divided into five traditional KPIs that were observed by SST even before this dissertation and the other five that have been developed within this work. Out of the new five, two account for the potential results that the sailor can achieve at the next Olympics, then two measure respectively the past and future rate of improvement and the last measures the risk. The mathematical formulation of the Objective Function remains unknown, and the interaction between the KPIs has not been investigated in this work. However, to compute the contribution of each athlete to the success of the team, we analyzed six different scenarios by changing the weights of an approximated Objective Function (Equation 44). From Figure 23, we learnt that the Swiss Sailing Team have athletes with different strength and weaknesses and so it can be secure in any domain but at the same time vulnerable if not carefully managed. Table 30 showed how each of the elite sailors contributes. From that summary, we can see that, accordingly with the mean-variance optimization; the 49er team is the one that is contributing the most to the team success on 5 of 6 scenarios. The Finn sailor contributes primarily on 3 of 6, mainly thanks to the new KPIs, but he scores last looking only at the classic KPIs. However, his contribution is qualitatively aligned to the Markowitz portfolio optimization [13]. Aligned with the mean-variance optimization too, then it comes the RSX. The windsurfer contributes the most in 2 of 5 cases, particularly looking at the classic KPIs or the potential results. However, as stressed in other section of this dissertation, the RSX carries the maximum of the risk too, and he is close to the plateau of his performance, so it gets tough to improve further. Then the other three teams contribute with their percentages to the success, with the 470M carrying the smallest contribution overall.

Decision-making and rewarding

The analysis of the scenarios presented above and the research of the new KPI take inspiration form Multi-Criteria decision processes [14]. With a more significant amount of data, that can be collected over time in the future, the decisional process at SST can be enhanced with a more hierarchical and integrated method, like, for example, the decision trees. For now, we closed our dissertation with a set of five new indicators to complement the previous ones. The SST management has now to get familiar with this new metric and judge its predicting power. However, we would recommend considering the opportunity to use the framework built in this thesis to structure a new rewarding method for the athletes [15]. In particular, we would propose starting a continuous athlete's observatory, with analysis at different time scales, and including the youth athletes. This approach would lead to increased knowledge about the athletes, including a quantitative measure of their strength and weaknesses. Therefore, the team membership, the potential and contribution assessment, and the support to offer would always be based on a reliable and comparable piece of information aligned with the SST Objective Function.

Annex

List of World-class Events

DATE	EVENT	VENUE	NATION	K_RSX	K_49er	K_470M	K_470F	K_Radial	K_Nacra17	K_Finn
02/02/2019	WORLD CUP SERIES - ROUND 2	Miami	USA	54	42	37	28	59		27
16/09/2018	WORLD CUP SERIES - ROUND 1	Enoshima	JPN	40	27	32	23	53		21
12/08/2018	ISAF/WS Worlds 2018	Aarhus	DEN	85	86	64	47	119		90
03/06/2018	World Cup Series Final - Marseille	Marseille	FRA	19		18	20	24		13
22/04/2018	World Cup Series - Round 3, Hyères	Hyeres	FRA	50	40	40	36	64		40
21/01/2018	World Cup Series - Round 2, Miami	Miami	USA	48	38	37	33	68		26
15/10/2017	World Cup Series - Round 1, Gamagori	Gamagori	JPN	19	20	24	14	35		
23/09/2017	RS:X Worlds	Enoshima	JPN	102						
10/09/2017	Goldcup Finn (Worlds)	Balatonföldvár	HUN							113
02/09/2017	49er Worlds	Porto	POR		81					
26/08/2017	Laser Radial Women's World	Medemblik	NED					99		
15/07/2017	470 M/F Worlds	Thessaloniki	GRE			72	60			
04/06/2017	Sailing World Cup Final - Santander	Santander	ESP	17	16	14	10	25		16
23/04/2017	SWC Series Round 2 - Hyères	Hyeres	FRA	45	28	35	23	55		34
22/01/2017	SWC Series Round 1 - Miami	Miami	USA	39	26	26	13	51		26
04/12/2016	Sailing World Cup Final	Melbourne	AUS	12	19	14	8	19		16
19/09/2016	Sailing World Cup Qingdao	Qingdao	CHN	15		16	9	24		9
20/08/2016	**Olympics 2016**	**Rio**	**BRA**	36	20	26	20	37	20	
12/06/2016	Sailing World Cup Weymouth & Portland	Weymouth & Portland	GBR	17	38	28	15	39	21	
01/05/2016	Sailing World Cup Hyeres	Hyeres	FRA	40	40	39	34	29	32	
20/04/2016	Laser Radial Women's World	Nuevo Vallarta	MEX					71		
27/02/2016	470 M/F Worlds	San Isidro	ARG			42	39			
27/02/2016	RS:X Worlds	Eliat	ISR	81						
14/02/2016	49er / Nacra 17 Worlds	Clearwater	USA		68				43	
30/01/2016	Sailing World Cup Miami	Miami	USA	52	61	21	17	81	47	
13/12/2015	Sailing World Cup Melbourne	Melbourne	AUS		10	5	4	20		
26/11/2015	Laser Radial Women's World	Al Mussanah	OMA					100		
21/11/2015	49er Worlds	Buenos Aires	ARG		61					
24/10/2015	RS:X Worlds	Al Mussanah	OMA	82						
17/10/2015	470 M/F Worlds	Haifa	ISR			59	42			
20/09/2015	ISAF Sailing World Cup Qingdao	Qingdao	CHN	29	2	26	16	28	10	
22/08/2015	Test Event 2015	Rio	BRA	28	20	22	18	28	17	
14/07/2015	ISAF Sailing World Cup Weymouth & Portland	Weymouth & Portland	GBR	17	39	37	27	36	31	
11/07/2015	Nacra 17 Worlds	Aarhus	DEN						66	
26/04/2015	Sailing World Cup Hyeres	Hyeres	FRA	40	40	40	39	40	39	
31/01/2015	ISAF Sailing World Cup Miami	Miami	USA	66	58	44	30	79	49	
14/12/2014	ISAF Sailing World Cup Melbourne	Melbourne	AUS	7	15	8	2	30	5	
30/11/2014	ISAF Sailing World Cup Final	Abu Dhabi	UAE	19	18	16	11	18	17	
21/09/2014	ISAF/WS Worlds 2014	Santander	ESP	98	80	74	54	120	68	
09/08/2014	Test Event 2014	Rio	BRA	28	19	23	17	25	18	
26/04/2014	ISAF Sailing World Cup Hyeres	Hyeres	FRA	91	80	81	51	79	77	
05/04/2014	ISAF Sailing World Cup Mallorca	Palma de Majorca	ESP	72	79	78	47	96	73	
01/02/2014	ISAF Sailing World Cup Miami	Miami	USA	28	33	29	10	50	31	
08/12/2013	ISAF Sailing World Cup Melbourne	Melbourne	AUS	9	12	9	6	20	8	
19/10/2013	ISAF Sailing World Cup Qingdao	Qingdao	CHN	18		13	8	19		
03/10/2013	Laser Radial Women's World	Rizhao	CHN					77		
29/09/2013	49er Worlds	Marseille	FRA		97					
10/08/2013	470 M/F Worlds	La Rochelle	FRA			116	53			
27/07/2013	Nacra 17 Worlds	The Hague	NED						65	
27/04/2013	ISAF Sailing World Cup Hyeres	Hyeres	FRA	51	51	62	30	54	28	
06/04/2013	ISAF Sailing World Cup Palma	Palma de Majorca	ESP	37	72	68	43	66	34	
06/03/2013	RS:X Worlds	Buzios	BRA	64						
02/02/2013	ISAF Sailing World Cup Miami	Miami	USA	20	15	9	9	29	7	
08/12/2012	ISAF Sailing World Cup Melbourne	Melbourne	AUS	3	10	12	4	23		

Table 31: list of World-class events considered. Highlighted in red, the events that have been discarded.

Pool of international Athletes Selected

Athletes RSX	Events
Mattia Camboni	19
Tom Squires	19
Cheng Chun Leung	18
Ivan Pastor Lafuente	18
Mateo Sanz Lanz	18
Sebastian Wang-Hansen	18
Byron Kokkalanis	17
Pierre Le Coq	16
Ricardo Santos	16
Andreas Cariolou	15
Daniele Benedetti	15
Dorian Van Rijsselberghe	15
Louis Giard	15
Nick Dempsey	15
Makoto Tomizawa	14
Piotr Myszka	14
Sergi Escandell Mari	14
Thomas Goyard	14
Aichen Wang	13
David Mier y Teran	13
Joan Cardona Bocarando	13
Kiran Badloe	13
Pawel Tarnowski	13
Ho Tsun Leung	12
Juozas Bernotas	12
Mariano Reutemann	12
Sebastian Fleischer	12
Ignacio Berenguer	11
Kieran Holmes Martin	11
Luka Mratovic	11
Marcantonio Baglione	11
Toni Wilhelm	11
Aron Gadorfalvi	10
Carson Crain	10
Max Oberemko	10
Nimrod Mashiah	10
Oleksandr Tugaryev	10
Pedro Pascual	10
Przemyslaw Miarczynski	10
Shahar Zubari	10
Joao Rodrigues	9
Juan Manuel Moreno Vega	9
Karel Lavicky	9
Adam Holm	8
Chunzhuang Liu	8
Daniel Flores	8
Dmitrii Polishchuk	8
Evgeny Ayvazyan	8
Federico Esposito	8
Julien Bontemps	8
Zachary Plavsic	8
Total Athletes	315
N_avg	12
Athlete Selected	51

Athletes 49er	Events
Diego Botín le Chever	25
Dylan Fletcher-Scott	25
Yannick Lefebvre	23
Benjamin Bildstein	22
James Peters	22
Yago Lange	22
Carl P Sylvan	21
Lukasz Przybytek	20
Kévin Fischer	19
Erik Heil	18
Jack Hawkins	18
Marco Soffiatti Grael	18
Ryan Seaton	18
Sebastien Schneiter	18
David Gilmour	17
Federico Alonso Tellechea	17
Jacopo Plazzi Marzotto	17
John Pink	17
Jonas Warrer	17
Mathieu Frei	17
Bradley Funk	16
Fritiof Hedström	16
Julien d'Ortoli	16
Yukio Makino	16
Benjamin Jose Grez	15
Carlos Robles	15
Jorge Lima	15
Justus Schmidt	15
Ruggero Tita	15
Uberto Crivelli Visconti	15
Levi Slap	14
Nico Delle - Karth	14
Stefano Cherin	14
Tomasz Januszewski	14
Luca Dubbini	13
Judge Ryan	12
Peter Burling	12
Carlos Paz	11
Frederick Strammer	11
Logan Dunning Beck	11
Nathan Outteridge	11
Thomas Barrows	11
Victor Bergström	11
Andrew Mollerus	10
Chris Taylor	10
Dante Bianchi	10
Lucas Rual	10
Mads Emil Stephensen Lübeck	10
Manu Dyen	10
Pavle Kostov	10
Stephen Morrison	10
William Phillips	10
Dominik Buksak	9
Isaac McHardie	9
Marcus Hansen	9
David Evans	8
Gustav Petterson	8
Hugo Fedrigucci	8
Joel Turner	8
Rory Hunter	8
Alec Anderson	7
Alexander Heinzemann	7
David Mori	7
Denis Shcheglov	7
Giuseppe Angilella	7
Jakob Meggendorfer	7
John Ferguson	7
Josh Porebski	7
Przemek Filipowicz	7
Andrea Savio	6
David Liebenberg	6
Gonzalo Pollitzer	6
Henry Lloyd Williams	6
Mario Segers	6
Nic Asher	6
Nils Carstensen	6
Peter Janezic	6
Sime Fantela	6
Tim Fischer	6
William Jones	6
Don Whitcraft	5
Erwan Fischer	5
Frederik Rask	5
Gabriel Skoczek	5
Jan Hauke Erichsen	5
Konstantin Nosov	5
Lauri Lehtinen	5
Nevin Snow	5
Pavel Kalinchev	5
Philipp Müller	5
Remy Oomens	5
Simone Ferrarese	5
Stylianos Sotiriou	5
Víctor Payá	5
Total Athletes	266
N_avg	11
Athlete Selected	94

Athletes 470M	Events
David Bargehr	25
Kazuto Doi	24
Stuart Mcnay	24
Jordi Xammar Hernandez	23
Luke Patience	23
Mathew Belcher	23
Panagiotis Mantis	23
Anton Dahlberg	22
Deniz Cinar	20
Paul Snow-Hansen	20
Pavel Sozykin	20
Carl-Fredrik Fock	19
Hao Lan	19
Matthias Schmid	18
Ferdinand Gerz	17
Sofian Bouvet	17
Naoki Ichino	16
Onan Barreiros	16
Asenathi Jim	15
Henrique Haddad	15
Malte Winkel	15
Matteo Capurro	15
Sime Fantela	15
Yannick Brauchli	15
Zangjun Xu	15
Giacomo Ferrari	14
Joonas Lindgren	13
Lucas Calabrese	13
Hippolyte Machetti	12
Jasper Wagner	12
Simon Diesch	12
Julian Autenrieth	11
Kevin Peponnet	11
Simon Sivitz Kosuta	11
Geison Dzioubanov	10
Guillaume Pirouelle	10
Martin Wrigley	10
Tetsuya Matsunaga	10
Alexander Conway	9
Antonio MATOS ROSA	9
Daichi Takayama	9
Eyal Levine	9
Gal Cohen	9
Jacob Chaplin-Saunders	9
Joao Villas-Boas	9
Kilian Wagen	9
Nikolaus Kampelmühler	9
Sosaku Koizumi	9
Tetsuya Isozaki	9
Angus Galloway	8
Chang Ju Kim	8
Mikhail Sheremetev	8
Pierre Leboucher	8
Vasilis Papoutsoglou	8
Balázs Gyapjas	7
Corentin Demanet	7
Emanuele Savoini	7
Panagiotis Kampouridis	7
Vianney Guilbaud	7
David Charles Vila	6
Denny Naujock	6
Fernando GWOZDZ	6
Francesco Falcetelli	6
Hugo Feydit	6
Maor Abu	6
Matthew Crawford	6
Miikka Nikkilä	6
Mike Wood	6
Nitai Hasson	6
Rayco Tabares	6
Wiley Rogers	6
Andres Ducasse	5
Balder Tobiasen	5
Chris Charlwood	5
Diogo Pereira	5
Jorge Martinez Doreste	5
Keiju Okada	5
Robert Gullan	5
Ryo Imamura	5
Sho Kaminoki	5
Stefan Scharnagl	5
Thomas Ponthieu	5
Vladimir Chaus	5
Total Athletes	284
N_avg	11
Athlete Selected	83

Athletes 470F	Events
Afrodite Zegers-Kyranakou	21
Tina Mrak	21
Agnieszka Skrzypulec	20
Elena Berta	20
Linda Fahrni	20
Bárbara Cornudella Ravetllat	19
Camille Lecointre	19
Fernanda Oliveira	19
Hannah Mills	19
Ai Kondo Yoshida	18
Amy Seabright	18
Alisa Kirilyuk	17
Nadine Boehm	17
Anne Haeger	15
Sofia Toro	14
Annika Bochmann	13
Joanna Aleh	13
Lara Vadlau	13
Nadja Horwitz	13
Noya Bar-Am	13
Shasha Chen	13
Cassandre Blandin	12
Marina Gallego	12
Roberta Caputo	12
Xiaomei Xu	12
Jess Lavery	11
Silvia Mas Depares	11
Sydney Bolger	11
Benedetta Di Salle	10
Gil Cohen	10
Sophie Weguelin	9
Xiaoli Wang	9
Angela Pumariega Menéndez	8
Anna Kyselova	8
Beste Kaynakci	8
Carrie Smith	8
Frederike Loewe	8
Jennifer Poret	8
Mano Udagawa	8
Maria Bozi	8
Renata Decnop	8
Sasha Ryan	8
Dimitra Pagida	7
Huimin Feng	7
Maëlenn Lemaitre	7
Marina Lefort	7
Yuki Hayashi	7
Alba Bou Serra	6
Annina Wagner	6
Enia Nincevic	6
Francesca Komatar	6
Michelle Broekhuizen	6
Olivia Bergström	6
Allison Surrette	5
Atlantic Brugman Cabot	5
Marjaliisa Umb	5
Mengxi Wei	5
Nia Jerwood	5
Rosa Lindqvist	5
Sara Carmo	5
Tsuf Zamet	5
Anna Burnet	4
Fabienne Oster	4
Greta Markfort	4
Hanka Chudejova	4
Ilaria Paternoster	4
Natalia Ivanova	4
Orsolya Sipos	4
Total Athletes	154
N_avg	10
Athlete Selected	68

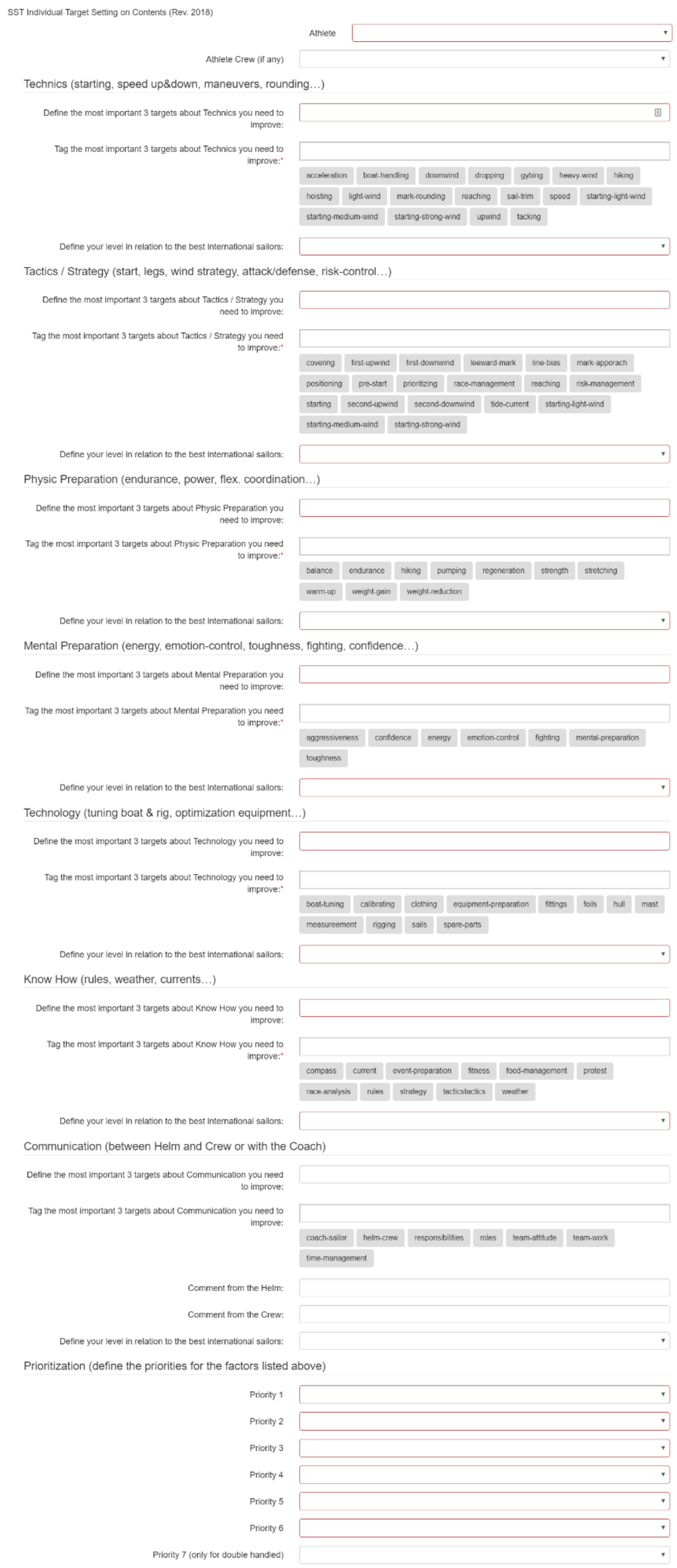
Athletes Radial	Events
Tatiana Drozdovskaya	28
Silvia Zennaro	26
Alison Young	25
Anne-Marie Rindom	25
Emma Plasschaert	25
Mathilde de Kerangat	24
Tuula Tenkanen	24
Marit Bouwmeester	23
Nazli Cagla Donertas	23
Josefin Olsson	22
Joyce Floridia	21
Manami Doi	21
Isabella-Anna Bertold	20
Marie Bolou	20
Pernelle Michon	20
Evi Van Acker	19
Agata Barwinska	18
Lucía Falasca	18
Paige Railey	18
Annalise Murphy	17
Ashley Stoddart	17
Dongshuang Zhang	17
Georgina Povall	17
Monika Mikkola	17
Erika Reineke	16
Hannah Snellgrove	16
Viktorija Andrulyte	16
Elizabeth Yin	15
Fernanda Decnop Coelho	15
Maité Carlier	15
Pauline Liebig	15
Svenja Weger	15
Amelie Riou	14
Brenda Bowskill	14
Ecem Güzel	14
Paloma Schmidt Gutierrez	14
Daphne van der Vaart	13
Dolores Moreira Fraschini	13
Line Flem Høst	13
Mária Érdi	13
Marie Barrue	13
Martina Reino Cacho	13
Maud Jayet	13
Maxime Jonker	13
Sarah Gunni Toftedal	13
Vasileia Karachaliou	13
Andrea Nordquist	12
Haddon Hughes	12
Sara Winther	12
Susannah Pyatt	12
Alicia Cebrian	11
Anna Pohlak	11
Chloe Martin	11
Elena Vorobeva	11
Isabella Maegli Agüero	11
Sandra Lulic	11
Sarah Douglas	11
Laura Cosentino	10
Milda Eidukeviciute	10
Stephanie Devaux-Lovell	10
Tina Mihelic	10
Tiril Bue	10
Veronika Kozelska Fenclova	10
Yumiko Tombe	10
Aoife Hopkins	9
Daniela Rivera	9
Hanne Weaver	9
Kelly-Ann Arrindell	9
Martha Faraguna	9
Marthe Eide	9
Maura Dewey	9
Sophie-marie Ertelt	9
Andrea Aldana	8
Anna Weinzieher	8
Athanasia Fakidi	8
Christina Sakellaris	8
Claire Merry	8
Ekaterina Zyuzina	8
Francesca Frazza	8
Gabriella Kidd	8
Kamolwan Chanyim	8
Min Gu	8
Sofiia Larycheva	8
Valentina Balbi	8
Christine Neville	7
Ekaterina Morgun	7
Kim Pletikos	7
Lijia Xu	7
Odile Ginaid	7
Oren Jacob	7
Paulina Czubachowska	7
Andela De Micheli Vitturi	6
Anna Brzozowska	6
Carolina Albano	6
Coralie Vittecoq	6
Corinne Peters	6
Elena Oetling	6
Eva-Maria Schimak	6
Gintare Scheidt	6
Kanako Hiruta	6
Kelly Cole	6
Lena Haverland	6
Magdalena Kwasna	6
Maria Cristina Knudsen Boabaid	6
Momoko Tada	6
Philipine Van Aanholt	6
Pia Kuhlmann	6
Sofie Slotsgaard	6
Sophia Reineke	6
Svetlana Shnitko	6
Total Athletes	338
N_avg	12
Athlete Selected	110

Athletes Nacra17	Events
Thomas Zajac	19
Ben Saxton	18
Matías Bühler	18
Vittorio Bissaro	18
Billy Besson	17
Nicole van der Velden	17
Gemma Jones	16
Luke Ramsay	16
Jason Waterhouse	15
Lucy Macgregor	14
Mandy Mulder	14
Sarah Newberry	14
Moana VAIREAUX	13
Euan McNicol	12
Paul Kohlhoff	12
Allan Norregaard	11
Federica Salvà	11
Iker Martinez de Lizarduy	11
Pablo Defazio Abella	11
Rupert White	11
Sergey Dzhienbaev	11
Sofia Bekatorou	11
Franck Cammas	10
Lin Ea Cenholt	10
Samuel Albrecht	10
Tom Phipps	10
Nicholas Fadler Martinsen	9
Renee Groeneveld	9
Darren Bundock	8
Enrique Figueroa	8
Francesco Porro	8
Ida Svensson	8
Jan Hauke Erichsen	8
Justin Liu	8
Lorenzo Bressani	8
Maxim Semenov	8
Pippa Wilson	8
Santiago Lange	8
Stefan Rumpf	8
Total Athletes	157
N_avg	12
Athlete Selected	39

Athletes Finn	Events
Anders Pedersen	9
Alican Kaynar	8
Ben Cornish	8
Edward Wright	8
Jorge Zarif	8
Josip Olujic	8
Tom Ramshaw	8
Fabian Pic	7
Jonathan Lobert	7
Kyle Martin	7
Nicholas Heiner	7
Tapio Nirkko	7
Henry Wetherell	6
Jake Lilley	6
Johannes Pettersson	6
Luke Muller	6
Max Salminen	6
Nils Theuninck	6
Oliver Tweddell	6
Ondrej Teply	6
Oskari Muhonen	6
Andre Hojen Cristiansen	5
Caleb Paine	5
Deniss Karpak	5
Ioannis Mitakis	5
Alex Muscat	4
Callum Dixon	4
Cameron Tweedle	4
Jock Calvert	4
Mikael Hyryläinen	4
Milan Vujasinovic	4
Nenad Bugarin	4
Pablo Guitian Sarria	4
Peter McCoy	4
Piotr Kula	4
Rockal Evans	4
Zsombor Berecz	4
Total Athletes	162
N_avg	6
Athlete Selected	37

Table 32: List of athletes selected by World-class event attendance. In bold are the Swiss Athletes, then highlighted in “bronze,” “silver” and “gold” are the medallists of Rio 2016 Olympic Games

Performance Development Process form



SST Individual Target Setting on Contents (Rev. 2018)

Athlete

Athlete Crew (if any)

Technics (starting, speed up&down, maneuvers, rounding…)

Define the most important 3 targets about Technics you need to improve:

Tag the most important 3 targets about Technics you need to improve:*

acceleration | boat-handling | downwind | dropping | gybing | heavy-wind | hiking | hoisting | light-wind | mark-rounding | reaching | sail-trim | speed | starting-light-wind | starting-medium-wind | starting-strong-wind | upwind | tacking

Define your level in relation to the best international sailors:

Tactics / Strategy (start, legs, wind strategy, attack/defense, risk-control…)

Define the most important 3 targets about Tactics / Strategy you need to improve:

Tag the most important 3 targets about Tactics / Strategy you need to improve:*

covering | first-upwind | first-downwind | leeward-mark | line-bias | mark-apporach | positioning | pre-start | prioritizing | race-management | reaching | risk-management | starting | second-upwind | second-downwind | tide-current | starting-light-wind | starting-medium-wind | starting-strong-wind

Define your level in relation to the best international sailors:

Physic Preparation (endurance, power, flex. coordination…)

Define the most important 3 targets about Physic Preparation you need to improve:

Tag the most important 3 targets about Physic Preparation you need to improve:*

balance | endurance | hiking | pumping | regeneration | strength | stretching | warm-up | weight-gain | weight-reduction

Define your level in relation to the best international sailors:

Mental Preparation (energy, emotion-control, toughness, fighting, confidence…)

Define the most important 3 targets about Mental Preparation you need to improve:

Tag the most important 3 targets about Mental Preparation you need to improve:*

aggressiveness | confidence | energy | emotion-control | fighting | mental-preparation | toughness

Define your level in relation to the best international sailors:

Technology (tuning boat & rig, optimization equipment…)

Define the most important 3 targets about Technology you need to improve:

Tag the most important 3 targets about Technology you need to improve:*

boat-tuning | calibrating | clothing | equipment-preparation | fittings | foils | hull | mast | measureement | rigging | sails | spare-parts

Define your level in relation to the best international sailors:

Know How (rules, weather, currents…)

Define the most important 3 targets about Know How you need to improve:

Tag the most important 3 targets about Know How you need to improve:*

compass | current | event-preparation | fitness | food-management | protest | race-analysis | rules | strategy | tacticstactics | weather

Define your level in relation to the best international sailors:

Communication (between Helm and Crew or with the Coach)

Define the most important 3 targets about Communication you need to improve:

Tag the most important 3 targets about Communication you need to improve:

coach-sailor | helm-crew | responsibilities | roles | team-attitude | team-work | time-management

Comment from the Helm:

Comment from the Crew:

Define your level in relation to the best international sailors:

Prioritization (define the priorities for the factors listed above)

Priority 1

Priority 2

Priority 3

Priority 4

Priority 5

Priority 6

Priority 7 (only for double handled)

Figure 26: a screenshot of the Performance Development Process available on www.teamdatalog.com

Performance Development Process data

Performance Development Process data are confidential and available only upon motivated request at: office@swiss-sailing-team.ch

Table 33: performance development process data (source: Swiss Sailing Team via TeamDataLog software).

Race Results and synchronized PDP data

Synchronized PDP data are confidential and available only upon motivated request at: office@swiss-sailing-team.ch

Table 34: SST elite's sailors results and synchronized PDPs in Log-Log scale (source: World Sailing and Swiss Sailing Team via TeamDataLog software).

PDP Fitness and synchronized Team Physical Test data

PDP Fitness and synchronized Team Physical Test data are confidential and available only upon motivated request at: office@swiss-sailing-team.ch

Table 35: PDP Fitness factor and synchronized physical test, endurance and strength. Fitness is expressed as % gap from the World Champion level (source: Hôpital la Tour of Geneva and Swiss Sailing Team via TeamDataLog software).

Analysis SPSS

Regression for Results with all Factors of PDP

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	KnowHow, Mental, TactStrat, Equipment, Technique, Fintess[b]	.	Enter

a. Dependent Variable: Rank

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,377[a]	,142	,025	,299920640

a. Predictors: (Constant), KnowHow, Mental, TactStrat, Equipment, Technique, Fintess

b. Dependent Variable: Rank

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,654	6	,109	1,212	,319[b]
	Residual	3,958	44	,090		
	Total	4,612	50			

a. Dependent Variable: Rank

b. Predictors: (Constant), KnowHow, Mental, TactStrat, Equipment, Technique, Fintess

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,411	,840		-,489	,627		
	Mental	,874	,367	,349	2,384	,022	,911	1,098
	Technique	,643	,912	,227	,706	,484	,188	5,318
	TactStrat	-,302	,659	-,112	-,458	,649	,326	3,071
	Fintess	-,069	,388	-,060	-,178	,860	,168	5,944
	Equipment	-,320	,595	-,150	-,538	,593	,250	4,001
	KnowHow	,215	,575	,115	,373	,711	,207	4,824

a. Dependent Variable: Rank

Collinearity Diagnostics[a]

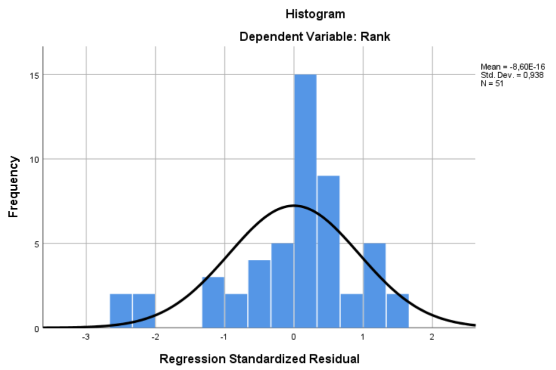
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	Mental	Technique	TactStrat	Fintess	Equipment	KnowHow
1	1	6,955	1,000	,00	,00	,00	,00	,00	,00	,00
	2	,028	15,742	,01	,04	,00	,00	,14	,00	,00
	3	,007	31,669	,00	,25	,02	,01	,18	,01	,15
	4	,004	40,779	,03	,14	,00	,15	,01	,38	,01
	5	,003	45,459	,01	,41	,01	,10	,01	,21	,31
	6	,002	62,205	,81	,15	,14	,14	,10	,01	,00
	7	,001	99,340	,13	,01	,83	,59	,56	,39	,52

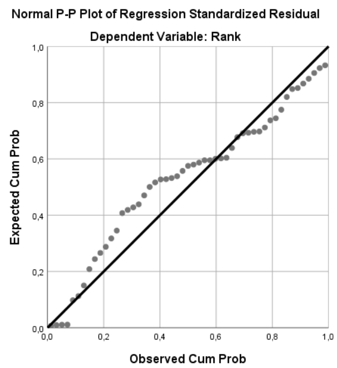
a. Dependent Variable: Rank

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,71892220	1,28846860	1,10519336	,114356529	51
Residual	-,742561996	,448414326	,000000000	,281350500	51
Std. Predicted Value	-3,378	1,603	,000	1,000	51
Std. Residual	-2,476	1,495	,000	,938	51

a. Dependent Variable: Rank





Regression for Result with only Mental and Technique of PDP

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Technique, Mental[b]	.	Enter

a. Dependent Variable: Rank

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,340[a]	,116	,079	,291445785

a. Predictors: (Constant), Technique, Mental

b. Dependent Variable: Rank

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,535	2	,267	3,147	,052[b]
	Residual	4,077	48	,085		
	Total	4,612	50			

a. Dependent Variable: Rank

b. Predictors: (Constant), Technique, Mental

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,415	,668		-,622	,537		
	Mental	,780	,344	,311	2,266	,028	,976	1,025
	Technique	,277	,389	,098	,712	,480	,976	1,025

a. Dependent Variable: Rank

Collinearity Diagnostics[a]

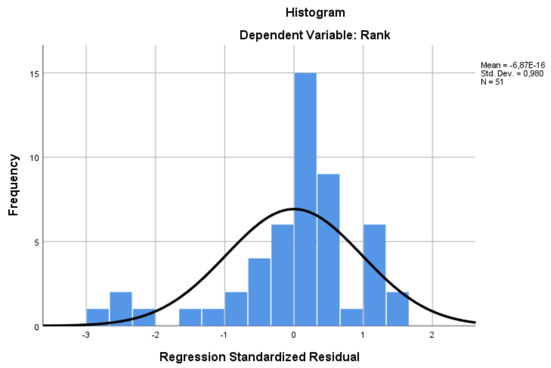
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Mental	Technique
1	1	2,992	1,000	,00	,00	,00
	2	,005	23,428	,00	,60	,55
	3	,002	34,674	1,00	,40	,45

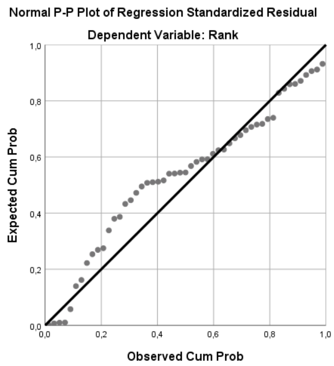
a. Dependent Variable: Rank

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,86989617	1,32149458	1,10519336	,103404543	51
Residual	-,844373345	,433967918	,000000000	,285557385	51
Std. Predicted Value	-2,276	2,092	,000	1,000	51
Std. Residual	-2,897	1,489	,000	,980	51

a. Dependent Variable: Rank





Regression for Mental within Factors of PDP

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	KnowHow, Fitness, Technique, Equipment, TactStrat[b]	.	Enter

a. Dependent Variable: Mental

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,633[a]	,400	,312	,152602384

a. Predictors: (Constant), KnowHow, Fitness, Technique, Equipment, TactStrat

b. Dependent Variable: Mental

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,528	5	,106	4,535	,003[b]
	Residual	,792	34	,023		
	Total	1,320	39			

a. Dependent Variable: Mental

b. Predictors: (Constant), KnowHow, Fitness, Technique, Equipment, TactStrat

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,534	,261		2,046	,049		
	Technique	,290	,201	,283	1,440	,159	,457	2,187
	TactStrat	,243	,243	,207	1,001	,324	,410	2,437
	Fitness	,266	,120	,336	2,204	,034	,761	1,313
	Equipment	,063	,133	,083	,475	,638	,581	1,721
	KnowHow	-,227	,175	-,207	-1,292	,205	,686	1,457

a. Dependent Variable: Mental

Collinearity Diagnostics[a]

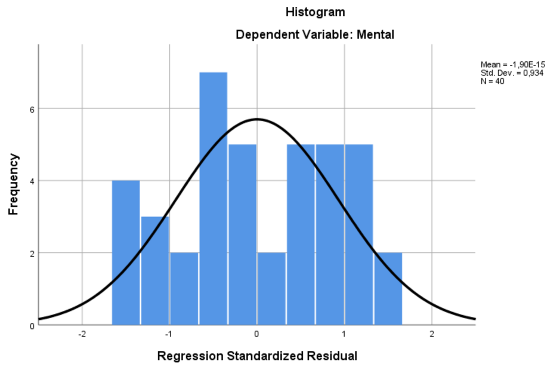
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Technique	TactStrat	Fitness	Equipment	KnowHow
1	1	5,942	1,000	,00	,00	,00	,00	,00	,00
	2	,024	15,746	,02	,02	,01	,59	,07	,05
	3	,016	19,090	,06	,00	,00	,31	,74	,00
	4	,008	27,104	,19	,45	,05	,02	,11	,19
	5	,006	31,655	,62	,00	,01	,09	,04	,76
	6	,004	40,715	,11	,52	,93	,00	,03	,00

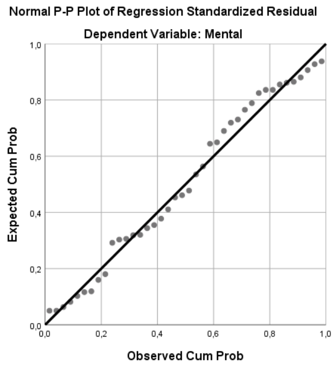
a. Dependent Variable: Mental

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,19068956	1,62004733	1,37520665	,116356800	40
Residual	-,250809997	,234186172	,000000000	,142484779	40
Std. Predicted Value	-1,586	2,104	,000	1,000	40
Std. Residual	-1,644	1,535	,000	,934	40

a. Dependent Variable: Mental





Regression for Technique within Factors of PDP

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Mental, KnowHow, Fitness, Equipment, TactStrat[b]	.	Enter

a. Dependent Variable: Technique

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,754[a]	,569	,506	,126236652

a. Predictors: (Constant), Mental, KnowHow, Fitness, Equipment, TactStrat

b. Dependent Variable: Technique

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,715	5	,143	8,975	,000[b]
	Residual	,542	34	,016		
	Total	1,257	39			

a. Dependent Variable: Technique

b. Predictors: (Constant), Mental, KnowHow, Fitness, Equipment, TactStrat

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,017	,229		-,073	,942		
	TactStrat	,565	,180	,493	3,143	,003	,515	1,944
	Fitness	-,040	,106	-,052	-,377	,709	,669	1,495
	Equipment	,059	,110	,080	,539	,593	,582	1,718
	KnowHow	,209	,144	,196	1,452	,156	,695	1,439
	Mental	,198	,138	,203	1,440	,159	,636	1,571

a. Dependent Variable: Technique

Collinearity Diagnostics[a]

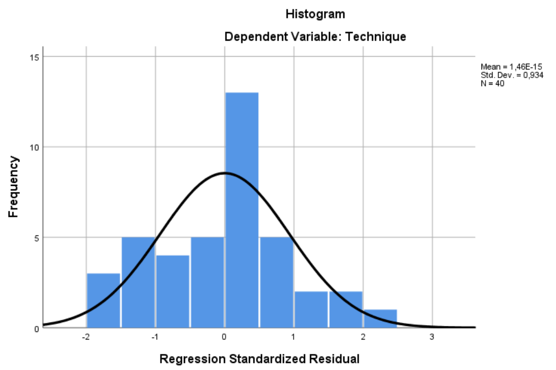
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	TactStrat	Fitness	Equipment	KnowHow	Mental
1	1	5,940	1,000	,00	,00	,00	,00	,00	,00
	2	,023	16,200	,04	,02	,49	,04	,09	,00
	3	,017	18,601	,04	,00	,12	,75	,00	,07
	4	,011	23,378	,00	,00	,36	,03	,17	,57
	5	,005	33,486	,87	,26	,01	,16	,16	,05
	6	,005	36,329	,06	,72	,01	,01	,58	,31

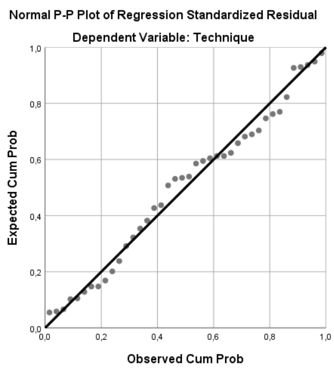
a. Dependent Variable: Technique

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,18987954	1,74470007	1,39293840	,135413912	40
Residual	-,201930732	,256992579	,000000000	,117867107	40
Std. Predicted Value	-1,500	2,598	,000	1,000	40
Std. Residual	-1,600	2,036	,000	,934	40

a. Dependent Variable: Technique





Regression for TactStrat within Factors of PDP excluding primary feed-back loop to Technique

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Fitness, KnowHow, Mental, Equipment[b]	.	Enter

a. Dependent Variable: TactStrat

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,697[a]	,485	,427	,118807622

a. Predictors: (Constant), Fitness, KnowHow, Mental, Equipment

b. Dependent Variable: TactStrat

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,466	4	,117	8,256	,000[b]
	Residual	,494	35	,014		
	Total	,960	39			

a. Dependent Variable: TactStrat

b. Predictors: (Constant), Fitness, KnowHow, Mental, Equipment

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,323	,208		1,550	,130		
	KnowHow	,343	,123	,368	2,801	,008	,850	1,176
	Equipment	,188	,099	,287	1,898	,066	,642	1,558
	Mental	,254	,122	,298	2,075	,045	,715	1,399
	Fitness	-,002	,100	-,003	-,017	,986	,669	1,495

a. Dependent Variable: TactStrat

Collinearity Diagnostics[a]

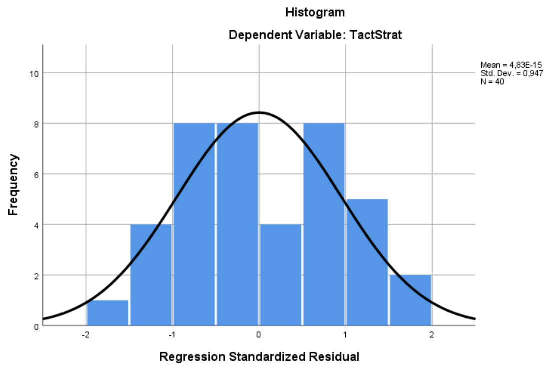
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	KnowHow	Equipment	Mental	Fitness
1	1	4,946	1,000	,00	,00	,00	,00	,00
	2	,021	15,226	,07	,15	,05	,00	,47
	3	,017	16,985	,03	,00	,83	,07	,14
	4	,011	21,374	,00	,19	,04	,66	,39
	5	,005	31,276	,90	,66	,09	,26	,00

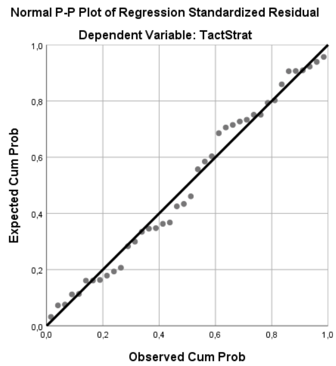
a. Dependent Variable: TactStrat

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,22898579	1,71388757	1,42163997	,109329969	40
Residual	-,220485076	,203861892	,000000000	,112550135	40
Std. Predicted Value	-1,762	2,673	,000	1,000	40
Std. Residual	-1,856	1,716	,000	,947	40

a. Dependent Variable: TactStrat





Regression for Fitness within Factors of PDP excluding primary feed-back loop to Mental

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Technique, Equipment, KnowHow, TactStrat[b]	.	Enter

a. Dependent Variable: Fitness

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,488[a]	,239	,152	,214106398

a. Predictors: (Constant), Technique, Equipment, KnowHow, TactStrat

b. Dependent Variable: Fitness

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,503	4	,126	2,742	,044[b]
	Residual	1,604	35	,046		
	Total	2,107	39			

a. Dependent Variable: Fitness

b. Predictors: (Constant), Technique, Equipment, KnowHow, TactStrat

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,575	,353		1,629	,112		
	KnowHow	-,104	,245	-,075	-,424	,674	,690	1,450
	Equipment	,405	,174	,418	2,322	,026	,671	1,491
	TactStrat	,192	,340	,130	,566	,575	,414	2,415
	Technique	,037	,282	,029	,132	,896	,458	2,186

a. Dependent Variable: Fitness

Collinearity Diagnostics[a]

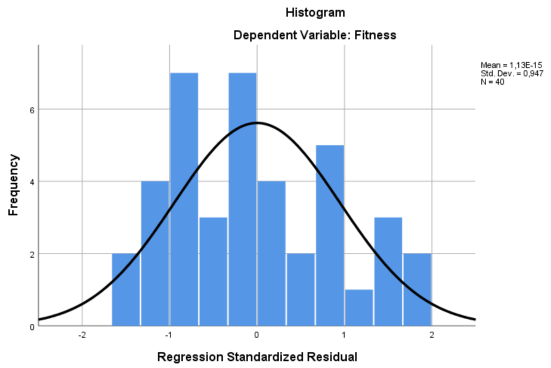
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	KnowHow	Equipment	TactStrat	Technique
1	1	4,964	1,000	,00	,00	,00	,00	,00
	2	,018	16,449	,07	,04	,86	,00	,01
	3	,008	24,611	,27	,12	,09	,05	,47
	4	,006	28,032	,53	,85	,00	,02	,00
	5	,004	37,209	,12	,00	,04	,93	,52

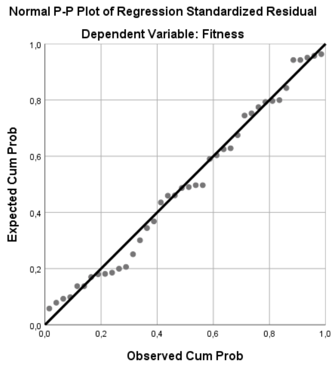
a. Dependent Variable: Fitness

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,02125919	1,50492036	1,28256142	,113546302	40
Residual	-,336532503	,383268028	,000000000	,202829614	40
Std. Predicted Value	-2,301	1,958	,000	1,000	40
Std. Residual	-1,572	1,790	,000	,947	40

a. Dependent Variable: Fitness





Regression for KnowHow within Factors of PDP excluding primary feed-back loop to TactStrat

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Fitness, Technique, Mental, Equipment[b]	.	Enter

a. Dependent Variable: KnowHow

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,549[a]	,302	,222	,148384936

a. Predictors: (Constant), Fitness, Technique, Mental, Equipment

b. Dependent Variable: KnowHow

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,333	4	,083	3,784	,012[b]
	Residual	,771	35	,022		
	Total	1,104	39			

a. Dependent Variable: KnowHow

b. Predictors: (Constant), Fitness, Technique, Mental, Equipment

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,866	,217		3,988	,000		
	Equipment	,158	,124	,226	1,275	,211	,636	1,573
	Technique	,444	,161	,474	2,764	,009	,678	1,476
	Mental	-,177	,162	-,194	-1,097	,280	,639	1,565
	Fitness	,014	,125	,019	,111	,912	,667	1,499

a. Dependent Variable: KnowHow

Collinearity Diagnostics[a]

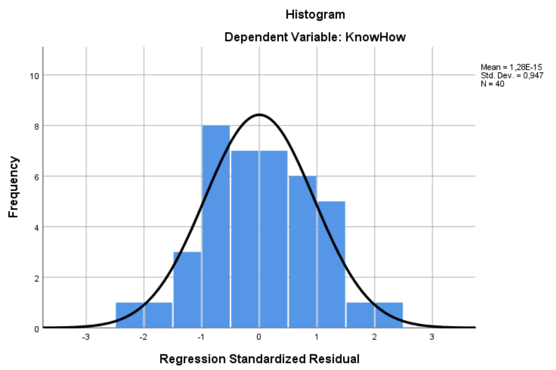
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Equipment	Technique	Mental	Fitness
1	1	4,948	1,000	,00	,00	,00	,00	,00
	2	,019	15,938	,10	,06	,11	,01	,60
	3	,017	16,993	,04	,80	,01	,05	,19
	4	,008	24,474	,46	,00	,00	,84	,09
	5	,007	26,060	,40	,14	,88	,09	,12

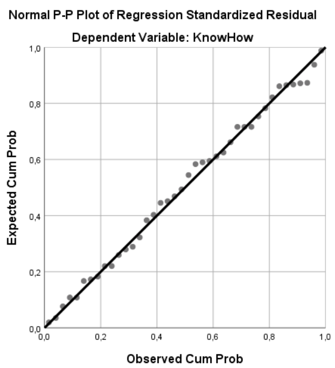
a. Dependent Variable: KnowHow

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,25381196	1,67515457	1,46758170	,092446176	40
Residual	-,306262046	,334018826	,000000000	,140569640	40
Std. Predicted Value	-2,312	2,245	,000	1,000	40
Std. Residual	-2,064	2,251	,000	,947	40

a. Dependent Variable: KnowHow





Regression for Equipment within Factors of PDP excluding primary feedback loop to Fitness

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	KnowHow, Mental, Technique, TactStrat[b]	.	Enter

a. Dependent Variable: Equipment

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,601[a]	,361	,288	,202731894

a. Predictors: (Constant), KnowHow, Mental, Technique, TactStrat

b. Dependent Variable: Equipment

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,811	4	,203	4,935	,003[b]
	Residual	1,439	35	,041		
	Total	2,250	39			

a. Dependent Variable: Equipment

b. Predictors: (Constant), KnowHow, Mental, Technique, TactStrat

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,217	,363		-,599	,553		
	Technique	,123	,274	,092	,450	,655	,435	2,297
	Mental	,272	,208	,208	1,305	,200	,719	1,391
	TactStrat	,475	,318	,310	1,496	,144	,424	2,356
	KnowHow	,217	,236	,152	,920	,364	,670	1,492

a. Dependent Variable: Equipment

Collinearity Diagnostics[a]

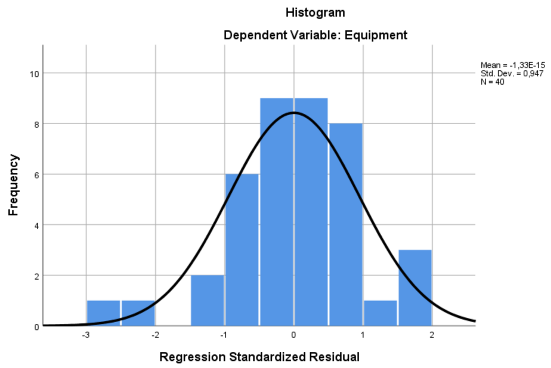
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Technique	Mental	TactStrat	KnowHow
1	1	4,970	1,000	,00	,00	,00	,00	,00
	2	,013	19,336	,00	,00	,59	,00	,22
	3	,009	24,161	,40	,36	,02	,05	,03
	4	,005	32,198	,53	,09	,38	,05	,74
	5	,004	36,677	,07	,55	,00	,90	,01

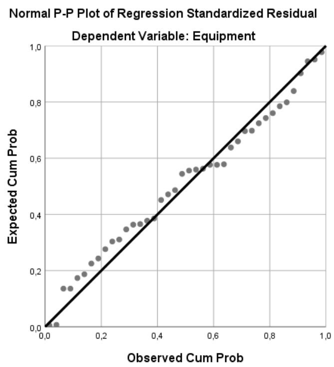
a. Dependent Variable: Equipment

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,10019720	1,69456720	1,32160386	,144234211	40
Residual	-,528332770	,405359417	,000000000	,192054194	40
Std. Predicted Value	-1,535	2,586	,000	1,000	40
Std. Residual	-2,606	1,999	,000	,947	40

a. Dependent Variable: Equipment





Regression Fitness within periodical Team Physical Tests (Endurance and Strength combined)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	m(4min) , s(ventral) , s(lateral) , s(dorsal) , Repetition , W/Kg , <W>(30s) , m(30s) , Kg[b]	.	Enter

a. Dependent Variable: Fitness

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,593[a]	,351	,198	12,692984774

a. Predictors: (Constant), m(4min) , s(ventral) , s(lateral) , s(dorsal) , Repetition , W/Kg , <W>(30s) , m(30s) , Kg

b. Dependent Variable: Fitness

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3314,728	9	368,303	2,286	,037[b]
	Residual	6122,251	38	161,112		
	Total	9436,979	47			

a. Dependent Variable: Fitness

b. Predictors: (Constant), m(4min) , s(ventral) , s(lateral) , s(dorsal) , Repetition , W/Kg , <W>(30s) , m(30s) , Kg

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	44,858	90,344		,497	,622		
	s(ventral)	,015	,081	,047	,180	,858	,249	4,012
	s(lateral)	-,286	,147	-,316	-1,947	,059	,649	1,540
	s(dorsal)	,096	,251	,107	,383	,704	,220	4,552
	Repetition	10,304	22,634	2,095	,455	,652	,001	1240,950
	Kg	-,141	,335	-2,853	-,423	,675	,000	2664,503

	<W>(30s)	,154	,517	1,753	,297	,768	,000	2035,662
	W/Kg	-17,634	26,436	-1,648	-,667	,509	,003	357,739
	m(30s)	,738	1,536	,858	,481	,633	,005	186,541
	m(4min)	-,073	,133	-,440	-,551	,585	,027	37,327

a. Dependent Variable: Fitness

Collinearity Diagnostics[a]

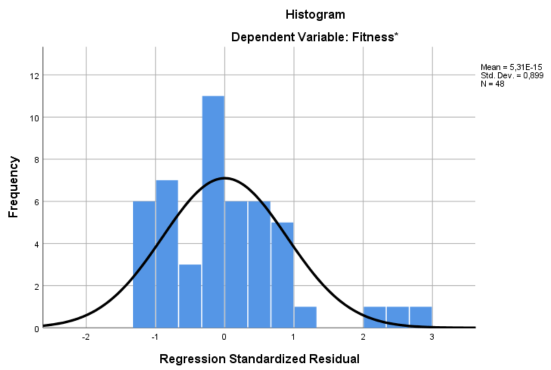
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions									
				(Constant)	s(ventral)	s(lateral)	s(dorsal)	Repetition	Kg	<W>(30s)	W/Kg	m(30s)	m(4min)
1	1	9,782	1,000	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00
	2	,120	9,032	,00	,01	,00	,01	,00	,00	,00	,00	,00	,00
	3	,036	16,592	,00	,09	,01	,00	,00	,00	,00	,00	,00	,00
	4	,028	18,558	,00	,03	,24	,06	,00	,00	,00	,00	,00	,00
	5	,019	22,476	,00	,07	,27	,13	,00	,00	,00	,00	,00	,00
	6	,011	30,184	,00	,07	,37	,07	,00	,00	,00	,00	,00	,00
	7	,003	55,571	,00	,32	,01	,00	,00	,00	,00	,01	,00	,00
	8	,000	146,218	,45	,21	,01	,16	,00	,00	,00	,00	,00	,10
	9	9,3E-5	323,013	,11	,05	,07	,03	,03	,03	,01	,06	,28	,29
	10	9,2E-6	1030,05	,42	,14	,02	,53	,97	,97	,99	,92	,72	,60

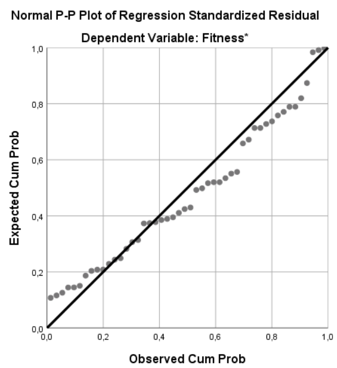
a. Dependent Variable: Fitness

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	9,34911728	39,47129822	26,35416667	8,397984045	48
Residual	-15,738660812	36,077339172	,000000000	11,413178995	48
Std. Predicted Value	-2,025	1,562	,000	1,000	48
Std. Residual	-1,240	2,842	,000	,899	48

a. Dependent Variable: Fitness*





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