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An Innovative Systematic Approach to Financial Portfolio Management via PID Control

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1. Introduction

Portfolio management is the art and science of modifying the asset allocation of a financial portfolio in response to and/or in anticipation of market conditions and dynamics of financial markets. The modification of the asset allocation is obtained by rebalancing and varying the relative weights of the assets comprising the portfolio on a periodic basis. The asset manager considers two distinct portfolios: the financial portfolio subject to his management technique (referred to here as the experimental portfolio, or Portfolio "A"), and a benchmark (or comparison) portfolio called Portfolio "B". The asset manager composes his experimental portfolio, also referred to as the benchmark-based portfolio, following, generally, two different types of strategies: active and passive (indexed) strategy. In this work, we analyze a fundamental aspect of portfolio management: the active asset allocation. The objective of this writing is to illustrate a new asset allocation technique to compose an experimental portfolio, which uses the Proportional, Integral, Derivative (PID) controller aiming to overcome a benchmarked portfolio. Therefore, the two portfolios taken into consideration are the experimental portfolio subject to the PID controlling methodology and a buy-and-hold diversified portfolio as the benchmark portfolio. The technique consists in managing portfolio asset-allocation revisions through PID control, a tool that is highly utilized and implemented in the engineering, industrial processing units and in production plants. The goal is to achieve a good portfolio performance trying to control volatility; in other words, the goal is to obtain good performance of risk adjusted returns. Thus, in finance, financial market assets forming a portfolio or a market benchmark represent the process plant controlled by the PID controller.
A brief literature review covering the comparison between strategic and tactical asset allocation introduces the topic, followed by some examples of tactical asset allocation techniques. Subsequently, this article illustrates how the PID controller functions. Then, it exemplifies the new asset allocation technique, functioning, and methodology. This work shows how a portfolio managed by this new technique attains fine results of risk adjusted returns compared with a benchmark.

2. Strategic and tactical asset allocation

Asset allocation can be defined as the action of allocating the various components of a financial portfolio in different asset classes according to the investor risk/return profile level. The portfolio construction is an articulated process based on the identification of the optimal asset mix, given a desired time horizon (holding period) and given the investor's risk aversion level.

The activity of asset allocation is a 3-phase procedure: analysis of investors' needs, consideration of investor's choices and inclinations, and investor's portfolio performance monitoring. At first, it is necessary to analyze investor's needs in order to understand his/her risk aversion level. The investment subsequent choices depend on the latter analysis, which is not so straightforward and easy to perform. The second phase, illustrated in more detail in the following sections, consists in the actual choice of the asset classes in which to invest, the determination of the relative weights assigned to each asset class and the choice of the securities to be bought and included in the portfolio management process. The third phase consists in the monitoring of the portfolio performance through the utilization of specific indicators enabling the observation of the return and the risk of the managing activity. In this phase, the risk-adjusted return indices (Sharpe Ratio, Sortino Ratio, etc) become important; they specify the return of the portfolio adjusted by the implicit and inherent risk underlying that specific asset management strategy.

As specified herein, the central activity of asset allocation is strictly bound to the investment choices. The portfolio manager first defines the macro asset classes to be considered. The macro asset classes are a set of financial activities or real activities with adequate future potential growth. Upon the definition of such macro asset classes, relative weights shall be determined strategically in order to obtain a diversified portfolio consistent and in line with the return/risk profile of the investor. This asset allocation can be achieved by using quantitative strategies, such as the implementation and utilization of Markowitz's efficient frontier technique (Markowitz, 1952), or qualitative approaches and methodologies based on the individual managers' expectations, experience, and estimates on future market conditions. This primary activity of asset allocation is called strategic asset allocation.

The definition of strategic asset allocation is a component of asset allocation, implemented by the identification of the optimal long-term mix, in compliance with the investor risk/return profile.

A second component of asset allocation is defined as the tactical asset allocation. This is an activity that aims to take, periodically, the most interesting investment opportunities by temporarily and partially deviating from the main strategic portfolio structure.

If in the long term, the adherence to investors' risk profile levels must be maintained; in the short term, the tactical asset allocation manager may deviate from the strategic asset allocation technique aiming to take further advantage from certain market conditions. For example, the tactical asset allocation manager may slightly vary the weights of the various asset classes or the individual securities contained in them, targeting to further increase portfolio returns.

Relative to strategic asset allocation, a fundamental choice to make is the adoption of a particular style of management relative to a benchmark. In defining the strategic asset allocation, the manager must decide which style of management to use relative to a benchmark. In fact, managers differentiate between active and passive strategies by analyzing the portfolio management strategy compared to a benchmark. Passive strategies aim to obtain benchmark returns, structuring a portfolio analogous to the benchmark composition. The asset manager chooses the same asset classes and the same relative or absolute weights as the benchmark. In this case, the risk/return profile level is consistent with the benchmark risk/return level. On the contrary, an active strategy aims to reach an active return compared to the benchmark. The active manager can select different asset classes relative to the benchmark, or different weights. In this case, it is the manager's responsibility to construct the portfolio based on his expectations. In literature, a vivid debate about the superiority of passive vs. active strategies and vice versa, comes forwards. The issue starts with the Efficient Market Hypothesis (Fama, 1965, 1970). This theory assumes that under strong efficient information conditions, it is not possible to have mispriced securities; all prices in the market are fair and balanced; therefore, it is impossible to outperform the market by using active strategies (Samuelson, 1974). Another important factor to consider is the transaction costs (Sharpe, 1991). In fact, even if active and passive strategies are able to achieve the same returns (market returns), the first strategy has unavoidably a diminished total performance, since transaction costs and research costs worsen the outcome. Normally, many active managers manage portfolios formed by index asset classes and liquidity; hence, outperformance compared to the benchmark results. When the market makes a severe downtrend, active portfolios achieve a better performance than the market thanks to the liquidity portion of the portfolios. Not all authors concur in the use and benefits of active strategies. Some authors (Gruber, 1996; Carhart, 1997) state that the active strategies' outperformance has no persistence and exhibits random behavior. Other authors confirm that active strategies produce an effective investment methodology (Gold, 2004).

In order to implement an active strategy, asset managers can apply different tactical asset allocation methods. Each of these active strategies aims to take opportunities when markets are non-aligned (Anson, 2004). Tactical asset allocation can be defined as "active strategies which seek to enhance performance by opportunistically shifting the asset mix of a portfolio in response to changing patterns of reward available in capital market" (Arnott & Fabozzi, 1988). Tactical asset allocation establishes the variations in the asset weights in a portfolio. The rebalancing is performed at different time intervals: on a monthly basis, quarterly or annually. Tactical asset allocation methodologies can be divided into two macro categories: dynamic asset allocation and pure tactical asset allocation (Sampagnaro, 2006). Dynamic asset allocation consists in a series of modifications following a set of precise rules (algorithms). The manager implements such rules such that the portfolio weight rebalancing allows the manager to achieve a predetermined target: to regain alignment to the strategic asset allocation weights, or to apply portfolio protection strategies (portfolio insurance).

Pure strategies of tactical asset allocation, on the other hand, include all those methodologies in which the manager aims to maximize the absolute return of the portfolio or the relative return of the portfolio compared to a benchmark. The manager could change the portfolio composition by removing securities and adding others, selecting those securities that present the best expected future returns. The manager could also modify the weights of the current securities producing a distance from the original strategic allocation weight determination. In literature, an extensive variation of methodologies to take advantage of financial markets is available. Some authors (MacBeth & Emanuel, 1993) suggest to use dividend yield price/earning ratio and price/book ratio to estimate market overvaluation or undervaluation. Others use the spreads between the earning/price ratio of the S&P 500 index and interest rates (Shen, 2003), or present the use of Beta drivers to decide the exposure to the financial market and Alpha drivers to underweight or overweight relative to the benchmark (Anson, 2004). As a final point, a research paper (Gandolfi et al., 2007) pioneers an innovative tactical asset allocation technique. The novelty embedded in this model consists in the application of the well-known PID feedback controlling mechanism, used in industrial plant production and engineering, to tactical financial portfolio asset allocation. The goal of their model was to attain long-term performance steadiness over time by controlling the risk adjusted return variable of portfolios. The main attribute to perceive was the achieved constancy and consistency of the Sharpe Ratio of the experimental portfolio (i.e. the portfolio managed by the PID methodology) in comparison to the benchmark. In the present work, the authors build up a new application based on this novel strategy. The target here is to seek a portfolio (Portfolio "A") capable of enhanced long-term risk adjusted performance and risk stability than the Buy-and-Hold portfolio (Portfolio "B").

3. The PID controller acting on the experimental portfolio

The most important attributes of the PID controller are illustrated in this section. It is vital to understand the functioning of this engineering feedback system since it underlies and stands at the basis of the new asset allocation technique presented herein. The PID (Proportional-Integral-Derivative) controller is broadly used and implemented in several industrial production plants; "it is been successfully used for over 50 years and it is used by more than 95% of the plants processes. It is a robust and easily understood algorithm, which can provide excellent control performance in spite of the diverse dynamic characteristics of the process plant" (Gandolfi et al., 2007). In industrial environments such as chemical plants, power plants, and engineering industries, numerous processes need to be accurately controlled to conform to the required specifications of the resulting products. PID control is straightforward, easily implementable method, still currently preferred by engineers and scientists to more complex systems (Skogestad, 2010). In finance, financial market assets comprising a portfolio or a market benchmark represent the process plant, controlled by the PID controller.

The PID controller is a feedback system. It has an input and returns an output. An iterative process forms it. The inputs of the system are the set-point, or desired value, and the controlled variable that is subject to the effect of the PID controller. The PID controller, working on the input variable, returns as output the same variable operated on by the PID operators. The output variable, in turns, is fed back as an input during the following iteration. The simplest and most basic PID control is formed by the linear combination of three components: the Proportional (P), Integral (I), and Derivative (D) components. During each iteration, the current output is compared to the set-point yielding an error. The goal of the PID control is to diminish this error to the minimum (Gandolfi et al., 2007). The continuous time expression of the PID controller is given by:

$$u(t) = k_p\left(e(t) + k_i \int e(\tau)d\tau + k_d \frac{de(t)}{dt}\right)$$

where:

$$\begin{aligned} &u(t) = \text{output} \\ &k_p = \text{Proportional Constant} \\ &k_i = \text{Integral Constant} \\ &k_d = \text{Derivative Constant} \\ &e(t) = \text{error} \end{aligned} \tag{1}$$

In this present work, the following recurrence relation, obtained by discrete time formulation and simple-lag implementation of the integral part (Gandolfi et al., 2007) yields:

$$u_n = \left(k_p e_n + k_i(e_n - u_{n-1}) + u_{n-1} + k_d(e_n - e_{n-1})\right) \tag{2}$$

where:

u_n=output at time n

u_{n-1}=output at time n-1

k_p=Proportional Constant

k_i=Integral Constant

k_d=Derivative Constant

e_n=error at time n

e_{n-1}=error at time n-1

A block diagram of the PID controller follow:

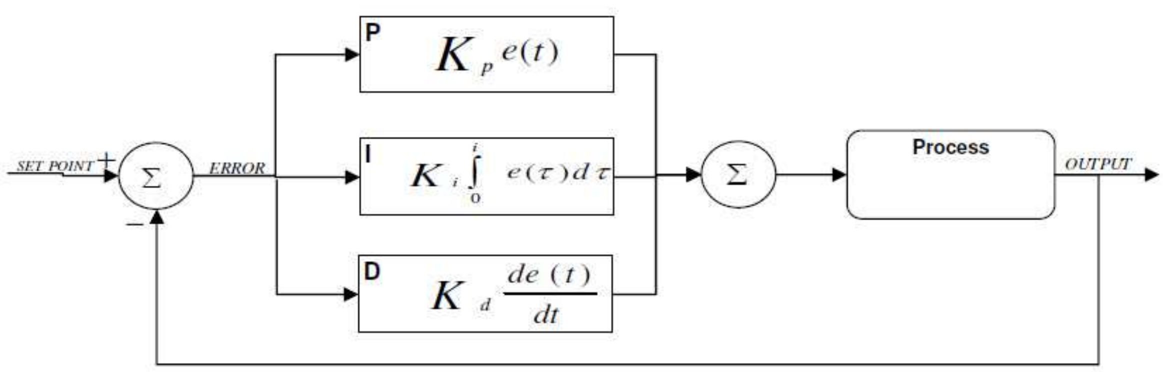

Fig. 1. PID control block diagram - This figure presents dynamics and processing of the error, Set-Point and controlled variable while subjected to the PID control action.
Set-point = Desired value. Error = (Output – Set-Point).

4. Mechanisms of action of the new asset allocation technique

This section presents an original method and system for allocating numerous assets in portfolios, via tactical asset allocation in order to achieve better return and long-term target stability (volatility control) over a desired time horizon. In particular, the present work illustrates a method and system for asset allocation of the 20 securities having each one, its own level of risk and return. The methodology consists in stabilizing the portfolio return . hence the decreasing of portfolio volatility based on the PID feedback control. By applying our strategy to a financial portfolio, financial market assets represent the process plant, controlled by PID controlling action. The assets mix of the portfolio determines the total portfolio return. The action of rebalancing the portfolio alters its return. In various aspects, this work offers methods and systems as an innovative approach to active strategy portfolio management. It is worth noting that the rebalancing of the experimental portfolio (Portfolio “A”) is not dictated by a forecast analysis of the various prices of the assets belonging to the portfolio. There is no use of a vector of expected returns and there is no need of determining a variance-covariance matrix. The rebalancing is rather driven by an asset selection technique consisting in the stabilization of return by means of the PID feedback control modeling procedure. The new model simply tends to follow and not predict the financial market oscillations and market variability, adjusting to such variations and oscillations. It takes into consideration past and current portfolio dynamics. It tunes to financial market fluctuations by performing smoothing and anticipatory actions in the attempt to hold as close as possible to the target, hence minimizing the error generated by the difference between the set-value and current portfolio return. The controlled process plant, namely the return variable, does not need to be modeled or defined by a mathematical closed form equation; assumptions, linearization, and simplification procedures on the dynamics of the plant are not required. The PID control modifies the portfolio asset weights, according to the PID algorithm. The methodology starts by presenting two initially identical portfolios: the benchmark, namely Portfolio "B", and the experimental portfolio, or Portfolio "A". The procedure uses a 12-year monthly frequency time-series per each of the securities of the Portfolio "B", covering the period February 1999 - February 2011. Portfolio "A" assets are rebalanced at the end of each month, according to the PID procedure. At the end of the observation period, namely in February 2011, the two portfolios, the Benchmarked Portfolio "B" and the experimental portfolio, Portfolio "A", are observed and compared, targeting to verify the efficiency of the new model compared to benchmarking. In this work, the comparison is carried out without taking into consideration tax and transaction costs. Portfolio "B" , namely the benchmark is composed by 20 assets chosen in such a way to form a well diversified portfolio. In particular, the following assets have been considered: a monetary index, 4 fixed-income (or bonds) indices, 7 stocks (equity) indices, 6 commodities indices, gold and a risk-free asset class denominated "cash". The inclusion and use of a risk-free asset in the experimental portfolio is been indicated by the consideration that the new model permits partial disinvestment of the risky portfolio by partially reallocating risky assets in risk-free assets (Qian, 2003). The following table illustrates how the strategic asset allocation of the well-diversified portfolio has been defined. The right-end-side column indicates the respective weights of each asset class:

Asset class	Weight
Monetary	6%
Bonds	40%
Equity	35%
Commodities	12%
Gold	5%
Cash	2%

Table 1. Strategic composition for macro-asset class of Portfolio "B". The table illustrates Portfolio "B" composition, namely the benchmark composition. It specifies the various macro-asset classes and their relative assigned weights.

After having presented which the strategic macro-asset classes are, for the benchmark portfolio, the following table is presented. It exhibits for each asset class, which are the selected indices in order to form the well diversified portfolio with its respective assigned weights.
Firstly, Portfolio "A" has the identical composition as that of Portfolio "B". Next, Portfolio "A" asset weights are varied following the PID signals. The rebalancing occurs on a monthly

basis. The constraints for rebalancing are the following: every asset can take on a minimum or a maximum weight within the portfolio. The minimal weight has been defined to be equal to 1% and the maximal weight has been defined to be equal to 20% under the effect of the PID control action.

The set-point value of this procedure, in order for the new model to achieve its target, is set to be equal to 0.5% monthly target portfolio return. The mechanism of action of this model is similar to a dynamic Exchanged Traded Fund (ETF), replicating an index in terms of underlying assets. On the opposite, it is different in terms of relative weights and, therefore, the model is a dynamic strategy.

The algorithm and implementation of the new model is the outlined in the following steps, using the expression:

Asset class	Index	Weight
Monetary	Deutsche Borse EUROGOV Germany Money Market (TR)	6%
Bonds	iBoxx Euro Index World Wide Performance Overall	10%
	Market iBoxx € Financials Total Return Index	10%
	Market iBoxx € Non Financials Total Return Index	10%
	Market iBoxx € Euro Sovereign Overall Total Return Index	10%
Equity	MSCI Daily TR Gross Europe Local Currency	5%
	STOXX 600 Total Return Index EUR	5%
	STOXX Style Index TMI Growth Return Index EUR	5%
	STOXX Europe Total Market Value (Net Return) EUR	5%
	MSCI Daily TR Gross Total Return World USD	5%
	MSCI Emerging Markets Daily Gross Total Return USD	5%
	MSCI Daily TR Gross North America Total Return USD	5%
Commodities	S&P GSCI Tot Return Indx	2%
	S&P GSCI Energy Tot Ret	2%
	S&P GSCI Industrial Metals Index Total Return	2%
	S&P GSCI Agricultural Index Total Return CME	2%
	S&P GSCI Livestock Index Total Return.	2%
	S&P GSCI Crude Oil Total Return CME	2%
Gold	S&P GSCI Gold Index Total Return	5%
Cash	Out of the market	2%

Table 2. Strategic Portfolio "B" composition: index specification. The table presents, for any macro-asset class, the specification of which particular selected indices form each macro-asset class. Furthermore, the relative weights are indicated.

$$\begin{aligned}
&return_n=\left(k_p e_n+k_i(e_n\text{-}return_{n-1})+return_{n-1}+k_d(e_n\text{-}e_{n-1})\right)\\
&\text{where:}\\
&return_n=output=\text{ return at time n}\\
&u_{n-1}=output=\text{ return at time n-1}\\
&k_p=\text{Proportional Constant} = 0{,}5\\
&k_i=\text{Integral Constant} = 0{,}6\\
&k_d=\text{Derivative Constant} = 0{,}5\\
&e_n=(return_n - 0{,}005)\text{ at time n}\\
&e_{n-1}=(return_{n-1} - 0{,}005)\text{ at time n-1}\\
&\text{SetPoint = desired return} = 0{,}005
\end{aligned} \tag{3}$$

- Define set-point = Desired Return = 0,005.
- Calculate portfolio return (controlled variable), $return_0$, for the initial portfolio, given current market conditions.
- At each iteration n, the PID controller designates a controlled value for the portfolio return, called $return_n$ given by equation [3]. The making of such rebalancing is necessary to minimize the error between current return (determined by current market conditions) and $return_n$ and set-point. Since the objective is to reduce the error, e_n defined by the difference between current return, $return_n$, and the set-point or desired return defined as 0,005, each iteration contributes in reducing e_n. The error decrease is generally counteracted by the dynamics of the markets. Given ideal market conditions, e_n approaches zero after the transient system response has died out.
- New market data acquisition and corresponding portfolio return, $return_n$, is calculated at end of each period (monthly).
- The previous items are iteratively re-executed until the end of the observation period.
- The PID parameters, chosen to be constant for all market conditions, are set to be:
  $K_p = 0{,}5$
  $K_i = 0{,}6$
  $K_d = 0{,}5$
- In this work, the parameters values were set according to an empirical criterion: under risk-free market conditions (portfolio with zero exposure to financial markets), the selection of a transient time domain response with a slight oscillatory response, exhibiting reasonable overshoot, and approaching set-point value within a small number of iterations was adopted.
- The objective of each iterations is to make returns as stable and consistent as possible given the contributions and interactions of the controller and the market dynamics influence. The change in asset mix is dictated by the controller indications and the market behavior of the underlying securities.

The main results of this methodology are illustrated in the following paragraph.

5. Portfolio "A" vs. Portfolio "B"

This section recapitulates the main results of the new model comparing the returns of Portfolio "A" to the returns of Portfolio "B". The comparison is performed in terms of return and volatility for the observation period.

Table 3 illustrates information about return and volatility. Portfolio “A” has an annualized return of 7,25% compared to 5,14% of Portfolio “B”. The cumulative return in the observation period (1999-2011) is 86,96% for Portfolio “A” and 61,66% for the benchmark. In terms of portfolio risk, the experimental portfolio realizes an annualized volatility of 7,93%, indicatively in line and consistent with 7,01% recorded by Portfolio “B”. Portfolio “A”, with only a slightly higher volatility, is able to obtain more satisfying results both in annualized and in cumulative data analysis.

	Portfolio "A"	Portfolio "B"
Annualized Return	7,25%	5,14%
Cumulative Return	86,96%	61,66%
Annualized Volatility	7,93%	7,01%

Table 3. Return and Volatility data. This table presents the comparison of annualized return, cumulative return and annualized volatility of Portfolio “A” and Portfolio “B”. Period of observation: February 1999-February 2011.

After having analyzed the data in the observation period, it is considered interesting to analyze the data on a monthly basis.
Table 4 demonstrates monthly data; scrupulously, it is evident that the mean monthly return of the Portfolio “A”(0,60%) is superior to the Portfolio “B” mean monthly return (0,43%). The set-point or target value for the model was 0,5% monthly; thus, the experimental portfolio reaches the ideal target. The mean monthly volatility for Portfolio “A” is 2,29%, whereas the benchmark (Portfolio “B”) exhibits a volatility of 2,02%.

	Portfolio "A"	Portfolio "B"
Mean Monthly Return	0,60%	0,43%
Mean Monthly Volatility	2,29%	2,02%

Table 4. Monthly Return and Volatility information. This table presents the comparison of average monthly returns and average monthly standard deviations of Portfolio “A” and Portfolio “B”. Period of observation: February 1999-February 2011.

Table 5 shows, in the first and second column respectively, Portfolio “A” returns and Portfolio “B” returns for each year of the observation period. It is important to specify that each year is considered by counting from February (t-1) to February (t). This allows the yearly periods to be defined by 12 periods of 12 month each one, considering that the given time series starts in February. This table demonstrates that the new model performance is, in most cases, equivalent or better than the benchmark portfolio performance for each analyzed year, except for three years 2004-2005, 2006-2007 and 2009-2010, where Portfolio “A” underperforms Portfolio “B”. The third and fourth columns of Table 5 display the annual volatility for the two portfolios. We can see that in many years, the new model presents higher volatility than Portfolio “B”, but it is necessary to remember what mentioned herein, that performances are also superior.

	Portfolio "A" Return	Portfolio "B" Return	Portfolio "A" Annual Volatility	Portfolio "B" Annual Volatility
1999-2000	16,05%	19,25%	7,62%	7,49%
2000-2001	6,07%	2,08%	8,67%	6,38%
2001-2002	2,97%	-1,25%	6,11%	6,90%
2002-2003	4,54%	-8,71%	7,90%	7,63%
2003-2004	8,27%	13,21%	11,94%	5,82%
2004-2005	-1,32%	8,06%	4,70%	2,57%
2005-2006	18,28%	14,74%	8,13%	4,99%
2006-2007	2,19%	3,55%	5,20%	2,84%
2007-2008	9,98%	1,99%	7,91%	4,83%
2008-2009	-16,27%	-24,22%	6,21%	9,94%
2009-2010	19,85%	22,83%	6,77%	5,62%
2010-2011	16,34%	10,13%	5,35%	4,16%

Table 5. Portfolio “A” and Portfolio “B” annual returns and volatilities. This table presents annual returns and annual standard deviations of Portfolio “A” and Portfolio “B” for each observed year. Period of observation: from February 1999 - February 2011.

The following chart illustrates, graphically, the dynamics of volatility of Portfolios “A” and ”B”. It can be noticed that the continuous line representing the volatility of Portfolio “A” is often higher than that of the benchmark. However, it is interesting to underline the stabilization effect starting from 2004 and becoming evident under the PID control action. As it is well known, this instrument needs a history before it can enable its efficient control action and make it functional.

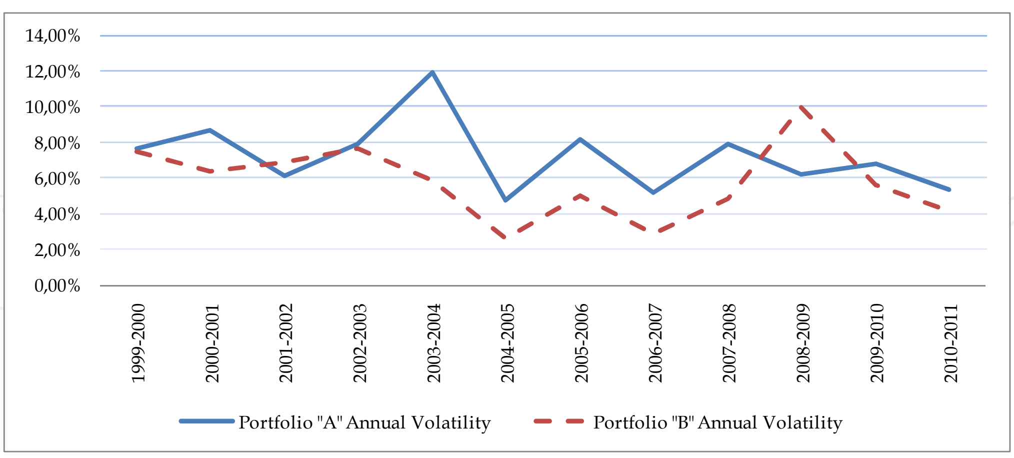

Fig. 2. Annual Volatility of Portfolio “A“ and Portfolio “B“. This chart presents the annual volatility dynamics of the two portfolios in the observation period February 1999-February 2011. The continuous line represents Portfolio “A”; the dotted line represents Portfolio “B”.

After having calculated the return and risk of the two portfolios, a comparison of the two portfolios is performed by using a risk adjusted return indicator, the Sharpe Ratio. This indicator is defined as the ratio of the difference between return and risk free return at the numerator, divided by the standard deviation of the portfolio returns. In order to define the risk free rate the average of the Libor values in the 12 years (1999-2011) of observation period are calculated. This calculation has yielded a value equal to 2,80%. The results are depicted in the table below:

	Portfolio "A" Sharpe Ratio	Portfolio "B" Sharpe Ratio
1999-2000	1,74	2,20
2000-2001	**0,38**	Negative
2001-2002	**0,03**	Negative
2002-2003	**0,22**	Negative
2003-2004	0,46	1,79
2004-2005	Negative	2,05
2005-2006	1,90	2,39
2006-2007	Negative	0,26
2007-2008	**0,91**	Negative
2008-2009	Negative	Negative
2009-2010	2,52	3,56
2010-2011	**2,53**	1,76

Table 6. Sharpe Ratio of Portfolio “A“ and Portfolio “B“. This table presents the results of a risk adjusted return indicator, namely the Sharpe Ratio applied to the two portfolios for every year in the observation period. In bold are illustrated the cases in which Portfolio “A” has outperformed Portfolio “B”.

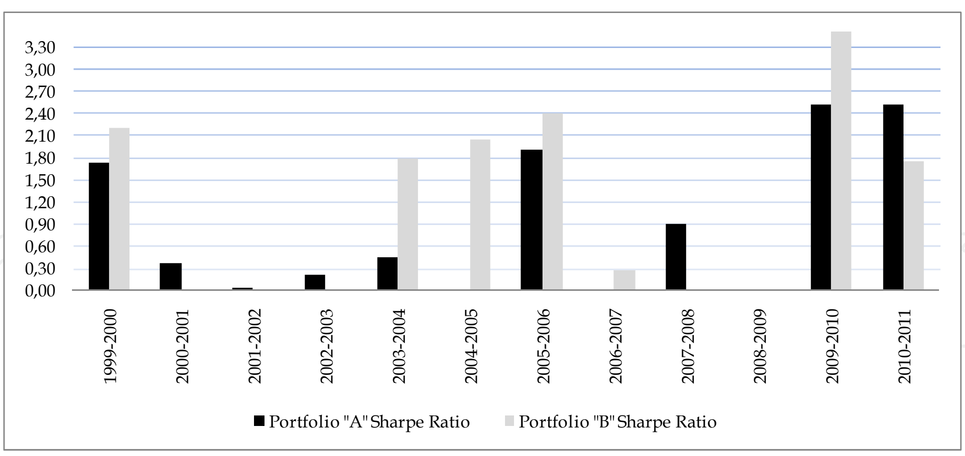

Fig. 3. Sharpe Ratio of Portfolio "A" and Portfolio "B". The chart presents, for each observation period, the Sharpe Ratio values of the two portfolios. In particular, in black the values belonging to Portfolio “A” are represented. In grey, the corresponding values for Portfolio “B” are illustrated. The absence of a column shows that the indicator value is negative, hence non-interpretable.

When in table 6, the word “Negative” is present, it means that for that specific year, it was not possible to record the indicator due to its negative value. The Sharpe Ratio is not

defined for negative values. Hence, the Sharpe Ratio becomes meaningless since a return net of the risk free is negative. The case of a negative numerator in the Sharpe Ratio formulation can occur in two situations: when the portfolio return for that period is negative, or when the portfolio return for that period is positive but inferior to the risk free rate of return.
The analysis of table 6 allows the reader to notice that Portfolio "A" is able to obtain better results than Portfolio "B" in 5 instances out of 11 (the observation for year 2008-2009 is eliminated since both portfolios have negative Sharpe Ratios). The consistent returns of Portfolio "A" in many cases, allow the overcoming of the risk free return when Portfolio "B" is not able to do so; hence, Portfolio "B" presents negative Sharpe Ratios (examples in the range 2000-2003).
Figure 3 represents the trend of Sharpe Ratios of the 2 portfolios.
When a column of one of the two portfolios is not visible, it means that one of the two values is negative.
It was considered interesting to investigate another risk adjuster return indicator: Sortino. This indicator of risk adjusted return, is defined as the ratio of the difference between the return and the risk free return, and, at the denominator, a risk measure defined as the Down Side Risk (DSR). The Down Side Risk is a measure of risk that considers only the volatility of the returns inferior to the risk free return. By calculating the Down Side Risk, we investigated the type of reduced risk, up or downside risk. We have analyzed if the new model acts more successfully in decreasing positive risk or downside risk.

	Portfolio "A" Annual DSR	Portfolio "B" Annual DSR
1999-2000	8,84%	8,19%
2000-2001	11,44%	11,06%
2001-2002	**10,74%**	12,20%
2002-2003	**11,43%**	14,40%
2003-2004	13,81%	8,27%
2004-2005	11,12%	7,81%
2005-2006	8,64%	7,38%
2006-2007	10,45%	9,13%
2007-2008	**10,18%**	10,33%
2008-2009	**15,68%**	19,42%
2009-2010	7,21%	5,76%
2010-2011	**7,09%**	7,87%

Table 7. The Down Side Risk of Portfolios "A" and "B". The table represents for every year in the observation period the comparison between the Down Side Risk of the two portfolios. The DSR is calculated considering the volatility of returns inferior to the risk free rate relative to the risk free rate itself.

The Down Side Risk (DSR) of Portfolio "A" and of Portfolio "B" was calculated and analyzed for this purpose. The main results of this study on downside risk are depicted in Table 7. As illustrated in this table, the new model exhibits a DSR lower than the benchmark in 5 cases out of 12.

This situation is interesting and it is visible in figure 4. It illustrates the stabilization effect of Portfolio "A" on Down Side Risk. The continuous line (new model) tends visibly to smooth out the extreme values better than the movement of the benchmark.

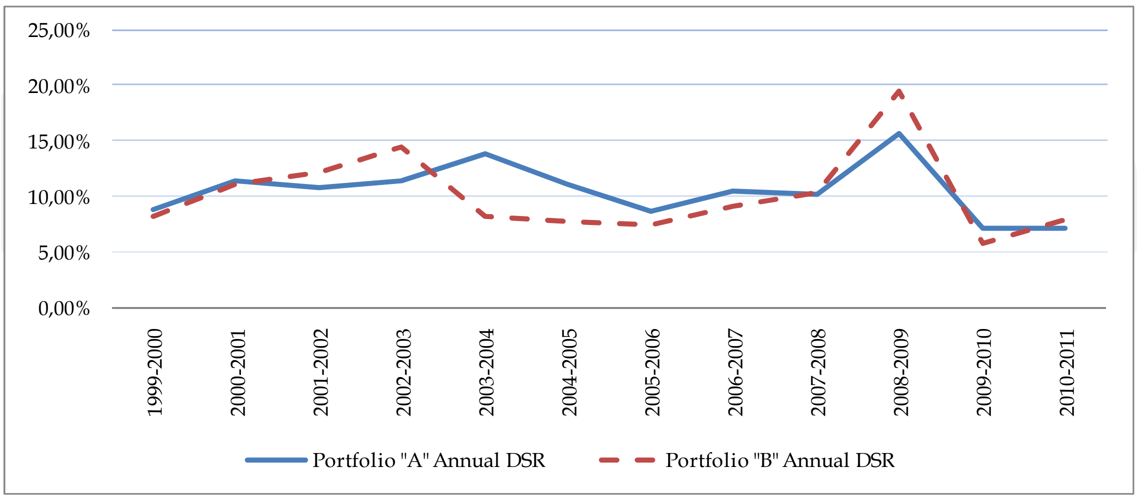

Fig. 4. Comparison between the Down Side Risk of Portfolio "A" and Portfolio "B". In the figure, the continuous line illustrates the DSR Portfolio "A". The dotted line serves for Portfolio "B".

After having calculated the value of the Down Side Risk, it is possible to calculate the risk adjusted return indicator defined above, Sortino ratio. Differently from Sharpe, this indicator has at the denominator, not the standard deviation, hence the volatility of the portfolio, but rather uses the DSR, hence the volatility defined for the returns below the risk free rate. As it can be observed from table 8, Portfolio "A" obtains better results than Portfolio "B" in 6 years out of 11 (the year 2008-2009 is not considered since both portfolios

	Portfolio "A" Sortino	Portfolio "B" Sortino
1999-2000	1,50	2,01
2000-2001	**0,29**	Negative
2001-2002	**0,02**	Negative
2002-2003	**0,15**	Negative
2003-2004	0,40	1,26
2004-2005	Negative	0,67
2005-2006	**1,79**	1,62
2006-2007	Negative	0,08
2007-2008	**0,71**	Negative
2008-2009	Negative	Negative
2009-2010	2,36	3,48
2010-2011	**1,91**	0,93

Table 8. Sortino ratio for portfolios "A" and "B". This table presents the results of the risk-adjusted return Sortino, applied to the two portfolios, for the whole observation period. In bold, the cases when Portfolio "A" over performs Portfolio "B" are highlighted. The indication "Negative" shows the fact that for a negative numerator, the indicator is not defined.

exhibited negative values). This indicates that, selecting the criterion of the most negative of the risk factors, the DSR, (that is the returns inferior to the risk free rate) the new model is bale to guarantee a better performance in comparison to the benchmark.
The following chart allows the visualization of the comparison of the two portfolios. It is to be remembered that when a column is missing, it indicates that its corresponding value is negative. In year 2001-2002, the column of portfolio A since its value is negligible. However, Sortino's value in that year is relevant.

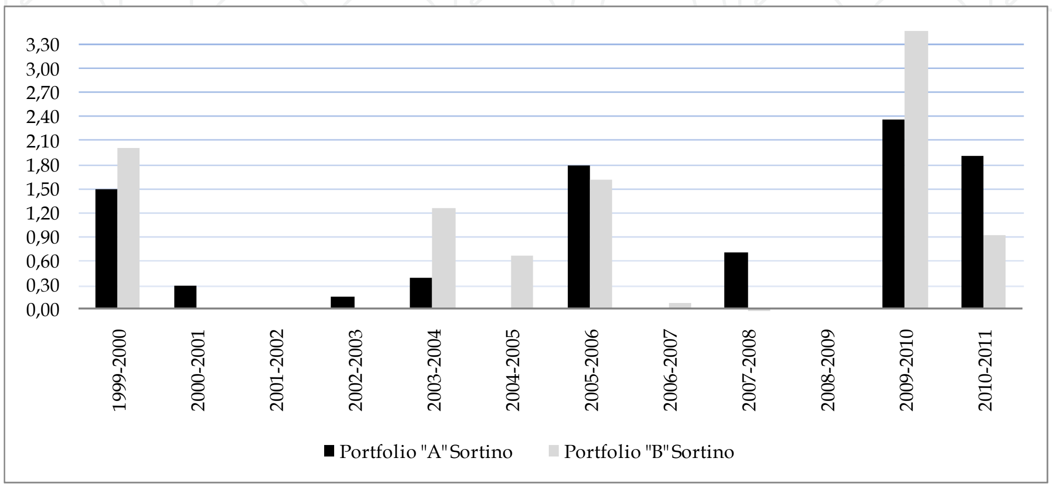

Fig. 5. Sortino ratio of portfolios "A" and "B". The chart represents per each year of observation, Sortino values for the two portfolios. In particular, in black the results for Portfolio "A" are represented. In grey, the results of Portfolio "B" are illustrated. The absence of a column indicates that the indicator value is negative, hence non-interpretable.

If Sortino and Sharpe Ratio results are compared it is evident the ability of Portfolio "A" to better perform in comparison of Portfolio "B". Since the difference between Sortino and Sharpe resides in the definition of the denominator portion of the formula, it is apparent that Portfolio "A" acts more efficiently on the DSR than on the total volatility. Hence, this selectivity capability of the model is a good feature. The PID control action on financial portfolios seems to function as a stabilizer of returns. Above all, it diminishes the worst component of the returns, namely the ones inferior to the risk free rate.

6. Conclusion

This work illustrates a portfolio management model with the aim to obtain good returns and decrease portfolio risk through stabilization of returns, by means of the PID control applied to pure returns. As demonstrated in the previous sections, the new model is able to obtain returns that are satisfactory in the observation period. In addition, it is able, in about half of the analyzed cases, to diminish the volatility relative to the benchmark. In particular, the best results are exhibited when the Down Side Risk is considered instead of the whole volatility. The results illustrated herein relative to the Down Side Risk are of a good quality. The new model, through asset rebalancing, in the observation period, successfully reduces the negative volatility factor in 5 cases out of 11 more than the negative volatility of the benchmark. This research work furthers the analysis of two indicators of risk adjusted returns: Sharpe and Sortino. Confirming and reiterating what just said, Sortino, which uses the DSR in its denominator, obtained the best performances.

Portfolio "A" presents, in 6 years out of 11, a risk adjusted return value for the Down Side Risk better than the benchmark. These initial results confirm that the PID based asset allocation technique seems to be a good instrument, adapt for adverse market conditions. It effectively controls and bounds negative volatility. At the light of the current results herein achieved, the authors desire to further and develop the model in the attempt to seek and understand relations, functions and interacting factors among the managed portfolio characteristics and intrinsic and endogenous parameters of the model, such as the set-point, aiming to maximize returns' stabilization effects.
The authors will further the model verifying and testing its applicability on various financial market indices and diversified portfolios, including the impact of transaction costs. The goal is to confirm broad-spectrum negative volatility controllability, steadiness and performance stabilization for financial portfolio managers.

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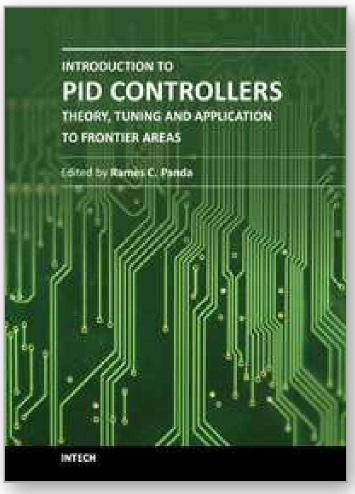

Introduction to PID Controllers - Theory, Tuning and Application to Frontier Areas
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This book discusses the theory, application, and practice of PID control technology. It is designed for engineers, researchers, students of process control, and industry professionals. It will also be of interest for those seeking an overview of the subject of green automation who need to procure single loop and multi-loop PID controllers and who aim for an exceptional, stable, and robust closed-loop performance through process automation. Process modeling, controller design, and analyses using conventional and heuristic schemes are explained through different applications here. The readers should have primary knowledge of transfer functions, poles, zeros, regulation concepts, and background. The following sections are covered: The Theory of PID Controllers and their Design Methods, Tuning Criteria, Multivariable Systems: Automatic Tuning and Adaptation, Intelligent PID Control, Discrete, Intelligent PID Controller, Fractional Order PID Controllers, Extended Applications of PID, and Practical Applications. A wide variety of researchers and engineers seeking methods of designing and analyzing controllers will create a heavy demand for this book: interdisciplinary researchers, real time process developers, control engineers, instrument technicians, and many more entities that are recognizing the value of shifting to PID controller procurement.