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Kendall WT/PE Methodology for Robust ER-Based Portfolio Engineering

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ABSTRACT

The article examines the Kendall methodology as an integrated quantitative WT/PE architecture that translates heuristic market intuition into a formalized language of signals, portfolio rules, and rigid verification procedures on long historical series. The growth of backtest overfitting risks drives the relevance of the study, demands for regulatory and institutional transparency, and the industry's shift toward integrated AI/ML pipelines, in which the verifiability of trading algorithms becomes as significant as their predictive power. The objective of the work is to articulate, in scientific terms, the internal logic of the WaveTech/PortfolioExpert linkage, the core of proprietary indicators (SMA bands 10/21/41, PPM oscillators, ER metric), and to demonstrate how thematic concentrated Top ER portfolios with a controlled risk profile are formed through signal confluence and ER-based selection. The scientific novelty consists in a systemic formalization of the robustness-by-design principle for a practical trading platform: multi-level timeframe alignment, a discrete signal refresh regime, outlier exclusion, strict in-/out-of-sample and walk-forward discipline, and a substantiated inclusion of ML-enhanced Genetic Evolution Algorithms as a meta-layer for searching interpretable strategies without transitioning to an opaque black box. The main results show that a portfolio constructed exclusively on ER logic and transferred statically from the in-sample period 2015–2020 into the out-of-sample window 2021–2025 preserves positive dynamics under an expected reduction in returns, which is interpreted as empirical evidence of construct transferability and of the limits of its adaptability to changing market regimes. The article will be helpful to researchers and practitioners of quantitative trading, portfolio managers, trading-platform architects, and risk specialists interested in reproducible and auditable algorithmic strategies.

1. Introduction

The quantitative trajectory of Robert Kendall over 45 years has shaped a methodology in which market intuition is translated into a strict, verifiable language of data and rules. This approach is most fully embodied in the WaveTech (WT) and PortfolioExpert (PE) platforms, where technical precision is combined with systemic discipline: signals and decisions are treated not as isolated conjectures, but as elements of a formalized model capable of retaining operability amid decades-long evolution of market regimes. The internal logic of the platforms rests on a broad investment universe and extensive historical memory: a database of more than 15,000 financial instruments is supported (predominantly equities and ETFs, as well as selected futures), while continuous opportunity scanning is reinforced by data in which a portion of the tests spans 45+ years, thereby providing a statistical foundation for detected regularities.

In applied and research terms, the Kendall framework was interpreted and extended through more than five years of academic work: the author conducted backtesting and real-trading deployment, complementing the original methodology with proprietary models of statistical evaluation, principles of asset selection, and portfolio construction. The outcome was a comprehensive scheme that united traditional trading principles with modern data-driven procedures for signal quality control. Within this scheme, strict risk management remains central, along with the operational rule that allows profits to run while simultaneously stopping the bleeding through loss cutting. Practical discipline is supported by an entry/exit checklist, a recommendation to trust only those signals that are confirmed by a sufficient trade history for the instrument (ideally 3–5 years), and to exclude statistically insignificant cases; additionally, a statistical overlay analyzes trade logs for outliers, including the exclusion of abnormally large wins, so that strategy expectations remain realistic.

This article presents a scientific review framework of the Kendall methodology, as it was presented and applied by the author, and lays the groundwork for its practical application to retail and institutional investors, family offices, and trading platforms. Particular attention is paid to transparency, as all trading activity and performance indicators are recorded in detailed logs that are updated on a daily or weekly basis, enabling continuous verification and external audit.

2. Materials and Methodology

This work relies on a two-loop corpus of materials: (i) practical-empirical artifacts of the Kendall trading ecosystem, architectural descriptions of WaveTech and PortfolioExpert, specifications of proprietary indicators (SMA bands 10/21/41 and PPM oscillators), rules for discrete signal updates (day/week), as well as trade journals and aggregated performance tables including in-sample (2015–2020) and out-of-sample (2021–2025) windows; and (ii) academic sources from the References list, which define methodological constraints and an interpretive language for the results. The theoretical quality-control framework includes studies on backtest overfitting and false discovery risks in financial tests [1], on procedural rigor of out-of-sample and walk-forward checks [11], and on the risk of spurious model selection and information leakage [10]. To substantiate the composition signal layer to portfolio layer, works on machine learning in the portfolio-selection paradigm [2] and on the concentration/diversification trade-off [4] are used; in discussing the extension of WT/PE via AI/ML, review and applied studies on financial forecasting and integrated analysis/validation pipelines are used [12], as well as reinforcement learning for trading/allocation [3, 14] and evolutionary methods for generating interpretable trading rules [17].

Methodologically, the article is constructed as a multi-layer mixed design that simultaneously decomposes the system and tests its transferability: (1) an architectural-functional decomposition of WT and PE with role fixation (top-down screening and generation of discrete long-only signals vs. portfolio construction and execution), followed by operationalization of key entities (confluence, model selectivity, signal update rule) in terms of robustness to regime changes [2]; (2) a comparative-explanatory analysis of the core indicators, where SMA bands are interpreted as a trend filter and PPM as a probabilistic proxy estimate of holding support/resistance, which is juxtaposed with empirical results on trend rules and momentum [7]; (3) protocol-driven empirical validation through strict separation of development and testing phases: a reproducible description of the in-sample stage, then a direct move forward in time into the out-of-sample window without changing portfolio composition and without additional tuning, which is treated as a key barrier against fitting and model mirages [11]. Additionally, to reduce the illusion of alpha from outliers, the research loop explicitly maintains the principle of expectation realism through log analysis and the exclusion of abnormally large wins as a source of unstable estimates, which is conceptually aligned with procedural verifiability requirements in applied algorithmic trading [1].

3. Results and Discussion

3.1. WaveTech (WT) & PortfolioExpert (PE): Architecture & Key Indicators

WaveTech (WT) and PortfolioExpert (PE) in the described trading system serve as two complementary subsystems, sharing a methodological foundation but with distinct points of application. WT is treated as a top-down analysis mechanism (from the overall market through sectors and groups down to a specific instrument) and a signal generation engine. In contrast, PE uses these signals as inputs for building thematic, relatively concentrated portfolios and for subsequent trade execution. At the architectural level, this implies a functional separation: WT is responsible for identifying entry/exit conditions (in terms of probabilistic edge and market context), and PE for how precisely this edge is realized via capital allocation, position-building rules, and risk control at the portfolio level [2].

At the top level, WT covers indices, commodity futures, ETFs, and individual securities. Signals are constructed from a combination of a large set of logics and quantitative technical indicators aggregated across multiple timeframes. Such a multi-component design is valuable not per se, but as an attempt to reduce the probability of false regularities arising from rule enumeration on historical data: the phenomenon of backtest overfitting is widely described in academic literature as a systematic source of mirages in test results and as a cause of strategy degradation out of sample [1]. In this sense, an orientation toward signal confirmation by multiple logics can be interpreted as a practical implementation of robustness-by-design, where predictive precision is subordinated to decision stability in the face of regime shifts.

WT output is formulated as long-only buy signals across four models: two models operate on a daily horizon and two on a weekly horizon. A crucial operational aspect is that signal updating is declared discrete: for daily models, it occurs at the end of the trading day. For weekly models, it happens upon completion of the week. Within the day or week, the signal is not recalculated. This regime, in essence, renounces high-frequency reactivity and reduces the influence of micro-noise, thereby facilitating entry/exit planning and aligning decisions among execution participants. Table 1 illustrates the signal update and execution schedule for daily or weekly models.

Table 1. Signal Update & Execution Schedule for Daily / Weekly Model

By Timeframe	Daily	Weekly
Update Completed	9:00 PM / MON - FRI	9:00 PM / FRI
Signal Entrance	Next morning	Following Monday

The logic of separating weekly and daily models is described in the system as a functional decomposition by risk-taking horizon. Weekly models are interpreted as contextual, as they filter out a substantial fraction of short-term noise and establish the dominant trend. In contrast, daily models are tactical, enabling more frequent entry and exit within a longer move. Multi-timeframe alignment practice is broadly consistent with the more general notion of reducing decision errors through a consistency requirement across different data representations, i.e., a quasi-ensemble approach in which multiple models must agree to reduce the probability of false triggering [3]. Table 2 shows the differentiation between daily and weekly models.

Table 2. Differentiation between Daily and Weekly Models

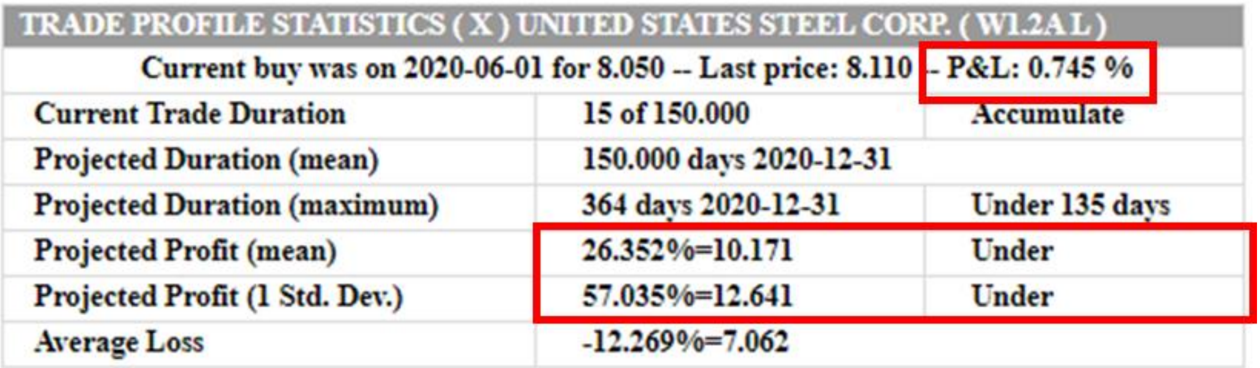
By Timeframe	Daily	Weekly
Aggressiveness	More	Less
Accuracy	Less	More

Within each timeframe, the models additionally differ by reaction speed. Models #3 are positioned as more conservative, as they utilize an additional momentum filter (PPM #4), becoming more selective and trading less frequently. By contrast, models #1 are treated as faster and more aggressive: in the absence of the specified filter, they can generate earlier signals; however, this is typically associated with an increased frequency of false entries and, consequently, a higher risk profile. Constructively, this creates an embedded robustness check. If a signal emerges only in the more aggressive configuration but is not confirmed by the conservative version or by the higher timeframe, the entry decision requires additional validation (e.g., waiting for weekly confirmation). Table 3 illustrates the differentiation between the #1 and #3 models.

Table 3. Differentiation between #1 vs #3 Models

By Model	#1	#3
Aggressiveness	More	Less
Accuracy	Less	More
V-Bottom	Often catch	Often miss

Next, the system introduces the concept of signal confluence: the author develops a statistical framework that describes how combinations of outputs from different models are transformed into an estimate of overall signal strength and how this estimate can be utilized in portfolio construction. Importantly, such frameworks must inevitably be tested for robustness to overfitting not only in the classical machine-learning sense, but also in the finance-specific sense of multiple testing and selection bias. Therefore, procedures of strict out-of-sample control and robust validation schemes are methodologically relevant [1]. Figure 1 illustrates the WT trade profile screen, which displays the projected trade duration, target profit, and stop-loss.



TRADE PROFILE STATISTICS (X) UNITED STATES STEEL CORP. (W1.2A L)		
Current buy was on 2020-06-01 for 8.050 -- Last price: 8.110 -- P&L: 0.745 %		
Current Trade Duration	15 of 150.000	Accumulate
Projected Duration (mean)	150.000 days 2020-12-31	
Projected Duration (maximum)	364 days 2020-12-31	Under 135 days
Projected Profit (mean)	26.352%=10.171	Under
Projected Profit (1 Std. Dev.)	57.035%=12.641	Under
Average Loss	-12.269%=7.062	

Figure 1. WT trade profile screen: projected trade duration, target profit, and stop loss

If WT is described as the layer of what and when to buy, PE is the layer of how exactly to buy, i.e., the circuit of portfolio construction, optimization, and execution. In particular, PE is oriented toward thematic, relatively concentrated portfolios, where concentration is understood not only as a small number of positions but also as a specific selection regime in which the trade-off between diversification and concentration becomes parametrically dependent on admissible risk and target constraints [4]. At the same time, the practical realization of concentration inevitably requires enhanced risk control at the position and portfolio levels, since reducing the number of components increases the sensitivity of outcomes to signal errors or market regime shifts.

In PE execution mechanics, elements of dynamic risk management are highlighted, including position sizing, partial profit-taking (profit slicing), and multi-level stop mechanisms, such as gradual exposure reduction as the confluence score deteriorates. From a scientific standpoint, such practices can be related to more general approaches to drawdown control and risk limitation via feedback rules and maximum drawdown constraints, which have been studied in both financial engineering and optimization settings [5]. At the level of individual trades, the use of stop levels and exit rules is also a subject of empirical research, which shows that correctly specified stop rules can substantially alter the distribution of strategy outcomes and their risk-adjusted characteristics [6].

As a result, WT and PE form a multi-level circuit: WT provides discrete, multi-timeframe long-only signals, while PE transforms them into portfolio decisions through thematic concentration, allocation rules, and risk-management procedures (scaled entry, partial closing, cascading stops). Importantly, such a composition itself imposes requirements for proving robustness: the richer the set of rules and the more complex the signal orchestration, the stricter the validation discipline must be; otherwise, the probability increases that the system will perform well in the past but poorly in new market regimes.

3.2. The heart of WT and PE - Kendall's proprietary Indicators & Metrics

The core of signal generation relies on a set of proprietary indicators and metrics that bind interpretations of trend, momentum, and probabilistic level holding into a unified rule system. As a foundational scaffold, SMA bands with periods 10, 21, and 41 are used: the model not only computes moving averages but also evaluates how price behaves relative to these lines and their mutual arrangement. In the internal terminology of the system, the 21-period SMA (PPM2) is treated as the Primary Demand Line, i.e., a key intermediate-demand line around which the notion of support in an uptrend is formed. SMA crossings (analogous to golden/death cross), combined with whether the price is above or below the relevant averages, determine trend state and subsequently enter entry/exit trigger conditions. In applied terms, this corresponds to the literature's common idea that moving-average rules are a compact form of trend filter, and that their effectiveness and sensitivity depend on horizon choices and market context [7].

If SMA bands define trend geometry and levels of potential mean-reversion dynamics, then PPM (Price Pressure Momentum) acts as a translator of momentum into a probabilistic language of support/resistance. In the system, PPM is represented as a set of oscillators that quantitatively estimate the probability that the price will remain above (or be pressed below) key moving averages. In this setup, PPM1, PPM2, and PPM3 correspond to the 10-, 21-, and approximately 40-period SMA, while PPM4 is used as an additional filter in selected, more selective models. This construct is conceptually similar to how modern studies describe the role of momentum: it does not replace price. Still, it often captures transitional phases and regime changes before they fully manifest in the trend component [8]. Figure 2 illustrates the PPM indicator visualization.

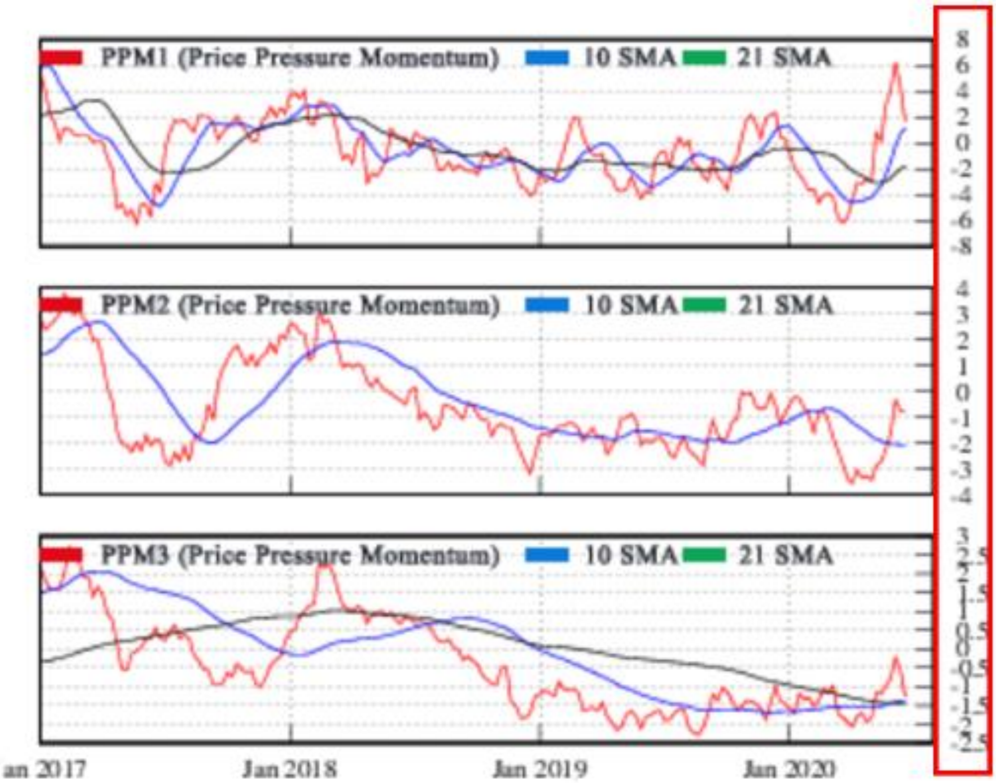


Figure 2. Price Pressure Momentum Indicator visualization

Practically, this means that a strong buy signal in WT, as a rule, implies coherently favorable PPM values across multiple timeframes, i.e., confirmation of support quality not only by the price position relative to the SMA but also by a pressure/momentum estimate interpreted as the probability of the level holding. Table 4 illustrates applicable actions for different PPM values.

Table 4. Reading PPM (Price Pressure Momentum) Indicator

PPM Values	Trend Description Based on the Value	Applicable Actions
PPM > 0.25	Confirmed **BULLISH (UP)** Trend mode with established **SUPPORT** ⇒ probability of the price to **DROP BELOW** the appropriate **SMA** is **LESS THAN 20%**	Consider **BUY**
0.15 < PPM ≤ 0.25	Unconfirmed **BULLISH (UP)** Trend mode with **SUPPORT** not established nor confirmed ⇒ probability of the price to **DROP BELOW** the appropriate **SMA** is **BETWEEN 20–40%**	**WL** or **BUY**
-0.15 < PPM < 0.15	**BE CAUTIOUS!** No **SUPPORT** could be determined, No Trade Zone, Indecision, Sideways movement likely to occur.	
-0.25 < PPM ≤ -0.15	Unconfirmed **BEARISH (DOWN)** Trend mode ⇒ **NO SUPPORT**, probability of the price to **INCREASE ABOVE** the appropriate **SMA** is **BETWEEN 20–40%**	**WL** or consider closing open positions
PPM < -0.25	Confirmed **BEARISH (DOWN)** Trend mode ⇒ **NO SUPPORT**, probability of the price to **INCREASE ABOVE** the appropriate **SMA** is **LESS THAN 20%**	Open positions are most likely closed or will be closed soon. **NO TRADE ZONE FOR LONGS; MAY CONSIDER SHORTING!**

The next logical layer is ER (Effectiveness Rating), a proprietary performance metric used primarily for comparing the quality of models across instruments and within a single instrument, rather than determining the current market state. In meaning, ER is closely related to the class of risk-adjusted measures, as it aggregates the historical trade outcomes of a model on a specific asset, indicating a more favorable return–risk relationship (or, more broadly, more reliable model behavior on the given asset) with a higher value. This directly links the WT signal block to the PE portfolio logic from the previous fragment: when a portfolio is constructed in a concentrated and thematic manner, the value increases of selection criteria that discipline instrument inclusion based on comparable risk-adjusted characteristics rather than merely on signal presence [9]. A detailed example of ER calculation is shown in Figure 3.

ER	141.25	= (% Win * 100) * Avr W/L Ratio %
% Win	41.8%	
Avr Win %	18.9%	
Avr Loss %	5.6%	
Avr W/L Ratio %	3.4	= Avr Win % / Avr Loss %

Figure 3. Detailed Example of ER Calculation

The author applies ER as an asset inclusion filter: a Top ER portfolio is formed by sorting instruments by average ER (aggregated across models), followed by iterative filtering of positions that do not improve the portfolio's aggregate characteristics. In addition, the system sets a practical minimum ER threshold for instrument eligibility (as an internal heuristic constraint), such that ER simultaneously functions as a proxy estimate of signal trust and as a formal selection criterion for increasing the robustness of portfolio decisions [9].

3.3. WT and PE Empirical Validation

The portfolio was initially constructed and tested over a six-year in-sample horizon, after which the author tracked and recorded its realized dynamics over the subsequent five years, using a quantitative selection procedure without fundamental overlays or discretionary adjustments. The stated values of cumulative return and derived annual indicators refer to the author's internal report and must be interpreted in conjunction with the underlying tables and equity curves shown below, since they act as the primary carriers of the statistics.

Table 5. Summary metrics of the top ER portfolio

Summary metrics		Annual Return	
# Symbols	21	2015	3%
$ Equity + Cash	59,162,729	2016	148%
Inception date	1/1/2015	2017	164%
Initial INV	1,000,000	2018	169%
ROI	5916%	2019	30%
Return / Year	1000%	2020	140%

Within the logic of the previous sections, this is important because alignment of horizons was declared as a robustness-enhancing mechanism. In contrast, the dominance of only one circuit typically increases the risk of regime fragility. At the same time, any exceptionally high in-sample values, by definition, require heightened discipline in overfitting checks, since financial backtests are particularly sensitive to multiple testing, hidden fitting, and inflated quality estimates under rule enumeration.

The process of constructing a Top ER portfolio constitutes sequential statistical filtration. First, a broad universe is formed (15,000 symbols are specified in the text), then each symbol is ranked by ER Average, defined as the mean ER value across all WT/PE models for the given instrument. After the initial ranking, a top group is selected (the top 100 in the text) and placed into a model portfolio of a specified capital scale. Subsequently, several cycles of iterative cleaning are executed, excluding instruments with negative net profit or net profit below a specified threshold. This functions as a test of the intrinsic value of Kendall's proprietary metrics: if a portfolio built exclusively on ER logic, without external filters and without expert intervention, demonstrates stable dynamics, the argument strengthens that ER reflects not an accidental correlation but a reproducible performance structure. However, in terms of modern backtesting methodology, the critical condition remains the correct separation of data and the absence of information leakage: even with formal training/testing splits, unintentional peeking of future information is possible, leading to the systematic inflation of out-of-sample expectations [10]. Summary metrics of the top ER portfolio by symbol (in-sample validation) are shown in Table 6.

Table 6. Summary metrics Top ER Portfolio by Symbol (in-sample validation)

#	Ticker	MDL	Net $ P/L	Net % P/L	% Win	ER Sym	ER Prtfl
1	ARWR	d1	6,433,000	20%	67%	215	247
2	VERI	d3	5,962,512	21%	64%	395	1,058
3	BYND	d1	4,366,290	23%	67%	343	468
4	NBEV	d1	4,341,640	13%	49%	230	469
5	CRMD	d3	3,076,577	20%	59%	298	421
6	TRIL	d3	2,699,510	8%	53%	308	312
7	ROKU	d3	2,176,355	7%	73%	271	291
8	NXST	d1	2,096,815	7%	60%	168	188
9	WHD	d3	1,703,150	13%	82%	403	376
10	NAK	w1	1,683,825	17%	72%	367	451
11	BWEN	w1	1,276,815	17%	75%	1,035	279
12	CBAY	w3	1,204,347	325%	67%	784	1,700
13	VKTX	w3	1,166,881	37%	63%	1,470	1,538
14	HEAR	w1	972,705	12%	57%	617	514
15	DCP	d1	955,666	3%	67%	143	222
16	EVRI	w1	683,117	13%	87%	277	404
17	LNTH	w1	405,986	7%	73%	1,573	1,870
18	IO	w1	359,175	8%	62%	235	394
19	TVTY	w3	314,816	6%	75%	336	241
20	SAGE	w3	264,037	7%	75%	641	772
21	GOOS	w3	206,264	8%	50%	587	455

Moving from in-sample to testing on unseen data, an out-of-sample stage is выделен, dated 2021–2025, and is treated as more stringent validation because it imitates moving forward in time and checks whether the positive effect persists after market regime changes. In the theory and practice of trading-strategy validation, exactly this regime (ideally walk-forward) is regarded as a key safeguard against fitting, as it preserves information-set discipline and forces the model to operate on data that could not have influenced its construction [11]. Figure 4 illustrates the equity curve of the top ER out-of-sample testing for 2021 - 2025.

Figure 4. Equity Curve of Top ER Out-Of-Sample Testing for 2021 - 2025

The in-sample period is interpreted as a development and tuning stage in a historical environment, where higher compounding indicators are typically observed, and parameter–data correspondence manifests more strongly. In contrast, the out-of-sample period is treated as a robustness check against the degradation of results after transfer to new time segments. The characteristic out-of-sample dynamics are emphasized: initial deterioration at the beginning of the window, followed by recovery in later years, which is interpreted as a sign of the construction's adaptability to regime change without requiring structural re-optimization. Such formulations are consistent with the general empirical observation that the gap between in-sample and out-of-sample results is the norm rather than an exception and should be assessed as part of strategy risk rather than as a test failure [1]. Tables and figures below illustrate the comparison.

Table 07. Monthly / Annual Rate of Returns Top ER Out-of-Sample testing for 2021 - 2025

Period	2021	2022	2023	2024	2025
ANNUAL	-9.6	-17.5	18.5	40.6	27.3
January	13.9	-0.3	13.1	-0.8	-0.3
February	7.2	-1.5	-1.7	31.5	-5.1
March	-7.8	1.9	-3.5	11.5	3.3
April	2.3	-13.3	9.6	-7.6	-0.9
May	1.0	-4.5	-3.1	4.8	6.4
June	4.3	-4.6	-3.0	-6.8	7.8
July	-6.2	9.9	9.9	5.8	2.2
August	-6.8	2.7	-11.6	-1.1	6.4
September	-2.7	-6.3	-6.0	4.4	10.6
October	4.7	4.4	3.3	-1.1	1.4
November	-8.9	5.6	0.2	-0.7	-6.2
December	-8.2	6.6	3.2	-0.5	-

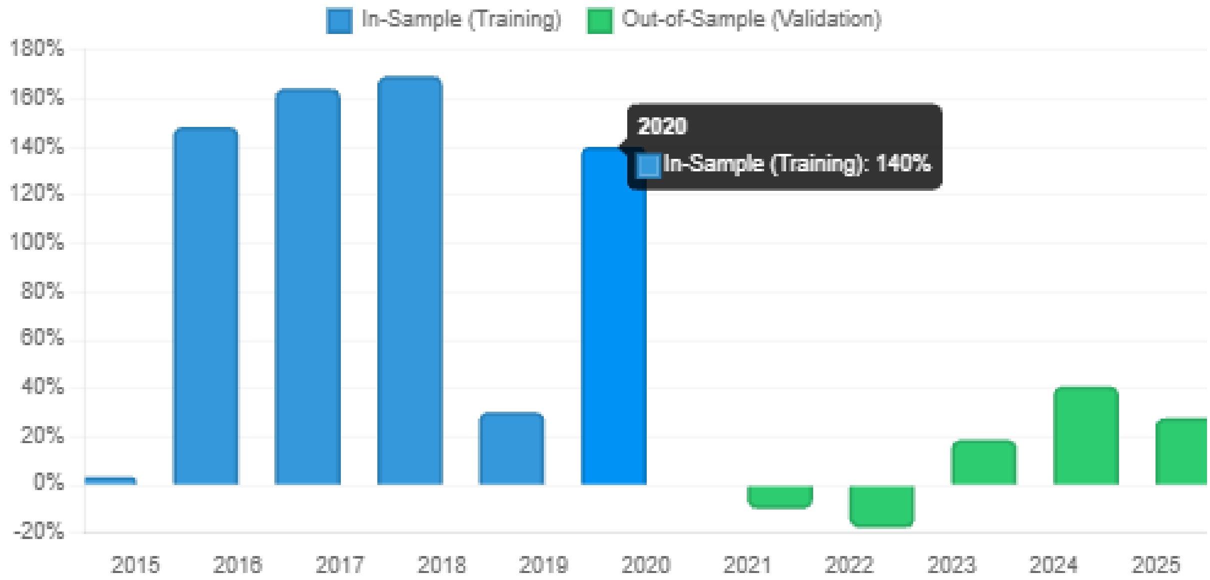


Figure 5. Annual returns comparison: Top ER Portfolio In-Sample backtesting vs Out-of-Sample validation

Table 08. Detailed Characteristics Comparison: Top ER Portfolio In-Sample backtesting vs Out-of-Sample validation

Metric	In-Sample (2015–2020)	Out-of-Sample (2021–2025 YTD)
Period Type	Training / Development Phase	Validation / Live Forward Testing
Average Annual Return	≈109%	≈8–10%
Data Usage	Used for model training & optimization	Strictly unseen for validation
Portfolio Composition	Fixed - no new, removed, or replaced symbols	Unchanged - identical universe
Applied Filters	Build methodology + ER-based filter only	Same filters applied, no tuning
Volatility Profile	High volatility with consistent positive drift	Initial drawdown followed by strong recovery
Best Year	2018: +169%	2024: +40.6%
Worst Year	2015: +3%	2022: -17.5%
Interpretation	Optimized high-performance learning phase	Realistic stress-tested market validation

The transition between phases was executed cleanly: the portfolio composition was not changed, no additional filters beyond the original ER methodology were introduced. Therefore, out-of-sample results should be treated as a direct test of the transferability of the initial construction, minimizing the risk of retrospective fitting and data leakage. From the standpoint of scientific integrity, this is a material clarification, because strategy robustness is determined not only by return magnitude but also by protocol transparency, decision traceability, and verifiability of execution logs, particularly in an applied domain where black-box claims often fail procedural scrutiny [10].

Continuing the logic of the previous sections, where WT sets signal discipline, and PE transforms it into reproducible portfolio execution (with an emphasis on robustness, cross-timeframe confirmation, and ER-based selection), the next step is naturally formulated as scaling this inherited alpha via modern AI/ML tools without loss of the original rule transparency. In practical terms, this concerns not replacing WT/PE with a neural network, but converting the system into a unified automated analytical-trading platform in which the computational core remains unchanged in meaning, while interfaces and decision circuits become faster, more coherent, and less manual; this is consistent with how modern literature describes the evolution of financial modeling from isolated signals to integrated end-to-end pipelines of analysis, validation, and application under changing regimes [12].

The technical trajectory of such a transition can be described as architectural unification: consolidation of WT, PE, and indicator modules (including compatibility with graphical layers at the TradingView level) into a centralized web environment with a shared backend and a unified database, potentially extensible to a mobile client. On this basis, the intelligent user-interaction layer shifts the main load from manual chart inspection to managed queries and reports, including signal screening templates, batch instrument evaluation, drill-down from market/sector to symbols, and aggregated analytics of signal strength, thereby reducing latency between the emergence of confluence conditions and decision-making. In parallel, visualization and backtesting are embedded into the same circuit: comparison of multiple model outputs on a single chart, native overlays of support/resistance levels and projections, and automated runs across markets, timeframes, and instruments, such an integrative design reduces the risk of divergence between research backtests and executable strategies through a common data source and unified calculation procedures [13].

At the portfolio level, PE development is conceptually described as a transition from a static rule set to a self-learning capital allocation scheme across themes and models. For example, in the reinforcement learning paradigm, an agent optimizes allocation under current constraints and observed market dynamics. Academic works on RL portfolio management demonstrate that such agents can directly optimize the portfolio objective function, bypassing a separate return-forecasting stage; however, interpretability and risk control remain critical, as the system otherwise becomes a difficult-to-audit black box [14]. In order not to undermine the robustness-by-design principle, a regime-adaptive ensemble appears reasonable: combining signals from different WT/PE models (as before) while adding contextual features, macro indicators, news/social sentiment, and, when expanding to crypto markets, on-chain metrics, so that the system can recognize regime shifts and change priorities without manual retuning, corresponding to modern approaches to detecting and early-warning regime switches [15].

Finally, the research circuit can be accelerated via ML-enhanced evolutionary optimization (genetic algorithms for hyperparameter tuning and feature selection across a grid of markets and timeframes), but only under strict out-of-sample and walk-forward discipline; otherwise, automation merely accelerates the production of overfit configurations. Empirical studies demonstrate that GA approaches can indeed enhance results compared to naive enumeration, albeit at the expense of complicating quality-control procedures [16]. When translating the system into end-to-end execution (signal generation, trade, rebalancing), the requirement for data integrity becomes as primary as the models themselves: automated ticker management (delistings, renamings, corporate actions), stable identifiers, and verifiable validation pipelines are necessary; otherwise, backtest and production begin to inhabit different realities.

In parallel, to preserve the previously stated verifiability and trust in results, it is advisable to design audit trails and control circuits in the spirit of regulatory expectations for algorithmic trading (documentation of algorithm life cycles, testing, monitoring, and the ability to reconstruct decisions), while launching a flagship portfolio on real capital in such a setup functions not as a marketing declaration but as a live-environment verification instrument under unchanged rules.

3.4. Justification for GEAs' application in Quantitative Strategy Optimization

Within the logic of the previously proposed circuit of WT/PE self-evolution through ML-enhanced Genetic Evolution Algorithms (GEAs), the key argument in favor of evolutionary optimization is not novelty effect but congruence between the method’s nature and the market’s nature. Evolutionary algorithms (genetic algorithms, genetic programming, and broader evolutionary metaheuristics) implement a bio-inspired search scheme in which competing strategy configurations undergo mutations and recombination, after which variants with superior objective-function values survive. In the context of trading systems, this is convenient because the search is conducted in discrete and discontinuous spaces of rules and parameters (where gradients are meaningless or unavailable). At the same time, the optimum is often jagged and multimodal. Such landscapes are treated as a typical case for large-scale evolutionary optimization tasks.

Markets remain nonstationary adaptive systems: relationships between features and returns shift with participants, liquidity regimes, and the regulatory environment; therefore, assumptions of static, smooth, and convex optimization prove excessively fragile. The practical strength of GEAs is that they, first, support diversified search (avoiding entrapment in a single local solution), second, naturally formulate as multi-criteria procedures (return, risk, stability, drawdown constraint), and, third, allow parallel testing of a large number of candidates without forcing the model to fit a single metric. This is particularly relevant for WT/PE, where robustness was previously elevated to a design principle (model confluence, timeframe separation, out-of-sample discipline), and where optimization must strengthen solution transferability rather than merely the beauty of the backtest.

From an applied standpoint, GEAs are convenient as a universal meta-layer for tasks that inevitably arise in an evolving WT/PE, including automated feature and filter selection, hyperparameter tuning, discovery of signal structures, and generation of interpretable trading rules (in the case of genetic programming). Notably, recent studies have applied genetic methods to both the construction/optimization of trading rules, as well as to tuning time-series model parameters. In these applications, GA is used to select network configurations or their hyperparameters, demonstrating practical value as a search engine over a complex variant space [17].

Finally, integrating GEAs within the WT/PE conceptually translates the system from a static design into a self-optimizing research–execution ecosystem: strategies can be continuously generated, selected, and validated, but only under the condition that fitness functions and testing protocols are rigidly protected against overfitting and leakage (otherwise, evolution will accelerate not alpha discovery but artifact production). Here, GEAs deliver not a miracle model, but a controllable search procedure, which WT/PE rules can discipline. The original multi-model logic and timeframe-alignment requirements become constraints on the solution space. At the same time, out-of-sample and walk-forward checks serve as the filter separating adaptivity from fitting.

4. conclusion

The presented review fixes the Kendall methodology as a rare example in applied trading of a systemic translation of market intuition into a formal, operationally executable language of rules, data, and verification procedures. The internal WT/PE logic rests on a broad instrument universe and long historical memory, fundamentally shifting emphasis from episodic finds to regime-change robustness: signals are treated not as isolated conjectures but as elements of a multi-level circuit, where WT provides top-down context and discrete long-only entry/exit conditions on daily and weekly horizons, while PE implements these conditions through thematic concentrated portfolios, parameterized allocation, position scaling, profit slicing, and cascading stops. An essential scientific implication of such an architecture is not so much a promise of accuracy as an attempt at robustness-by-design: multi-component indicator logic, timeframe alignment, and the confluence requirement are interpreted as pragmatic barriers against backtest overfitting and false regularities, while discrete signal updates (upon completion of day/week) reduce the role of micro-noise and increase execution reproducibility.

The key technical semantics of the system are reduced to the core proprietary metrics: SMA bands (10/21/41) form trend geometry and reference levels. At the same time, PPM translates momentum into a probabilistic interpretation of price holding relative to corresponding averages, thereby linking a trend filter to an assessment of the quality of support and resistance. Above this, ER is introduced as a historical effectiveness metric, functionally close to the class of risk-adjusted criteria and performing the role of a disciplining inclusion filter: the Top ER portfolio is built by sequential statistical filtration, from ranking by mean ER across models to iterative cleaning by position effectiveness, i.e., within a logic where signal alone is insufficient without a proxy estimate of trust. Thus, WT and PE form a closed methodological chain: from probabilistically interpretable conditions (PPM/SMA) and confluence signal strength to portfolio implementation, where concentration is understood as a controlled risk regime requiring strengthened control procedures, transparent entry/exit checklists, and reliance on sufficient statistical trade history per instrument with exclusion of statistically insignificant and outlier cases.

The empirical section, despite the declared impressive power of the in-sample phase (2015–2020), is conceptually valuable primarily because it emphasizes the distinction between a training phase and a testing phase and presents the out-of-sample window 2021–2025 as a transferability test under unchanged portfolio composition and without additional tuning, i.e., as a more stringent robustness regime against regime shifts. The recorded gap between in-sample and out-of-sample dynamics is interpreted as the normal cost of honest validation. At the same time, the observed deterioration at the beginning of the window, followed by recovery, is treated as a sign of construction adaptivity without structural re-optimization. At the same time, the high complexity of rule orchestration strengthens the methodological imperative of strict out-of-sample/walk-forward protocols and leakage control, since otherwise the richness of logics becomes not a source of robustness but a fitting accelerator. Within this framework, the proposed extension via AI/ML and GEAs appears not as replacing rules with a black box, but as an attempt to industrialize search and tuning in a discrete parameter space while preserving original verifiability: evolutionary methods are positioned as a meta-layer for multi-criteria optimization and generation of interpretable rules, but only under the condition that transparency discipline, audit trails, and validation filters remain primary, otherwise self-evolution will reproduce not alpha but testing artifacts.

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