Peach Innovators 2.0

Enhancing Rowing Performance Analysis Through Environmental Normalization

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Introduction

Rowing is a complex sport where crew speed depends on several interdependent factors, including stroke rate, effective stroke length, and power output. Athletes sit facing backward, pushing against foot stretchers with a four-phase stroke: catch, drive, finish, and recovery. The catch is where the blade enters the water, setting up the stroke. The drive is the power phase, where rowers push against the foot stretchers, transferring force through their legs and back. The finish is the final part of the stroke, where rowers complete the movement before extracting the blade. The recovery is the reset, where rowers slide back up the slide to prepare for the next stroke. Precise synchronization of rowers amplifies these factors, making it challenging to isolate individual contributions to overall boat speed. The goal is to move the boat efficiently over a set distance, typically a 2-kilometer course, either individually or as a team.

To analyze rowing performance accurately, telemetry systems like the PEACH system have become extremely valuable. These systems provide detailed metrics on oar angles, stroke rate, power output (watts), and other stroke mechanics, allowing for precise timing and measurement of how effectively rowers apply power, how cleanly they release the blade, and the synchronization of the crew. With a cumulative rowing experience of over 30 years, our team has encountered numerous theories regarding the factors influencing boat speed. Initially, our project (Peach Innovators) aimed to empirically determine which telemetry-derived metrics most significantly impacted boat speed. However, early results highlighted significant limitations caused by uncontrolled environmental factors such as wind and tide conditions, considerably impacting the validity of our findings. This project, therefore, aims to clearly demonstrate how key factors contribute to boat speed by addressing these environmental limitations.

Initial Approach and Limitations

Our original Peach Innovators project was designed around three primary hypotheses derived from extensive rowing experience: (1) increased average crew watts positively correlates with boat speed, (2) increased effective stroke length positively correlates with boat speed, and (3) reduced variance in crew wattage positively correlates with boat speed. By analyzing telemetry data from approximately one year of collection, comprising 992 unique data rows, we sought insights into the factors contributing to rowing performance. These data points included detailed attributes such as Watts, Effective Length, Stroke Rate, and Speed.

Initial Pearson correlation tests provided promising individual results: average watts and effective stroke length each showed significant positive correlations with boat speed, while variance in watts displayed a significant negative correlation. However, these relationships became less clear when all variables were analyzed together in a multiple regression model; only average watts retained statistical significance.

Further validation using a KERAS sequential machine learning model highlighted substantial limitations. Despite employing rigorous 4-fold cross-validation, the model yielded a high Root Mean Square Error (RMSE) of 0.53 m/s. Given the actual variance in our dataset of only 0.16 m/s, this error margin indicated significant predictive inaccuracies due to uncontrolled external environmental conditions, notably wind and tidal currents.

The collected data had inherent limitations and challenges, primarily due to the varied stream conditions on a tidal river. Additionally, differences in crew compositions, influenced by rowers' abilities, potentially biased results as stronger rowers typically produced higher wattages. Furthermore, manual data transcription introduced potential inconsistencies. Rigorous data cleaning was employed to address NULL values and anomalous sensor readings, underscoring the need for an improved methodological approach to accurately capture and analyze rowing performance.

Peach Innovators 2.0: Improved Approach

To address these limitations, Peach Innovators 2.0 focused on advanced data normalization techniques to mitigate the significant impact of environmental conditions. The goal was to adjust raw telemetry data to reflect neutral environmental conditions, isolating intrinsic rowing performance from external influences.

Collecting reliable environmental data posed considerable challenges due to approximate historical wind measurements and general tidal data lacking precise current strength details. Additionally, inherent variability in rowing sessions, such as changes in course direction and intensity, complicated efforts to standardize conditions.

By systematically removing noise introduced by weather and water conditions through environmental normalization, this project aimed to provide clearer insights into the true relationships among stroke rate, power output, effective stroke length, and boat speed. An extensive dataset was complemented by historical weather and tidal data, forming the basis for a robust normalization model capable of accurately adjusting for external environmental factors.

Methodology

The Peach Innovators 2.0 dataset comprised approximately 10,000 telemetry data points collected from Brown Men's Crew rowing sessions. In addition to telemetry metrics such as watts, effective stroke length, and stroke rate, environmental data was manually gathered from historical databases to incorporate wind and tide conditions. Wind data was collected from Weather Underground's historical weather archives, while tidal data was sourced from NOAA's tidal records. Given the complexity of accurately modeling precise wind direction impacts on rowing performance, the wind conditions were simplified into three categorical options: "tailwind", "headwind", and "crosswind", along with corresponding wind speeds. Similarly, tide conditions were categorized into "with", "against", or "slack", reflecting their directional impact relative to the rowing course. This categorical simplification made it easier to model the pieces individually, as they typically follow a structured pattern: the first piece is rowed downstream along the race course, the second upstream, and the third downstream again. This consistency allowed straightforward flipping of wind and tide conditions for each piece, enhancing the accuracy and interpretability of the normalization model.

The normalization algorithm had its issues. Initially, normalization was attempted individually for each rower, which introduced variability and failed to account for uniform environmental impacts across the boat. Subsequent attempts grouped rowers by boat, reducing individual variability but failing to capture nuanced individual rower differences adequately. The final successful method normalized each rower's speed individually, then averaged these normalized speeds across all rowers in a boat. This hybrid approach significantly improved normalization reliability and accuracy. All the approaches have been uploaded to github.

When the normalized data was finally acquired, a linear regression model provided a baseline assessment of fundamental relationships within the data. Subsequently, a more sophisticated machine learning technique - XGBoost, was employed to explore and capture complex, nonlinear interactions among variables. The model generated a new csv file, containing the normalized speed which was later run through the same tests performed in Peach Innovators.

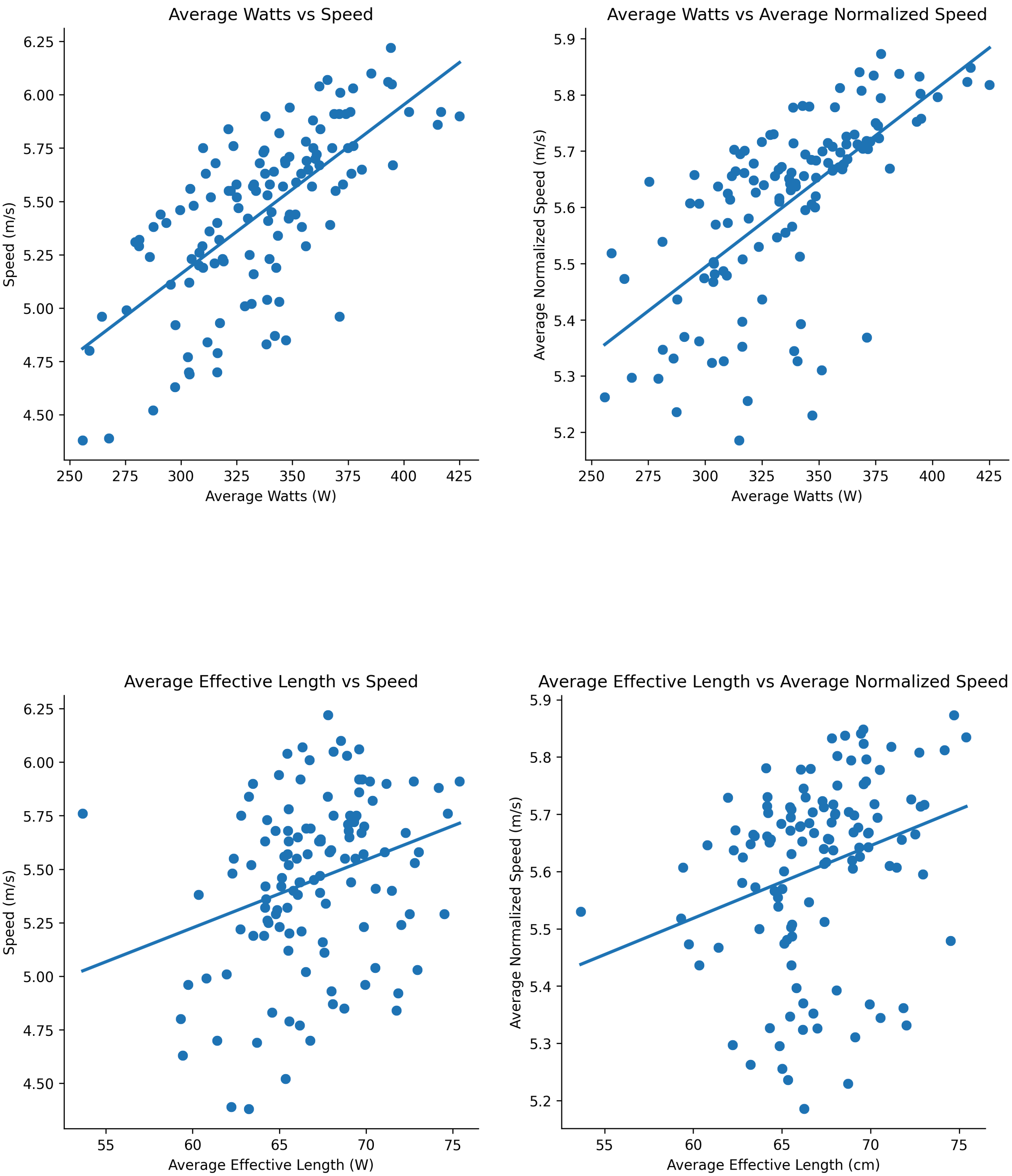
Results and Analysis

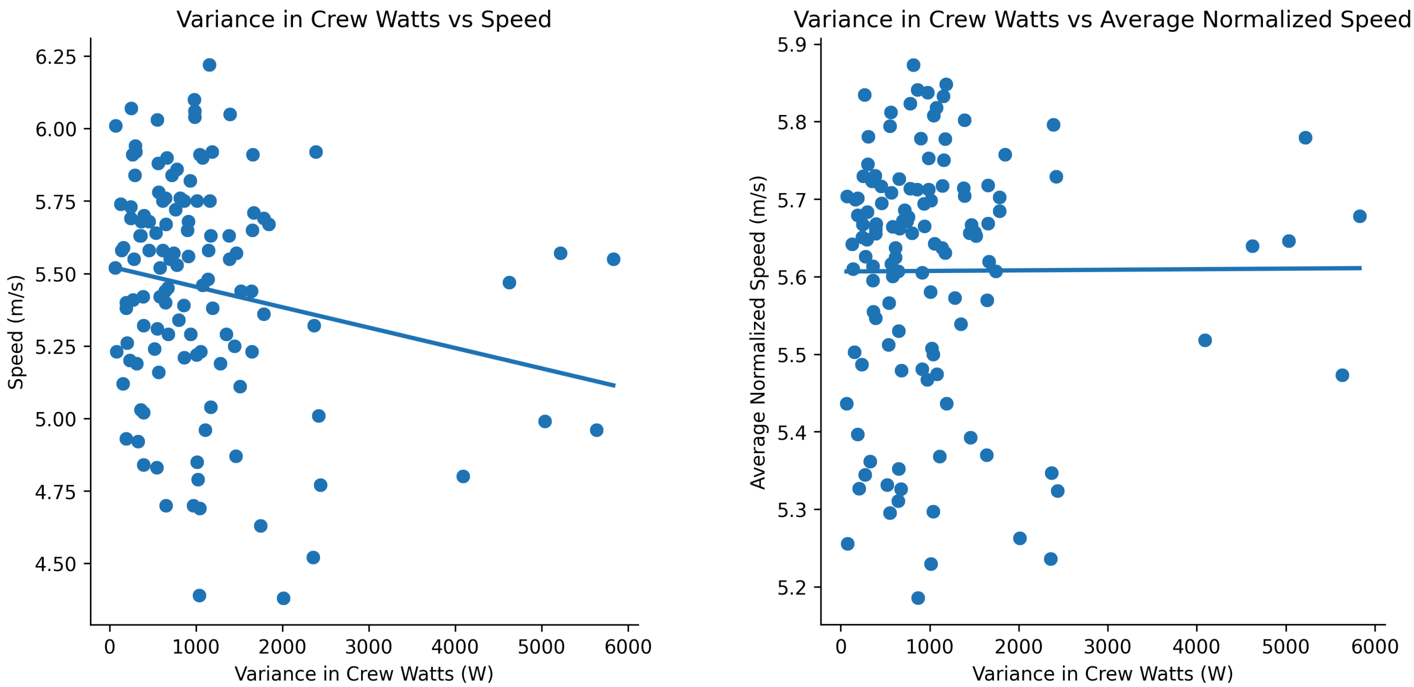
Pearson correlation analyses provided detailed insights into the impact of normalization. For original raw speed, average watts exhibited a strong positive correlation (r=0.686, p1.4e-18), variance of watts had a weak negative correlation (r=-0.200, p0.026), and effective length displayed a moderate positive correlation (r=0.292, p~0.001). After normalization, average watts still showed a strong correlation, slightly reduced (r=0.658, p4.8e-122). The variance of watts no longer demonstrated meaningful correlation (r=0.005, p0.88), suggesting that external conditions significantly amplified the negative impact of inconsistent power output. Effective stroke length remained moderately correlated with performance (r=0.278, p~7.7e-19), highlighting its stability as a performance indicator across conditions.

Normalized speed effectively removed environmental noise, clearly illustrating rowing performance under neutral conditions and enhancing the clarity of relationships between stroke metrics and boat speed. Despite a slight drop in correlation strength for watts, normalization provided a cleaner analysis by minimizing confounding external factors.

Machine learning validations offered further clarity. Multi-Layer Perceptron (MLP) regression results showed significant improvement for normalized speeds over raw speeds, with lower RMSE (0.5600 reduced to 0.4954) and reduced average MSE (0.3280 to 0.2499). Normalized speed predictions demonstrated tighter variance and stability, enhancing model robustness and prediction accuracy. Ordinary Least Squares (OLS) regression confirmed these results, showing substantial performance improvements with normalized data. For raw speed, the R-squared was 47.4% with an RMSE of 0.285, whereas normalized speed had a slightly lower R-squared (45.4%) but significantly lower RMSE (0.119) and MSE (0.014 compared to raw's 0.081), indicating higher prediction accuracy and consistency across folds. Multicollinearity remained an issue for both models, as indicated by high condition numbers (~30,300), suggesting strong interdependencies among predictors.

Normalized speed proved to be a superior metric for predictive modeling due to its significantly improved accuracy, consistency, and stability across validation metrics. Although raw speed still offers practical relevance for immediate coaching feedback, normalized speed provides clearer analytical insights into intrinsic rowing performance. Unfortunately, the results still don't indicate that our hypothesis is correct, and once again the Watts are the only metric with significant correlation to boat speed.


Average Watts vs Speed
Speed (m/s)
Average Watts (W)
Average Watts vs Average Normalized Speed
Average Normalized Speed (m/s)
Average Watts (W)
Average Effective Length vs Speed
Speed (m/s)
Average Effective Length (W)
Average Effective Length vs Average Normalized Speed
Average Normalized Speed (m/s)
Average Effective Length (cm)



What Worked and What Didn't

Environmental normalization significantly improved the analytical precision, providing clearer insights into intrinsic rowing performance by reducing environmental noise from wind and tide conditions. This allowed for a more accurate evaluation of critical metrics such as average watts and effective stroke length. However, several challenges remained due to factors beyond direct measurement and control.

Precise conditions during rowing practices were difficult to capture accurately due to variability in practice times and unforeseen changes in weather patterns. For example, wind conditions could drastically change within short periods, making consistent tracking of wind impacts challenging. Additionally, gust data was often incomplete or missing from historical records, limiting the accuracy of wind impact assessments.

Similar challenges arose in analyzing tide conditions. While directionality of tides was considered, measuring exact current strength was impossible with available resources. Tide conditions near slack tide can transition rapidly from slow to strong currents, further complicating accurate normalization. Additionally, the orientation of rowing pieces often varied, with coaches making real-time decisions based on conditions, potentially creating anomalies in the data.

Other uncontrollable variables included varying workout intensities, rate-capped workouts, and differences in training schedules relative to competition days. Factors such as fatigue, crew synchronization, and subtle technical inefficiencies also significantly influenced boat performance but remained uncaptured by existing telemetry and environmental datasets.

Despite these complexities, the normalization algorithm demonstrated considerable potential to isolate intrinsic rowing performance, supporting the validity of the original hypotheses. Further refinements in environmental data collection and more sophisticated modeling techniques hold promise to enhance accuracy and reliability further.

Future Improvements

Future work should enhance the normalization model by integrating more detailed environmental data, such as real-time weather data and precise tidal measurements. Incorporating metrics related to crew synchronization, physiological fatigue, and technical efficiency could further refine predictive accuracy. Exploring advanced machine learning models, including ensemble methods or neural network architectures designed for time-series analysis, could capture complex variable interactions more effectively.

Conclusion

Our comparative analysis of Peach Innovators 2.0 reveals significant advancements in understanding rowing performance. Average Watts maintained its strong positive correlation with boat speed, affirming our initial hypothesis that power output positively impacts performance. Effective stroke length showed consistent moderate correlation, indicating its reliable influence regardless of environmental normalization. Interestingly, Watt Variance lost significance after normalization, highlighting its sensitivity to environmental conditions.

The improved performance metrics, such as significantly lower RMSE and MSE values in our models, clearly indicate the advantage of environmental normalization. Nonetheless, persistent limitations, such as multicollinearity and incomplete control over external variables, emphasize the ongoing need for methodological refinements. Overall, these results substantially confirm our original findings while highlighting avenues for future exploration and improvement.