Sensor Technologies for Determining Cyclist Power Output:
A Comparison of Smartphone, Opposing Force and Strain Gauge Power Measurement Technologies Using Spatial Analysis

by

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Dedication

I dedicate this thesis and journey through USC graduate school to my children Dylan and Walker Daniels. For all those times that dad was in his office with the door closed, working on projects, papers, data analysis and of course this thesis, I love you for helping dad make it through the long hours and seeing the light at the end of the tunnel.

As you get older, I hope you take a moment to reflect on why your dad wanted to do this and understand that learning is a never-ending process, no matter how old you are! Set lofty goals for yourself, thinking bigger than what was previously known possible and always remember that hard work pays off.

Love you always, Dad

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I would also like to thank Jason Chilcote, the founder and developer of the Innovative App Designs (IAD) smartphone power meter application. I appreciate the countless hours in answering my questions related to application design, performance, results and overall sounding board for my thesis abstract.

Lastly I would like to acknowledge Ray Maker (professional fitness device blogger and founder of dcrainmaker.com) and Kevin Flanagan (Google software engineer and founder of fitfiletools.com) for their development of the DC Rainmaker Analyzer. Thank you for allowing me early access to the application as without it, many hours would have been spent in “spreadsheet hell” working to get my power data into meaningful comparison visualizations and charts. Can’t wait to see the final product and allowing other cyclist to make the most from their own fitness data.

List of Abbreviations

3DEP	Three Dimensional Elevation Program
A-GPS	Assisted Global Positioning System
ANT+	Low power wireless protocol used for data communications
AP	Average Power
BLE	Bluetooth Low Energy
dBm	Decibels (dB) per milliwatt
DEM	Digital Elevation Model
DFPM	Direct Force Power Meter
E911	Enhanced 911 Emergency System
GDOP	Geometric Dilution of Precision
GLONASS	Globalnaya Navigazionnaya Sputnikovaya Sistema - Russian GPS System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IAD	Innovative App Designs (Smartphone power meter application)
KML	Keyhole Markup Language
NP	Normalized Power
NoSQL	Not Only Structured Query Language
OFPM	Opposing Force Power Meter
PPA	Power Profile Assessment
RDBMS	Relational Database Management System
RMSE	Root Mean Square Error
RPM	Revolutions Per Minute
RSSI	Received Signal Strength Indicator
SWOT	Strengths, Weakness, Opportunities, Threats grid analysis
SQL	Structured Query Language
TEE	Typical Error Estimate
USGS	United States Geological Survey

Abstract

Smartphones have revolutionized the way users interact with the world and have helped pave the way for hundreds of new and exciting mobile applications. A complex array of sensors exists within smartphones, including GPS, barometer, accelerometer and other positional sensors that are leveraged by these mobile applications. These sensors are capable of providing location, speed, gradient, altitude, and acceleration data that are foundational for providing a new generation of mobile fitness applications. One such example is the development of cycling power meter applications within the sport of road biking that provides new insights into the real time power expenditure and overall cycling efficiency. This research focuses on the potential of using a smartphone and opposing force power meter (OFPM) as a replacement for traditional and expensive direct force power meters (DFPM) that have been the “de facto” standard over the last ten years. Field collected power meter cycling data, combined with spatial analysis, is used to compare various dimensions of power meter accuracy, GPS road network accuracy, elevation agreement, and cost. The overall results of this field study showed that using a smartphone power meter application performed within +/- 10% on average when compared to a traditional DFPM meter, but only when the application had access to high quality location and speed data from the smartphone’s GPS sensors. The results also showed that on average, the OFPM system performed within +/- 2% on average when compared to the DFPM reference power meter but was challenged with data latency on quick changing terrain and accelerations. Concluding the research, a summary analysis is provided as a way for cyclist to quickly understand how well each power meter performed and to determine if a specific power meter system is better suited for a rider’s individual needs.

Chapter 1: Introduction

As more accurate and diverse location and positional sensors are added to next-generation smartphones, new health and fitness applications have been developed that leverage the power of these sensors. One such example application is the ability to measure a cyclist power output, using a power meter application, to understand the amount of energy being generated while riding. Power output is often associated with the amount of effort and energy expended by a cyclist to maintain a given level of speed or performance (Cycling Power Lab 2016).

Bike power meters have become essential tools for a cyclist looking to take advantage of performance information, as it provides a real time summary of the effort required to keep a cyclist in motion. Additionally it allows for a cyclist to pinpoint and map their performance levels after a ride to gain further insights based on location. The understanding of power output, measured in watts, is often viewed by cyclist as the “uber” metric for providing an accurate picture of how efficiently the body is performing. “Power is absolute, it’s exactly what you’re doing,” said Mathew Hayman, a Tour de France veteran at age 38. “Everybody is training more scientifically than they used to and it’s brought the science of power measurement to the masses” (Austen 2016, SP9).

Historically, the measurement of cycling power has come at a high cost and complexity due to technical challenges in measuring the amount of force and torque that is being generated and then converted via algorithms into power output. Specialized “strain” gauge sensor technology is affixed to various bicycle components (i.e. cranks, pedals or hubs) in which torque measurements are taken and then multiplied by crank cadence (Cycling Power Lab 2016) to determine power output. Known as direct force power meters (DFPM’s), these systems produce technically solid results, are performance tested and proven over many years. But DFPM power meters are also very expensive, often costing more than a two thousand dollars, are complex to install and require factory recalibration after extended use.

The goal of this study is to compare and contrast two competitive power meters technologies: a smartphone power meter app developed by Innovative App Designs (Innovative App Design 2016) and the PowerPod opposing force power meter (OFPM) developed by Velocomp (PowerPod 2016). The comparison uses the Stages Cycling DFPM power meter

(Stages Cycling 2016) as the “reference standard” power meter for which various dimensions of accuracy is compared across three unique study routes.

The Innovative Application Designs (IAD) app utilizes smartphone derived GPS speed, location, elevation and other opposing forces including wind speed and heading to estimate power output. The PowerPod OFPM power meter system leverages both internal and external sensors including road gradient, wind speed, acceleration and atmospheric inputs. Externally mounted bike sensors provide for both ground speed and crank cadence. Additionally the PowerPod is paired with the Garmin Edge 500 bike computer for GPS data used in determining power output at a given location.

Once the power output and location data is collected, the results of the field study are presented using various visualizations tools including comparison line graphs and maps as shown in example Figures 1 and 1.1. From these results, conclusions are drawn regarding how well the two power meter systems compare to the reference DFPM system and the associated tradeoffs made between accuracy, route geography, cost and complexity.

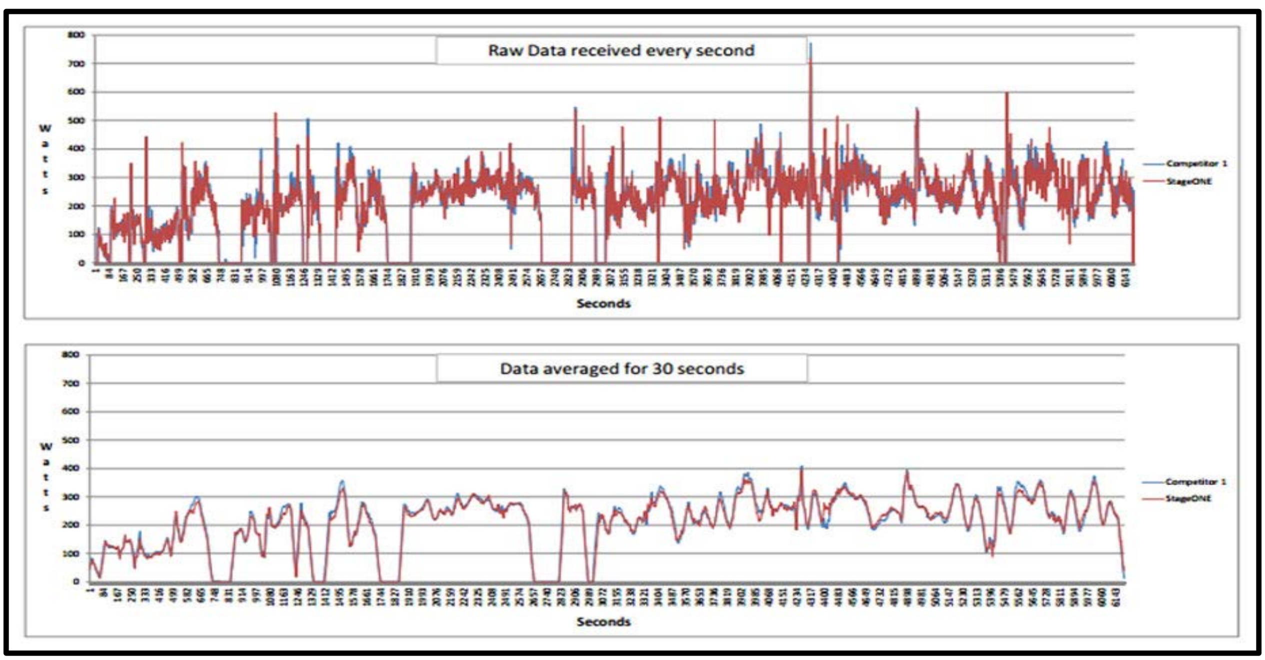

Figure 1 Example power data line graph representing power outputs across 2 different power meters StageONE and Competitor 1 (Fatbirds 2016)

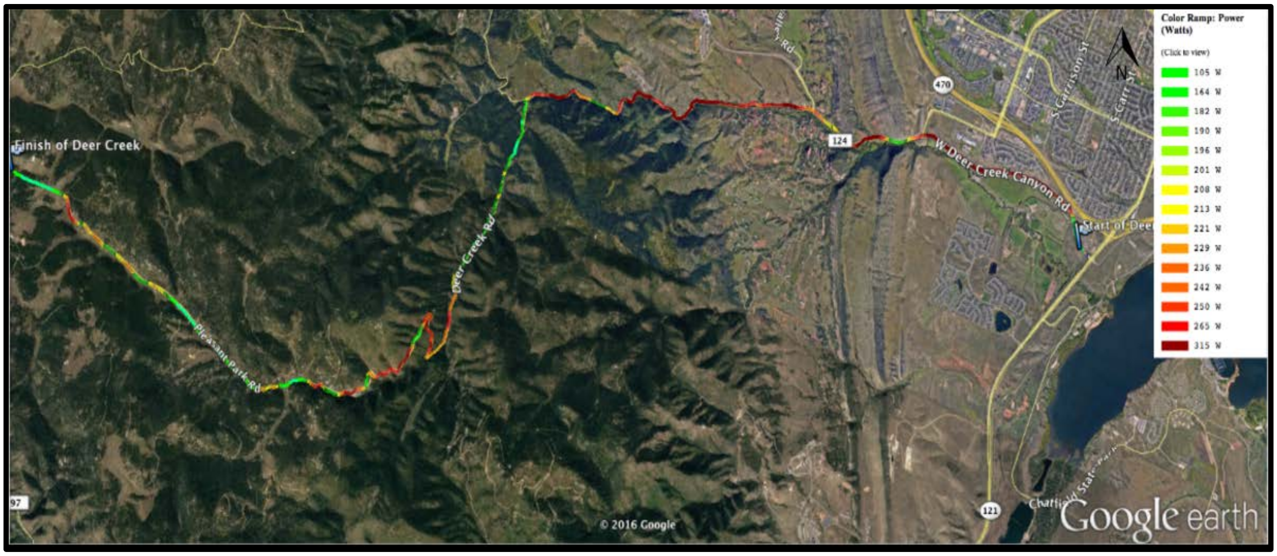

Figure 1.1 Deer Creek Canyon ride representing different power outputs

1.1 Motivation

As an avid road and mountain biker, I have always used bike computers to measure distance, heart rate, speed, cadence, slope and a variety of other outputs that help provide a "measured fitness" approach to my training rides. Most cycling computers today derive distance, speed, and slope from GPS and the remaining heart rate and cadence data derived from external sensors placed on the body and bicycle. Missing from my current collection of sensor devices is the concept and measurement of physical power output.

Traditionally, power measurement and analysis comes at a high cost that is traditionally reserved for professionals, coaches and the cycling elite. Training with power data also takes time to understand the most efficient ways to ride and how to take advantage of power data measurements to reach maximum performance. Once these power variables are understood, cyclist can leverage these data points for both training and racing in which maximum effort can be expended without the risk of using too much energy, too soon and not performing at maximum levels.

This study is unique in providing field captured power data, collection and analysis across three unique power meter systems including the Stages Cycling reference power meter, PowerPod OFPM and IAD smartphone power meter. Detailed spatial analysis and visuals will compare how well each systems compares to the DFPM reference standard. At the conclusion of the study, the potential for using a smartphone or OFPM system, as a "poor man's" power meter will be summarized and results presented to determine the levels of accuracy and tradeoffs made between each system when compared to the reference DFPM system.

1.2 Project Overview

In order to begin field data collections for the various power meter systems, three different power meters were purchased and installed on an Orbea Orca road bike (Figure 1.2), including Garmin bike computers in which the power meter data were collected for both the PowerPod and Stages power meters. The IAD application collects and transmits the power meter data as part of the smartphone application and doesn't require an external bike computer.

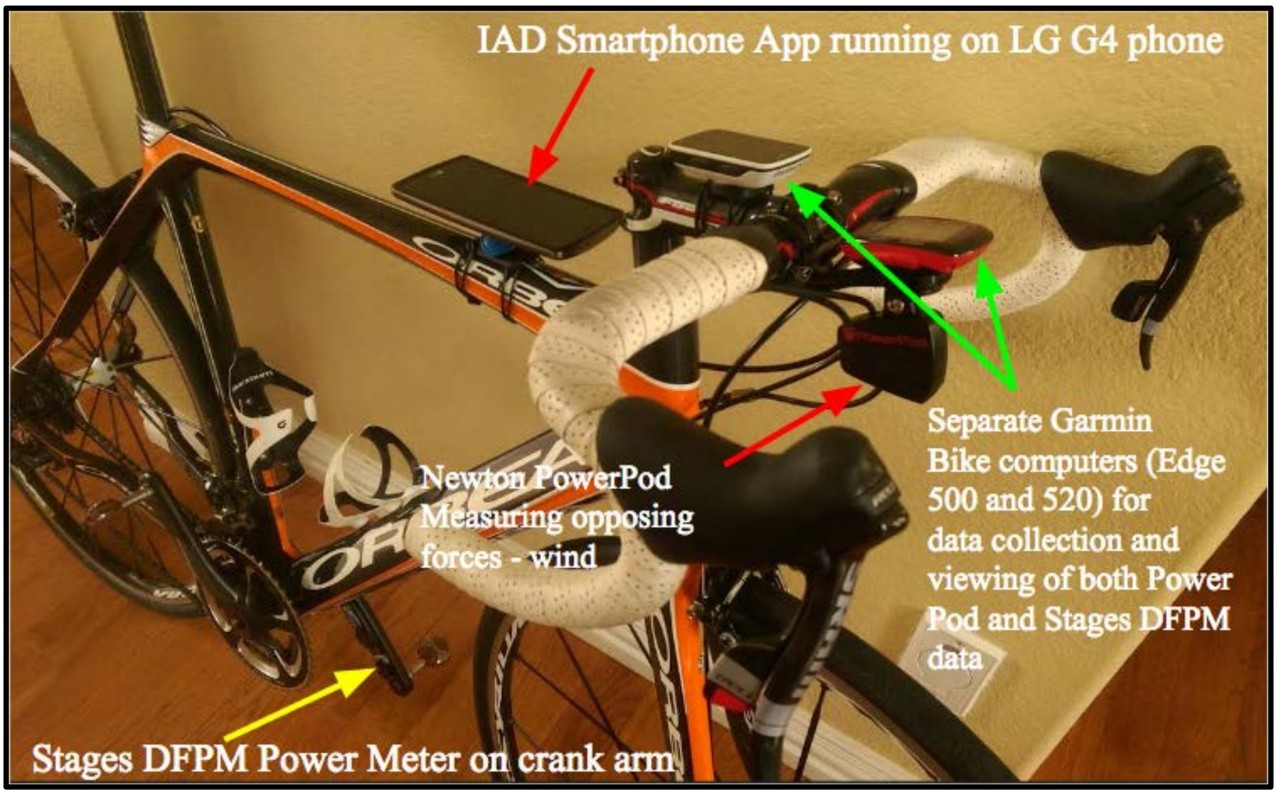

Figure 1.2 Orbea Orca bike installed with Stages Cycling Power meter, PowerPod and IAD smartphone power application

For the field data collection phase, three different study routes have been selected as shown in Figure 1.3. These routes were picked specifically to allow for power meter data to be collected across a wide range of riding geographies including rolling hills, a steep mountain climb and a steep mountain sprint.

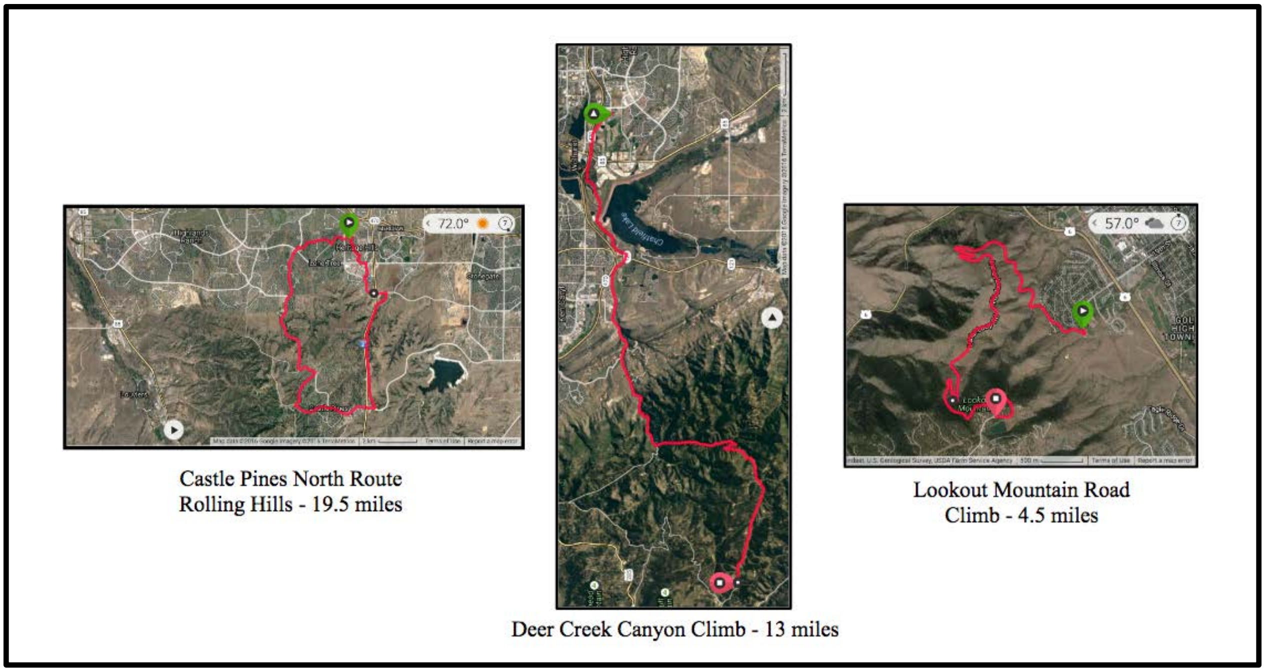

Figure 1.3 Map overview of route study areas

Once the field data is collected from the above study routes, the power meter data is downloaded as either a proprietary .fit or .tcx file format. The DC Rainmaker Analyzer (web application) and Isaac (desktop software) applications are used for generating power meter data comparisons, map visualizations and other spatial analysis. Table 1 represents the data model for the various data fields collected including GPS timestamp, distance, power, cadence, speed, altitude, latitude, longitude and slope.

Table 1 Data model and fields collected during field study routes.

GPS Time	**Distance**	**Power (Watts)**	**Cadence (rpm)**	**Speed (mph)**	**Altitude (ft.)**	**Latitude**	**Longitude**	**Slope**

The DC Rainmaker Analyzer tool is used for comparing all three power meters along the dimensions of Average (AP) and Normalized Power (NP) averages (measured in Watts), cadence (measured in rpm), elevation data (measured in feet) and mapping of the power output data. Figure 1.4 shows an example line graph comparing the three different power meters measuring power output in watts (y-axis) and time (x-axis) for a given route.

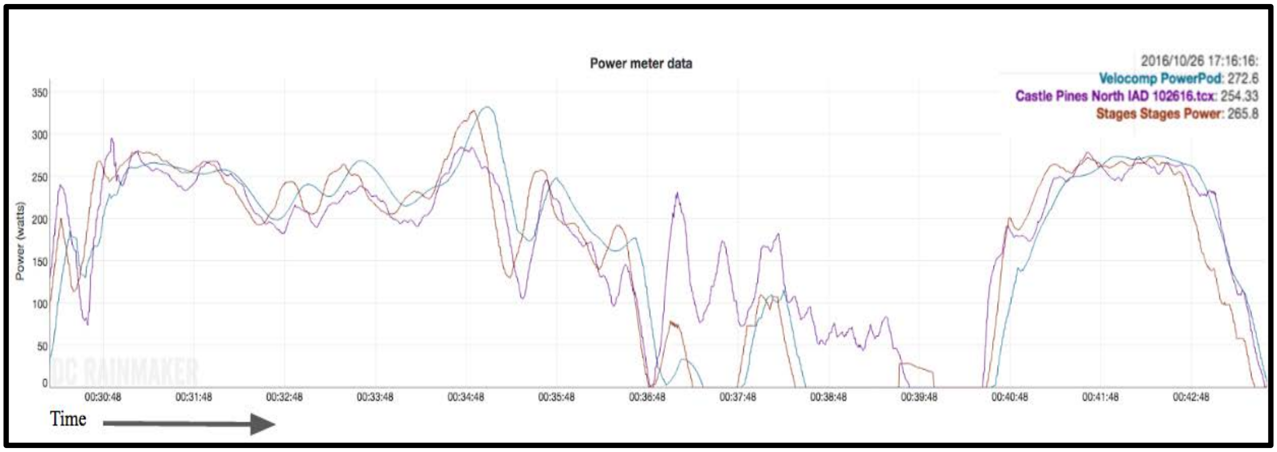

Figure 1.4 Line graph comparing the power output of the 3 power meters (Stages, PowerPod and IAD power app) over time

Additionally Figure 1.5 shows a map comparing the power output (color ramp = green for lower power, yellow/orange = mid power, red/maroon = max power output) to a location on a Google Earth map.

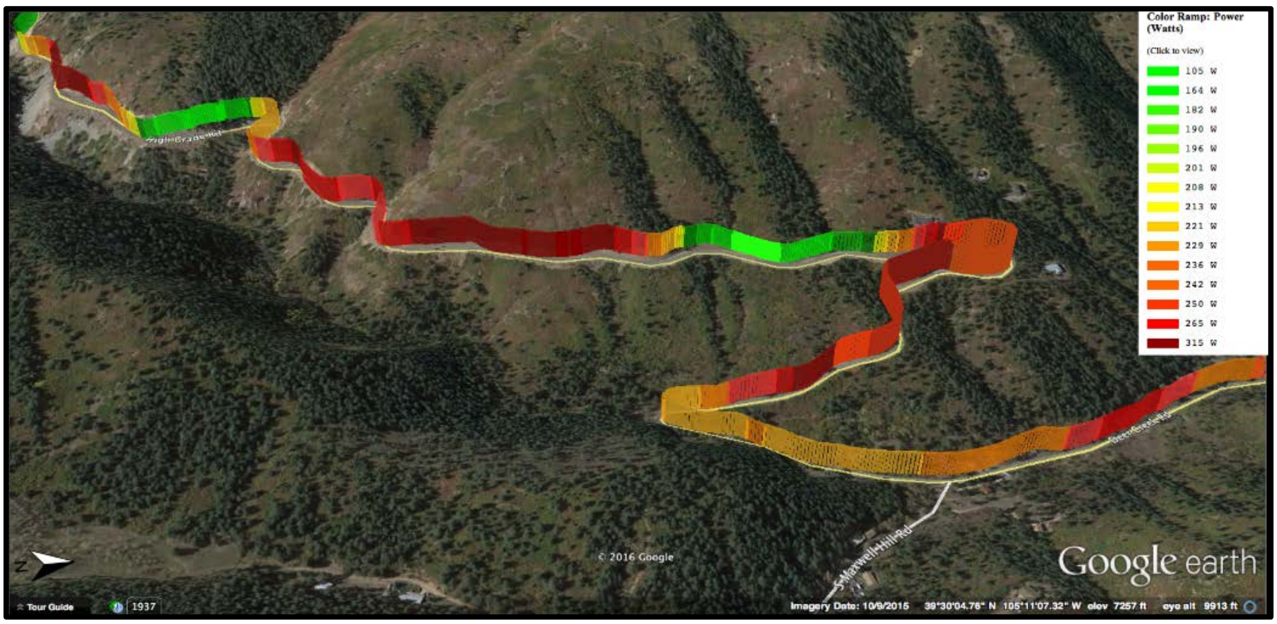

Figure 1.5 Google Earth map showing power output in relation to location

1.3 Thesis Organization

This research is divided into five chapters that include this Chapter 1 Introduction. Chapter 2 provides a summary of the background and related research that has been done in the field of various DFPM power meters types and accuracies. Smartphone Assisted Global Position Systems

(A-GPS) research is also reviewed to determine the level of accuracy achieved in using both A-GPS smartphones and autonomous GPS devices using the dimensions of location and speed accuracy for various testing methodologies. Chapter 3 provides the research design and methods for which the three power meter systems were configured, tested and analyzed. Chapter 4 reviews the results of the research and determines if the original hypothesis holds true in accordance to how accurate smartphone and OFPM power meters are in comparison to the DFPM reference system. Chapter 5 concludes the results and reviews the impacts of future technologies that could potentially improve the overall accuracy of using smartphones for cycling power meters.

Chapter 2: Background and Related Work

The science behind determining a cyclist power output via a power meter is a well-understood and documented technology within the cycling industry. Many power meter products use traditional “strain” gauges that are affixed to a bike’s crankset, pedals or hubs, which then provide very accurate power output measurements for a cyclist to view while riding. The power output information is then used by a cyclist to determine the level of effort expended while riding, training or racing (Isvan 2014). Historically having access to power meters has come at great expense and complexity, costing anywhere from six hundred dollars ($600.00) for a basic power meter system to well over three thousand dollars ($3,000.00) for the most complex systems (Competitive Cyclist 2016) used by many pro cycling teams.

To address the high cost and complexity of traditional power meters outlined above, new smartphone apps and OFPM systems have been developed over the last several years to provide cyclist with many of the same power meter features, but at a fraction of the cost and complexity. With the advancements in smartphone GPS sensors, the determination of cyclist power output can now be calculated using speed, cadence, elevation gain and opposing wind speeds, all without the need to affix strain gauge power meters to bicycle components.

In order to determine if smartphones are capable of providing comparable power measurement accuracy in relationship to traditional strain gauge approaches, it is important to understand prior research, sensor technologies, data models and collection methodologies used in determining a cyclist power output.

This chapter overviews previous work related to the measurement of power output from cyclist that compares traditional strain gauge based direct force power meters (DFPM) to one another. Of these DFPM studies, each comparison uses the SRM cycling power meter (SRM 2016) as the “reference standard” in which other DFPM cycling power meters are compared. The SRM product selection is mostly due to prior research that has shown the SRM power meters to produce very accurate and reliable power data (Gardner 2004) that is within 2% of Typical Error of Estimate (TEE) calculations. To date, comparison research data has been collected for the Garmin Vector system (pedal-based DFPM power meter), PowerTap system (hub-based DFPM system) and several other DFPM systems that will not be covered for sake of simplicity.

Newer power meter sensor research compares the Newton PowerPod system to the SRM power meter system. The PowerPod calculates power using both opposing forces as well as external speed and cadence sensors for determining an inferred power output. Unlike the SRM power meter that uses up to 20 different strain gauges, the PowerPod system only uses sensors to measure road gradient, opposing wind forces, barometric pressure and accelerations. With the exception of pairing the OFPM device to an external speed and cadence sensor, the PowerPod is external of any bike components and mounts to most bike handlebars. For viewing location data during or after a ride, the PowerPod system also has the option of being paired with a bike computer that leverages the internal GPS sensor. Given the PowerPod is a relatively new power meter device, the number of published field trials is limited compared to various DFPM power meter studies.

Concluding Chapter 2 are two research papers (Zandbergen 2011 and Neale 2016) in which Assisted GPS (A-GPS) smartphones and autonomous GPS devices are compared for accuracy using position, speed, and elevation against a reference data source. These test include both static indoor and outdoor as well as dynamic (moving) indoor and outdoor environments. The accuracy comparisons are made both using high-precision GPS reference units as well as location comparisons to position benchmarks that have been referenced against high-accuracy orthoimagery. This provides a basis for prior research in comparing smartphone A-GPS sensor accuracy using the dimensions of speed, location and elevation data when compared against high accuracy reference sources.

2.1 Power Measurements between Garmin Vector and SRM Cycle Power Meters

This study, developed by Andrew Novak and Benjamin Dascombe (Novak 2016) of the Applied Sports Science and Exercise Testing Laboratory, University of Newcastle, Ourimbah, Australia, provides a detailed testing method for comparing power outputs between the SRM and Garmin Vector DFPM power meter systems. The study was conducted using twenty-one male competitive cyclists ranging in age from 25 to 39, with weight ranging from 145 lbs. to 175 lbs. Each cyclist completed seven (7) tests ranging from 5 to 600 seconds in durations, using a combination of rolling and standing start positions. All totaled, 147 test were completed, in which average power, peak power, typical error and Pearson’s correlations were calculated as shown in Table 2 below.

The SRM power system was selected for the Garmin Vector comparison given previous testing results showed the accuracy to be within 2% after a full 11 month season of racing (Gartner 2004). Additionally SRM was the first company to build a commercial power meter in 1987 (SRM 2016) and has extensive experience within the field of developing power meters and software for measuring cyclist power outputs.

Testing was performed indoors using a Lemond Revolution cycling ergometer (indoor cycling trainer) in which various sized bicycles were mounted and adjusted to the test riders needs. Each bike has both the SRM system and the Garmin Vector pedals installed (Figure 2.1) on the bike, along with a cadence sensor mounted on the non-drive side of the bike. The testing apparatus provided for a controlled environment (no head winds, rolling resistance or other opposing forces) in which the test riders performed the seven tests outlined in Table 2.

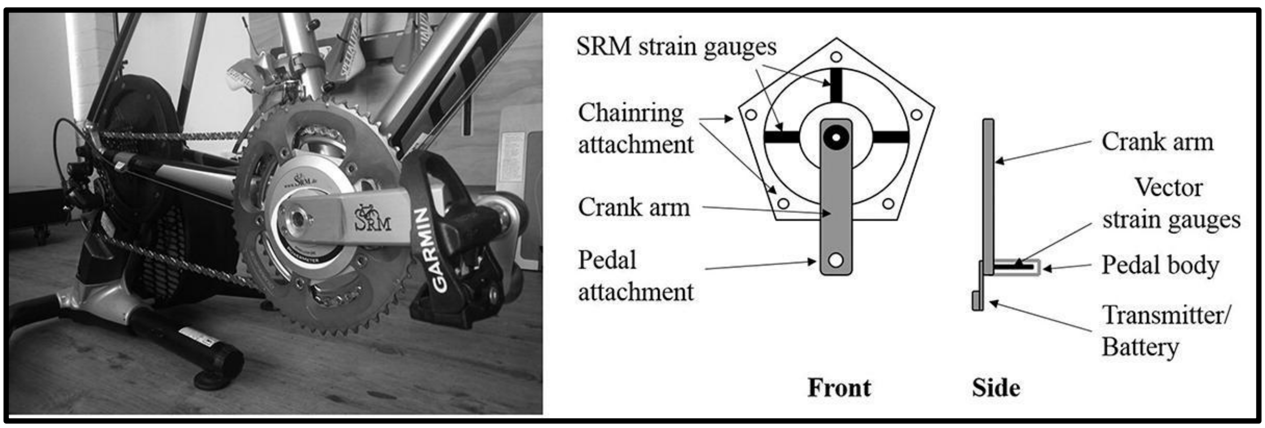

Figure 2.1 Bicycle fitted with SRM cranks and Garmin Vector pedals that is attached to a Lemond Revolution indoor trainer

The key results within the below Table 2 are the Typical Error (confidence limits %) and *r*-values (Pearson's correlation coefficient) produced when comparing the two power meters. When averaged across all 147-test rides, the Typical Error Mean was 3.3%, with a confidence range of 3.0% to 3.8% between the Garmin Vector and the SRM systems. In addition, the *r*-value determines the linear relationship (strength) between the two power meters, with *r*-values of .90 to .99 having a near perfect relationship and 1.0 being perfect (Hopkins 2002). As shown in Table 2.1, both the mean values within all seven (7) independent tests show very high relationships between the two meters.

Table 2 Mean power, peak power, typical error and Pearson's correlations (r) between Garmin Vector and SRM power meters

	Effort	*n*	SRM (W)	Garmin (W)	Slope	Intercept	Typical Error (confidence limits; %)	*r*
Mean	All	147	626 ± 296	645 ± 299	0.99	−9.9	3.3 (3.0–3.8)	.99
	5 s *S*	21	989 ± 122	989 ± 126	0.91	92.0	4.9 (3.7–7.4)	.93
	5 s *R*	21	988 ± 124	1,024 ± 131	0.93	34.7	2.6 (1.8–3.8)	.98
	15 s	21	801 ± 83	828 ± 80	1.00	−27.9	2.8 (2.1–4.1)	.97
	30 s	21	616 ± 46	636 ± 47	0.91	35.6	2.7 (2.1–4.0)	.94
	60 s	21	449 ± 46	468 ± 45	0.99	−14.7	2.5 (1.9–3.6)	.97
	240 s	21	294 ± 39	307 ± 39	0.98	−8.7	3.2 (2.5–4.8)	.97
	600 s	21	261 ± 40	274 ± 39	1.00	−11.5	3.3 (2.5–4.9)	.98
Peak	5 s *S*	21	1,114 ± 155	1,068 ± 143	1.07	−27.2	2.1 (1.6–3.1)	.99
	5 s *R*	21	1,103 ± 144	1,048 ± 137	1.04	11.8	1.6 (1.2–2.3)	.99
	15 s	21	1,002 ± 133	962 ± 129	1.02	24.6	2.4 (1.8–3.5)	.98

Note. CL = confidence limits; *n* = number of efforts; *r* = Pearson's correlation coefficient; *R* = rolling start; *S* = stationary start.

In reviewing the Power Profile Assessment (PPA) of each rider and power meter system, there is a strong correlation between Mean Power Output (Figure 2.2) and the time variable of each of the six (6) tests. The 5-second stationary start test was excluded in the below Figure 2.1.2 results. The Garmin Vector is shown to have a slightly higher level of power measurement, which is consistent with other field trials (Abbiss et al. 2009). This is most likely caused by the pedal being directly connected to a cyclist shoe and thus minimal power distortion occurs between the different bike components.

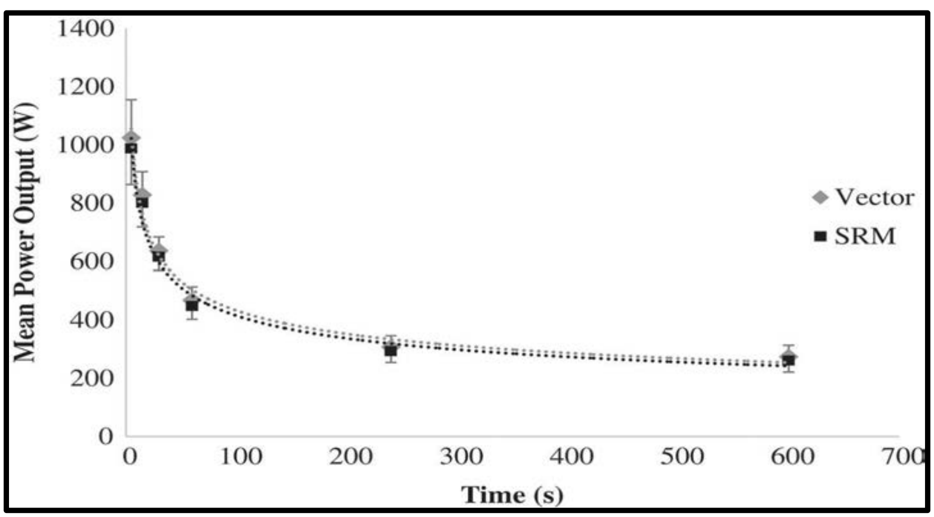

Figure 2.1.2 PPAs produced between the SRM and Garmin Vector systems

In conclusion, both the SRM crank-based DFPM and the Garmin Vector pedal-based DFPM systems had very similar results, with the Garmin system providing slightly higher power values. This can be expected from having lower power distortion between a cyclist shoe and pedal system. Given the simplicity of the Garmin system to install and the lower price point (Garmin

Vector costing $600.00 vs. SRM costing $2200), the Garmin system seems to provide a very high price to performance ratio when measured against the SRM reference system.

2.2 Power Measurements between PowerTap and SRM Cycle Power Meters

The PowerTap system, developed by CycleOps of Madison, WI, is another DFPM power meter that measures power output at the rear hub of a bicycle wheel (versus at the pedal per the previous power comparison study). The International Journal of Sports Medicine published this particular study in 2005 and thus the research is dated from a technology and results perspective. W. Bertucci and a multi university team (Bertucci 2005) from the Université of France Comté, France and the Université de Reims Champagne, Reims, France, facilitated the study.

The study was conducted using just one male competitive cyclist, age 25 and weighing 163 lbs. The subject performed three (3) cycling test protocols, listed below, each day for 10 days. The culmination of the 10-day test was a 3-hour field test in which the subject road a hilly road course that included various seating positions to simulate the conditions of the lab testing. The three (3) testing protocols consisted of the following below:

1. Sub-maximal incremental test: performed across 4 slope angles, 3 different gear ratios, 2 different speeds and 2 different standing positions. In all, 27 test trails were conducted across the 10-day test period.
2. Sub-maximal continuous test: performed across a 30 minute test period consisting of a 2% slope, 16 mph velocity and 80 rpm.
3. Sprint test: consisted of 3 eight-second sprints using 3 different gear ratios to determine max power output.

Key results from the various tests are shown in both Figure 2.2 and Table 3 below. Figure 2.2 shows the maximum power output (PO) from both the SRM and PowerTap systems using three (3) different gear ratios. In reviewing the data, the SRM provided a consistent power ramp ranging from 875 watts using a 39/14 gear ratio to 925 watts using a 39/23 gear ratio. When comparing the SRM power output data to the PowerTap data, the results appear to peak at the middle gear ratio (39/17) at approximately 875 watts. Both the 39/14 and 39/23 gear ratios have similar power outputs of approximately 840 watts.

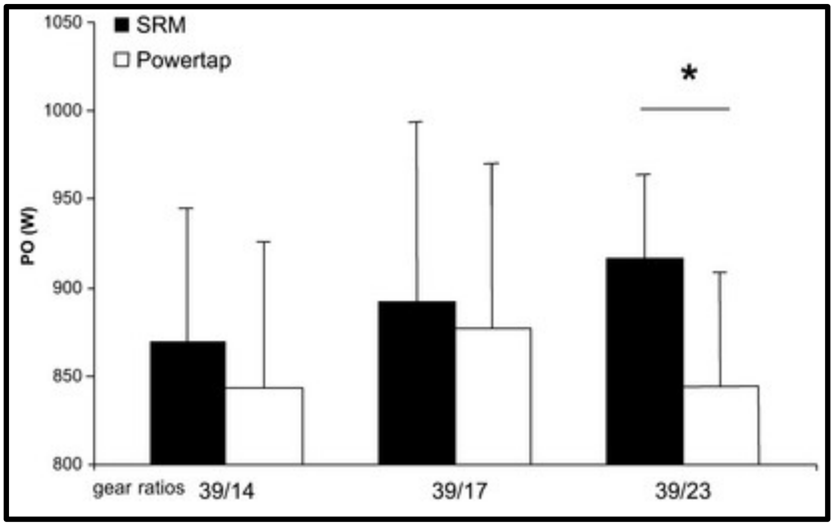

Figure 2.2 PowerTap and SRM Max Power Output (PO) during max test using 3 gear ratios

Table 3 represents the mean data results for both maximum PO for both the SRM and PowerTap devices, including the four (4) different grades at two (2) different velocities and three (3) different pedaling cadences during the sub-maximal incremental test. Of interest within this data table is the consistently higher power values of the SRM system when compared to that of the PowerTap system. Though only slightly higher than the PowerTap (average difference of +/- 2.5 watts across all test types), the same logic could be applied from the previous Garmin/SRM test in that that closer the strain gauge sensors are to the actual power source (the left and right legs generating the source power), the higher the power reading. In the case of the PowerTap system, the hub is the furthest component away from the power source.

Table 3 Mean Power Output (PO) at different grades, velocities and pedaling cadences during sub-maximal incremental test

Grade (%)	Slope %	Velocities (km/h)	Pedalling cadence (rpm)	Mean POSRM (W)	Mean POPT (W)	SRM CV (%)	PowerTap CV (%)
Seated	2	15	47.5 ± 0.3	106.6 ± 2.3	104.8 ± 2.7	2.1	2.6
			60.1 ± 0.1	107.0 ± 2.4	104.8 ± 2.9	2.3	2.8
			73.0 ± 0.1	108.0 ± 2.0	105.0 ± 2.2	1.8	2.1
	2	25	80.1 ± 0.1	184.8 ± 3.6	181.6 ± 5.3	1.9	2.9
			101.7 ± 0.3	186.1 ± 3.6	182.6 ± 4.8	1.9	2.7
			123.1 ± 0.3	188.1 ± 3.9	183.5 ± 5.4	2.1	2.9
	4	15	47.7 ± 0.2	179.0 ± 1.7	177.5 ± 2.3	1	1.3
			60.3 ± 0.3	180.0 ± 1.2	177.8 ± 1.9	0.7	1.1
			73.2 ± 0.3	180.3 ± 1.4	177.3 ± 2.5	0.8	1.4
	4	25	80.3 ± 0.3	306.5 ± 4.6	303.9 ± 2.8	1.5	0.9
			101.9 ± 0.3	307.7 ± 4.2	304.5 ± 3.2	1.4	1.1
			123.4 ± 0.3	310.3 ± 5.2	305.4 ± 3.9	1.7	1.3
	6	15	47.8 ± 0.1	245.6 ± 2.7	245.8 ± 3.2	1.1	1.3
			60.4 ± 0.2	247.1 ± 3.3	246.3 ± 3.9	1.4	1.5
			73.3 ± 0.3	247.6 ± 3.5	244.6 ± 3.9	1.4	1.6
	6	25	80.3 ± 0.3	417.5 ± 6.7	415.3 ± 9.8	1.6	2.4
			102.0 ± 0.1	419.1 ± 5.1	416.1 ± 8.0	1.3	1.9
			123.5 ± 0.3	421.9 ± 6.8	413.8 ± 6.2	1.6	1.5
Standing	6	15	47.7 ± 0.2	246.7 ± 3.5	245.5 ± 3.3	1.4	1.3
			60.4 ± 0.2	248.6 ± 3.0	247.2 ± 3.7	1.2	1.5
			73.2 ± 0.2	251.1 ± 4.1	248.3 ± 4.0	1.6	1.6
Mean						1.5 ± 0.4	1.8 ± 0.6
Confident Interval ($p < 0.05$):						1.7 - 1.3	2.1 - 1.5

In conclusion, the PowerTap hub-based DFPM system provides both a valid and reliable system when compared to the SRM crank-based DFPM, with the PowerTap hub-based system providing slightly lower power values in the 100 to 450 watt power range. For higher intensity power loads like sprinting, the PowerTap consistently underestimated the power output due to possible mechanical distortions across the drivetrain including pedal, crank and chain. Overall the PowerTap system is a very capable power meter for road cycling and racing. Though not as simple as the Garmin system to install, the lower price point (PowerTap Hub only costing $600.00 vs. SRM costing $2200) also provides a better price to performance ratio when measured against the SRM reference system.

2.3 Power Measurements between Newton PowerPod and 3 different DFPM Cycle Power Meters

The Newton PowerPod power meter system, manufactured by Velocomp of Juniper, Florida, uses a completely different approach for measuring power output. The physics within the system design focus entirely on understanding and measuring the opposing forces that a cyclist is constantly applying in order to move the bike forward. This concept is also proven with Newton's Third Law in which applied forces must equal opposing forces (Resnick 1992). Unlike the previously discussed strain gauge based power meters, the PowerPod system uses a combination of gradient, atmosphere, wind speed, ground speed, and acceleration to determine power output.

The study was conducted using just one male competitive cyclist, Ray Maker (DC Rainmaker 2016), age 35 and weighing approximately 175 lbs. All testing was done in an outdoor environment, using three (3) different route geographies ranging from city urban riding to rural mountain climbs. All ride lengths varied in time from forty minutes to an hour and forty-five minutes. During the testing phase, the PowerPod was measured against 3 or 4 different DFPM power meters including the PowerTap G3 Hub, PowerTap P1 Pedals, Stages Power and Quarq Riken. The testing method provided for a well rounded use of a pedal-based DFPM (Garmin), a hub-based DFPM (PowerTap), a crank/chain ring DFPM (PowerTap) and a left crank-arm only DFPM (Stages Power).

In the first test, the rider performed for an hour-long ride that consisted of both city and park riding. Figure 2.3 shows how well the four power meters compared to each other, with the exception of a quick sprint at minute 39:20 to 39:35. On an earlier section of the ride, Figure 2.3.1 shows a steady state and very good agreement between all the power meter types.

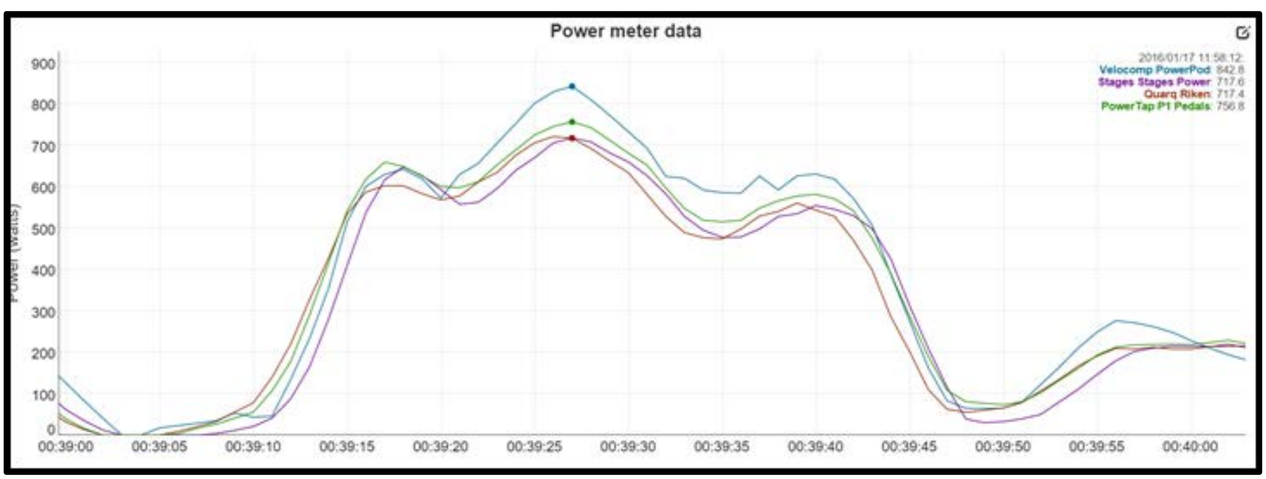

Figure 2.3 Sprint section of the ride, using 30 second power smoothing. PowerPod (blue line) overestimate the output power by approximately 100 watts

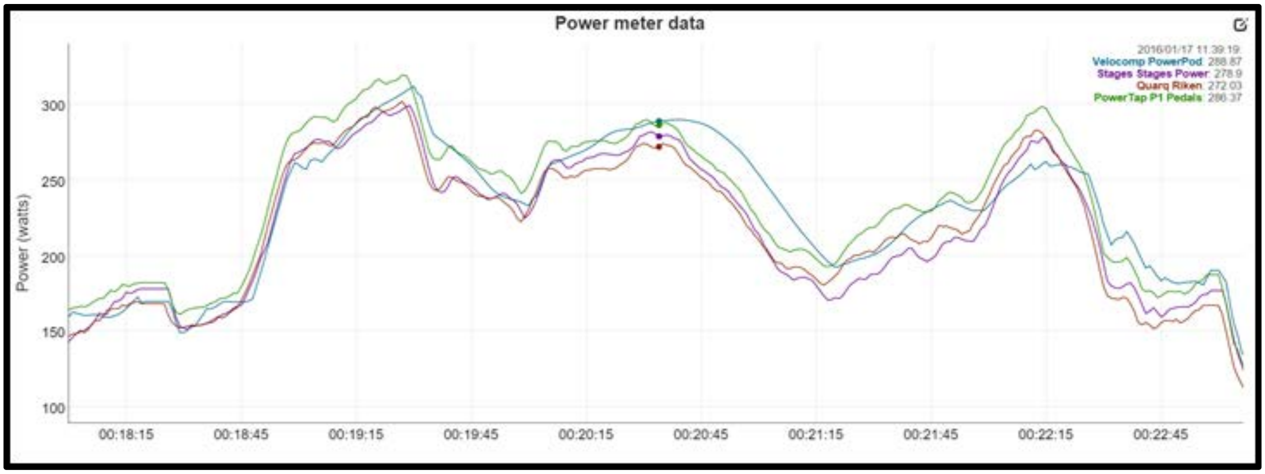

Figure 2.3.1 Very tight agreement across all 4 power meters

When changing riding geography to a mountain course, the PowerPod also has very similar power output characteristics, but seemed to overestimate the power output at the end of the climb but recovered on the descent as shown in Figure 2.3.2.

Figure 2.3.2 PowerPod compared to PowerTap P1 Pedal in Palma Majorca mountain ride

In conclusion, the PowerPod system, using opposing force as its main power output algorithm, is a very reliable power meter system in most riding situations. For medium to high intensity power loads typical of climbing and sprinting, the PowerPod consistently overestimated the power output, but this could be related to DFPM meters that measures power at both the hub or crank having a higher power loss distortion than at the pedal. In viewing the data results, this seems to be consistent with the previous studies.

Overall the PowerPod system is a very capable power meter for all types of road cycling, including racing. Given the simplicity of the PowerPod system to install and the lowest price point tested (PowerPod costing $249.00 vs. remaining DFPM system costing greater than $600), the PowerPod system has the highest value based on price to performance ratios.

2.4 Positional Accuracy of Assisted GPS Data (A-GPS) from High-Sensitivity GPS-enabled Mobile Phones

This research, conducted by Paul Zandbergen, Department of Geography, University of New Mexico and Sean Barbeau from the Center for Urban Transportation Research, University of South Florida (Zandbergen 2011) provides a detailed field test for comparing Assisted GPS (A-GPS) and autonomous GPS device positions against a high accuracy benchmark location. The comparison of location accuracy uses two feature phones (Sanyo SCP-7050 and Motorola iDEN i580) and two handheld GPS devices (GPSMAP 76 and June ST) from Garmin and Trimble. The study was conducted using both indoor static and dynamic positions as well as outdoor dynamic positions. All totaled, indoor testing within a house structure was conducted for 1 hour, in which 1800 position fixes (sampled at a rate of 2 second intervals) were used within each test. Outdoor dynamic testing was conducted on a cloverleaf intersection of an interstate for 23 minutes (test route driven 10 times). Statistics were collected in which horizontal and vertical accuracy (indoor testing only) was measured in meters using minimum, maximum, average, 50th, 68th, 95th and RMSE statistics as shown in Table 4 and 5 below.

Table 4 Horizontal and vertical error statistics for static outdoor test

Unit Type	GPS Type	Sample Size	% GPS fixes	Horizontal Error Statistics (metres)						
				Min	Max	Avg	50th	68th	95th	RMSE
Motorola	Assisted	1791	99·9	1·04	23·85	7·18	6·41	8·25	15·04	8·28
Motorola	Assisted	933	100·0	0·48	27·59	9·46	8·52	11·13	20·26	10·84
Motorola	Assisted	1712	99·9	0·53	58·35	10·14	8·57	11·41	23·90	12·50
Motorola	Assisted	1762	99·9	1·00	13·93	5·93	5·81	6·70	11·59	6·65
Sanyo	Autonomous	1736	99·9	0·29	66·49	9·81	8·03	10·78	23·16	12·57
Sanyo	Assisted	897	99·9	0·29	29·69	7·01	6·41	8·20	15·13	8·21
Sanyo	Assisted	1130	100·0	0·34	16·15	5·31	5·01	6·37	10·26	5·98
Sanyo	Assisted	1748	99·9	0·20	17·85	5·60	5·35	6·50	10·37	6·23
Sanyo	Assisted	1584	99·9	0·27	43·34	6·03	5·64	6·96	11·92	6·88
Sanyo	Autonomous	1128	100·0	0·34	19·07	6·53	5·84	7·93	13·19	7·44
Garmin	Autonomous	1800	100·0	0·03	3·38	1·36	1·27	1·63	2·60	1·52
Garmin	Autonomous	1800	100·0	0·54	7·34	4·67	4·69	5·19	6·36	4·80
Juno	Autonomous	1800	100·0	0·02	9·62	2·31	1·90	2·80	5·68	2·85
Juno	Autonomous	1800	100·0	0·21	6·34	3·43	3·37	4·03	5·82	3·67
				Vertical Error Statistics (metres)						
Motorola	Assisted	1791	99·9	0·75	58·75	25·92	26·75	29·75	43·75	27·81
Motorola	Assisted	933	100·0	0·75	71·75	28·80	26·75	33·51	48·75	31·07
Motorola	Assisted	1712	99·9	0·25	70·75	26·45	25·75	30·75	48·20	29·10
Motorola	Assisted	1762	99·9	0·71	44·29	23·15	24·29	26·29	33·29	24·13
Garmin	Autonomous	1800	100·0	0·16	6·57	2·41	2·24	3·21	4·65	2·77
Garmin	Autonomous	1800	100·0	0·23	13·22	3·08	2·17	3·61	9·38	4·09
Juno	Autonomous	1800	100·0	0·00	22·00	5·86	5·01	6·40	12·93	6·93
Juno	Autonomous	1800	100·0	0·00	20·26	6·27	5·49	7·14	11·79	7·20

Table 5 Horizontal error statistics for dynamic outdoor tests

Unit Type	GPS Type	Sample Size	% GPS Fixes	Horizontal Error Statistics (meters)						
				Min	Max	Avg	50th	68th	95th	RMSE
Motorola	Assisted	630	99·8	0·00	19·73	3·01	2·25	3·41	8·51	4·09
Sanyo	Assisted	682	99·9	0·00	7·53	1·80	1·62	2·28	4·04	2·20
Garmin	Autonomous	695	100·0	0·00	4·75	1·14	0·96	1·42	2·89	1·45
Juno	Autonomous	695	100·0	0·00	5·29	1·20	1·06	1·52	2·68	1·44

In viewing the results, all the devices had the ability to capture a GPS fix but depending on the device type determined the level of accuracy within the tests. For example, the test shows the Garmin and Trimble devices had average errors between 1.36 and 4.67 meters while the Sanyo and Motorola A-GPS phones showed errors ranging from 5.93 to 10.14 meters depending on the test (Figure 2.4).

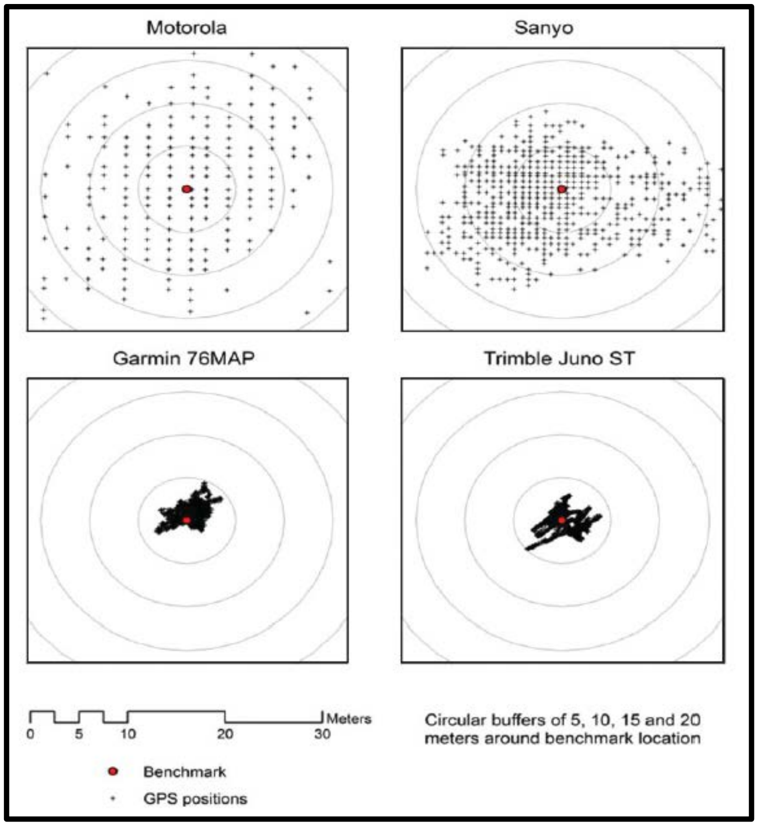

Figure 2.4 Sample scatter plots of static outdoor accuracy tests

In reviewing the outdoor dynamic results, all the devices had the ability to capture a GPS fix while moving at average speeds of 25 miles per hour as shown in Figure 2.4.1. In comparing the horizontal accuracy data for outdoor dynamic positions, the test show the Garmin and Trimble devices having average errors between 1.14 and 1.20 meters, while the Sanyo and Motorola A-GPS phones showed errors ranging from 1.80 to 3.01 meters depending on the test (Table 4). Surprisingly, the dynamic outdoor test showed better results for the A-GPS devices than indoor fixed positions but a limited sample size prevented a more rigorous statistical comparison of accuracies and what might have caused the improved results.

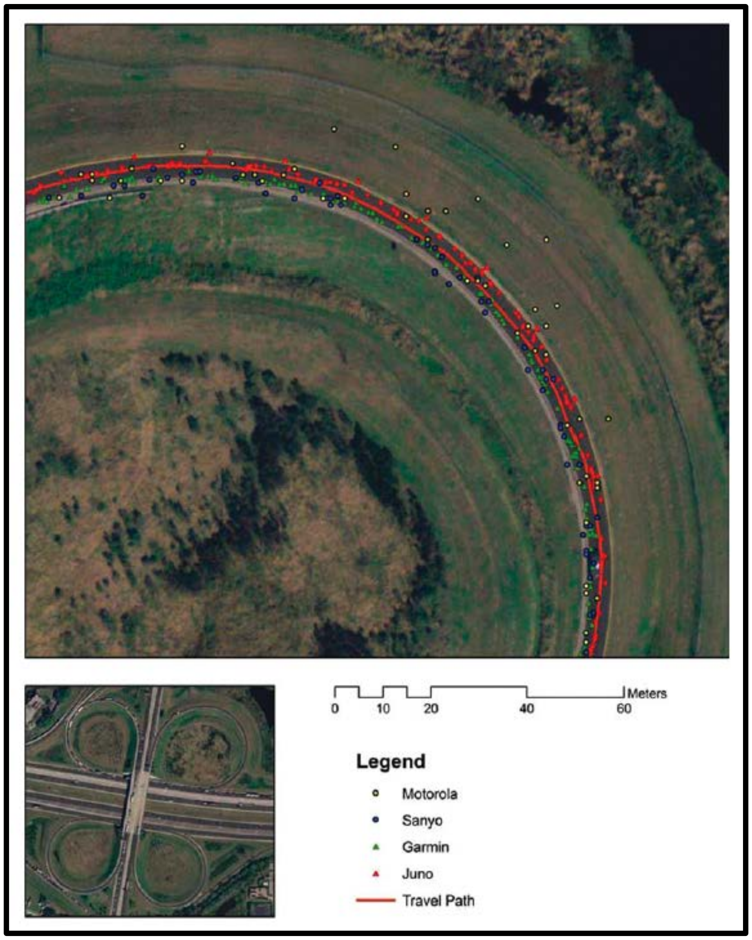

Figure 2.4.1 Sample of position fixes during outdoor dynamic accuracy tests

In conclusion, the horizontal error of position fixes for A-GPS phones was substantially higher than the autonomous GPS devices from Garmin and Trimble. Vertical accuracies were very unreliable for the A-GPS devices in the dynamic outdoor test and thus were removed from the study findings. Overall, these limitations should be considered by application developers in need of high accuracy location in order to make the user experience valuable.

2.5 Data Acquisition using Smartphone Applications

This research, conducted by William Neale, David Danaher, Sean McDonough and Tomas Owens of Kineticorp, LLC (Neale 2016) provides a detailed field test using three popular smartphone applications used for tracking (Strava, MapMyFitness, Runtastic) and three smartphones including the Apple iPhone 6, Motorola Droid Maxx and Samsung Galaxy S5. The research focuses on providing application data in which speed, elevation change and location accuracy when compared against high accuracy imagery and the high-accuracy Race Logic V-BOX GPS Data Acquisition Unit (DAU). The field data was collected using a backpack rig (Figure 2.5) in which the 3 phones and the V-BOX DAU were mounted for consistent orientation to the sky. A total of two courses were established within a Denver area business park including Start Position A for the motorcycle course and Start Position B for the bike and rollerblade course (Figure 2.5.1). All totaled, 3 test were completed for comparison of maximum reported speed and elevation change across the course.

Figure 2.5 Backpack rig with smartphones and V-BOX units mounted on frame

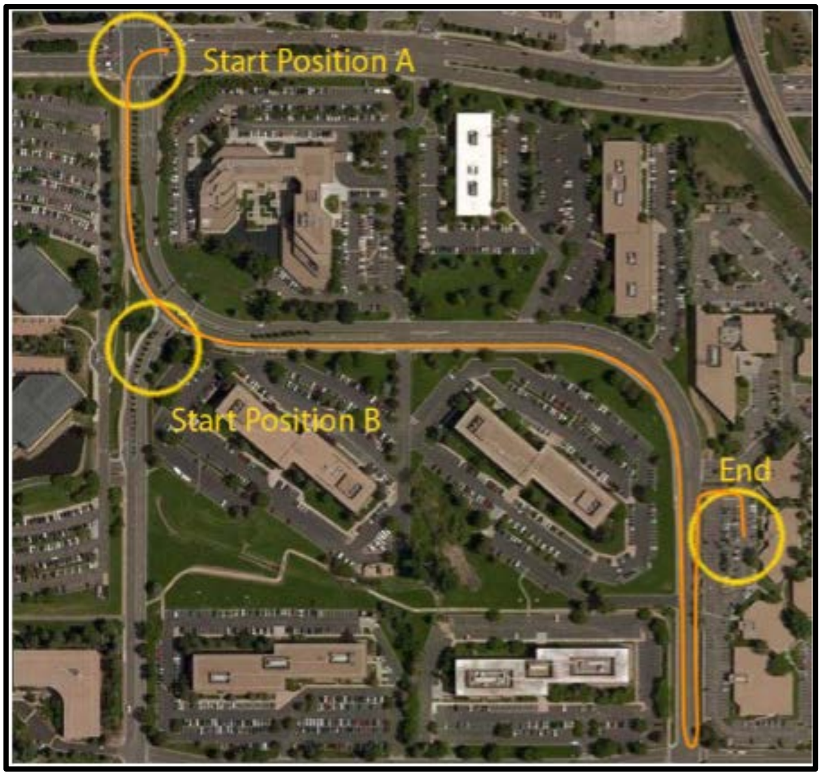

Figure 2.5.1 Imagery showing the study route path

In reviewing the results, all three smartphones had the ability to capture GPS location fixes while moving thru the testing course. On average across all the applications, the percentage (%) error for max speed when compared to the V-BOX reference was slightly less than 6%, with the lowest average error of 2.5% for the Runtastic application. All applications performed generally well when compared across larger time intervals (>10 seconds) as shown in Figure 2.5.2. But when compared at discrete points in which fast speed changes occurred, both the smartphone and application showed differences of up to 48.8% as shown in Figures 2.5.3 and 2.5.4. This can mostly be attributed to the GPS sampling rate of the V-BOX reference being 20 Hz (20 samples per second) and the smartphones having a maximum sampling rate of 1 Hz. Thus having rapid changes in speed or terrain (weakening of GPS signal) resulted in larger negative impacts when compared against the reference device due to less location samples.

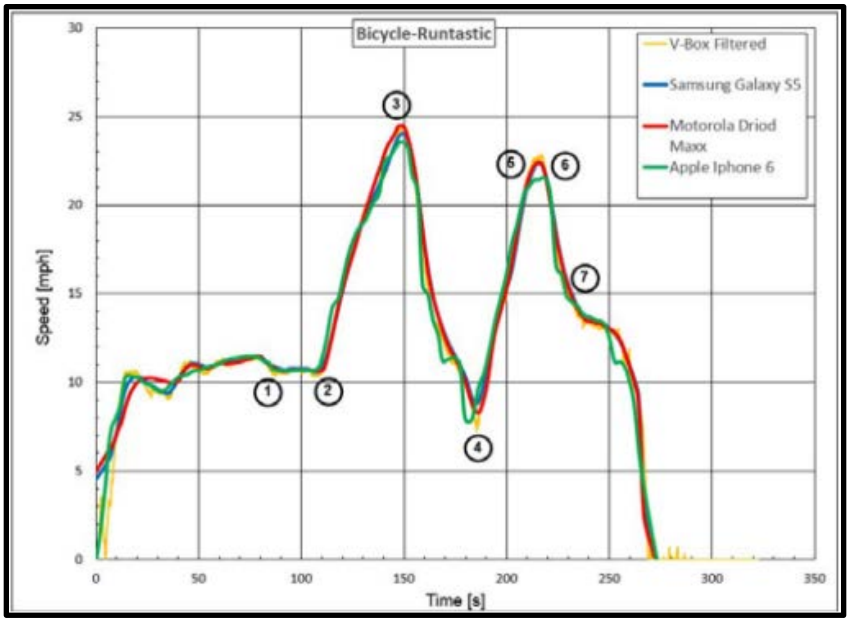

Figure 2.5.2 Bicycle with Runtastic applications compared to V-Box reference

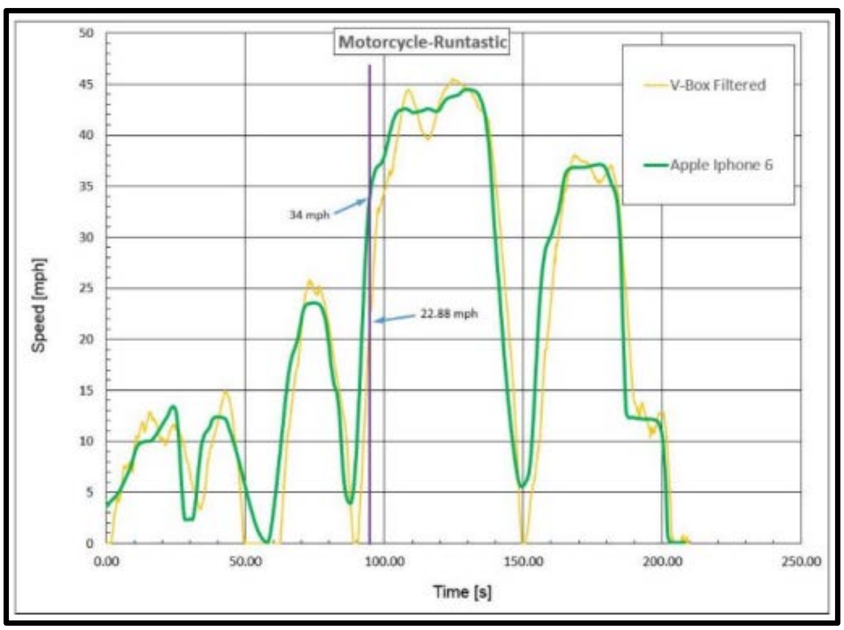

Figure 2.5.3 Comparing Apple iPhone 6 running Runtastic application to V-Box reference

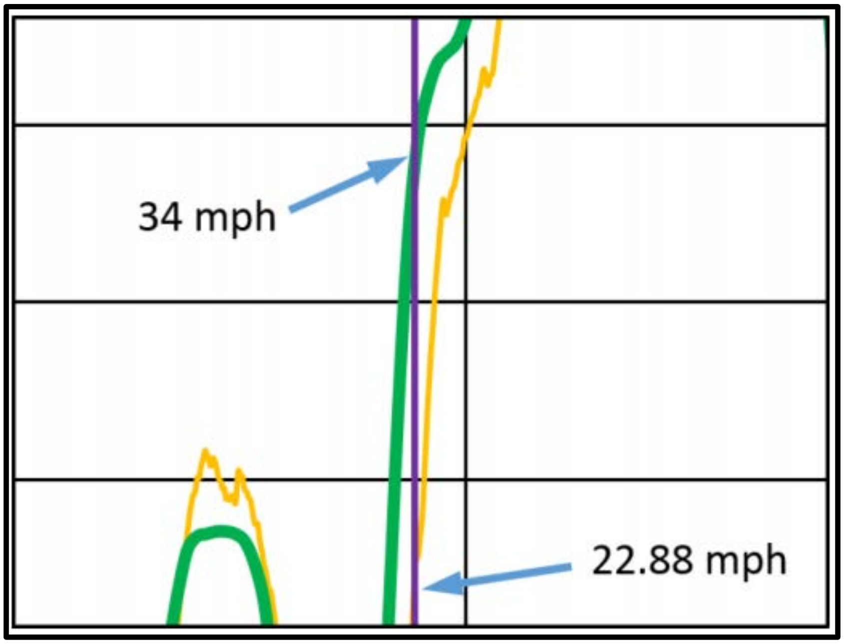

Figure 2.5.4 Close up image at 95 seconds of speed differences

In comparing elevation change accuracy, the results showed the applications collected elevation data reasonable well and within 3' to 4' feet of known ground control points. But in areas with tree coverage, buildings or sharp changes in slope, the elevation accuracy was off by as much as 10' to 20' feet as shown in Figure 2.5.5.

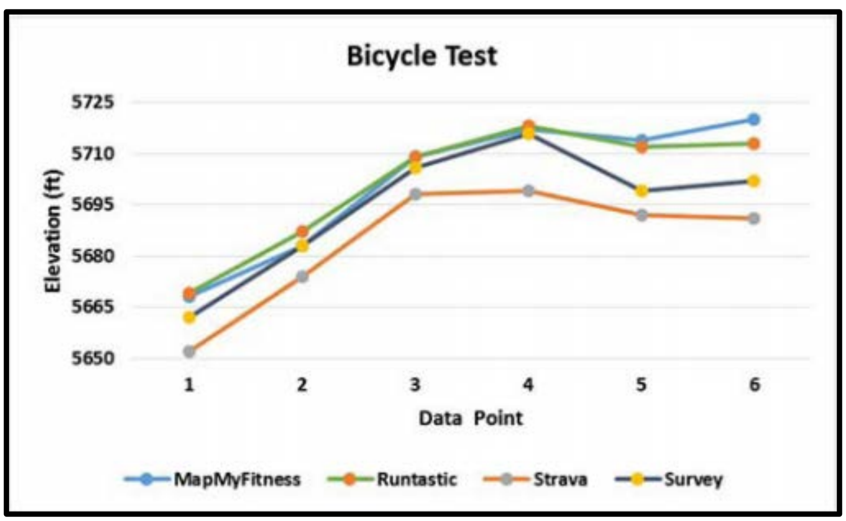

Figure 2.5.5 Comparison of elevation points across applications and survey points

In conclusion, all three applications and smartphones tested performed similarly well with regards to speed, elevation change and location agreement when observed over periods of times greater than 10 seconds. The observed errors within the spatial data is primarily attributed to rapid changes in speed or terrain (weakening of GPS signal caused by natural or man-made objects) that is amplified by the differences in GPS data sampling rates of the V-BOX (20 Hz) and smartphones (<1 Hz). Overall, these limitations should be considered by application developers in need of high accuracy speed and elevation data based on the observed limitations of using a smartphone's GPS sensors with limited sampling rate.

Chapter 3: Research Design and Methods

Chapter 3 outlines the process used in the collection of three distinct data sets to compare the levels of power output generated while riding three different road courses. Understanding a cyclist power output is an important fitness and efficiency metric as it truly measures expended physical effort at any given point in time. Power measurement is also important in the process of understanding how well training goals are being met and at what levels an athlete push his or her body to achieve maximum output and performance.

For this study, a “reference” power meter is established in which both IAD smartphone and OFPM power meter applications will be compared against for accuracy and effectiveness. All three applications utilize different sensors, physics, processing algorithms and technologies to measure power output, with the primary goal of being able to determine if a smartphone and OFPM power meter can provide a reliable estimate of power output when compared to the DFPM reference standard using spatial analysis.

3.1 Data Collection Equipment and Applications

Below details the various power meter equipment, configurations, route study areas, and data comparison applications that were used to collect and visualize the cyclist power data. These measurements ultimately are used to determine the overall effectiveness of the two power applications and the tradeoffs between accuracy, simplicity and price.

Historically within the cycling industry, the measurement of cycling power has come at a high cost and complexity due to technical challenges in measuring the amount of force that is used to measure power output that is generated by a cyclist. Specialized “strain gauge” sensor technology, known as direct force power meters (DFPM’s), have been developed and used over the years to convert strain into applied torque (Martin 1998). These torque measurements, along with crank cadence, is used to algorithmically determine power output measured in watts. DFPM systems are typically integrated within the crank arms or spindle of the front drive train, but other DFPM systems have been developed over the last several years including pedals, rear hubs, and within cycling shoes.

For the purposes of this study, a Stages Cycling DFPM is used as the reference standard in which the two competing power meter applications will be measured. The Stages DFPM system is considered one of the most accurate power meter systems available and most recently was used by Team Sky's Chris Froome, the winner of the 2016 Tour de France (Stages Cycling 2016). Additionally the price point range of the Stages Cycling power meter system ($530.00 to $700.00 depending on make and model) makes it one of the more affordable DFPM meters on the market and thus selected for the field trial.

3.2 Specifications of Stages Cycling Power Meter (Model FSA 360)

The Stages Cycling power meter is used as the reference standard for which the IAD smartphone app and PowerPod OFPM will be compared against. The Stages system uses proprietary "strain gauges" to measure applied force to the crank in which metallic strain sensors are embedded within the crank arm for detecting very small electrical resistance changes. Even very small amounts of flex, not detectable to a cyclist, are measureable using this sensitive strain circuit design. The strain calculations are then applied as a torque measurement in which power can be derived using the below power algorithm.

Table 6 Stages FSA 360 EVO Technical Specifications

Power Meter: Stages Power Model	Cost $	Stated Accuracy	Weight	Power Range (Watts)	Wireless Connectivity	Additional Notes
FSA 360 EVO	$530.00	+/- 2%	20 grams to left crank arm	0-2500 Watts	ANT+ and BLE	$28.00 to install Stages system

Stages power formula: Power = Torque/Force * Cadence

1. Stages Power Measurement Formula and Algorithm = 2*[(F/Ave * 9.8 * Length of Crank (172.5) x (R x .1047)]
2. Torque = 2*(F/Ave x 9.8 x L)
    a. F/Ave = Force Average per Revolution
3. 9.8 = Gravitational Constant
    a. L = Length of Crank Arm (options: 170, 172.5 and 175mm)
    b. R = Rotations of crank measured by accelerometer within left crank arm.
4. .1047 = Variable input based on outside temperature sensor built into the power meter module.

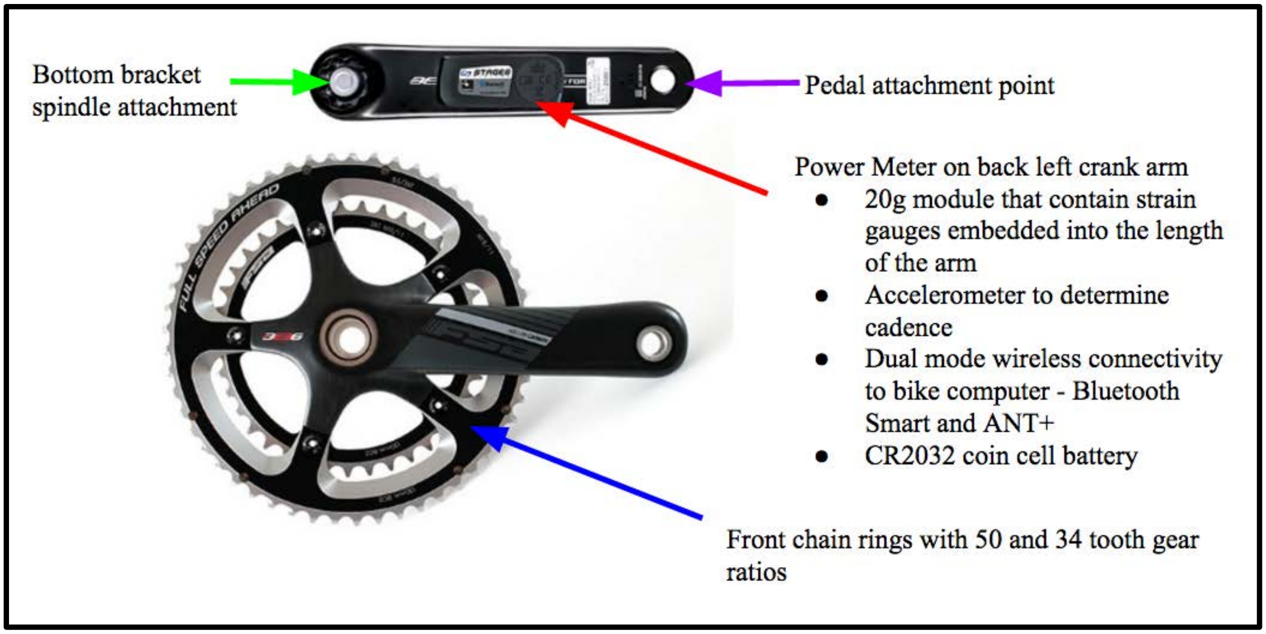

Figure 3.2 Stages FSA 360 EVO DFPM Crankset Features

3.3 Specifications of PowerPod Power Meter

The PowerPod power meter is one of the two competing power meters used in the study for comparison with the Stages Cycling Power reference system. The PowerPod system is unique in that it leverages both internal sensors (used to determine opposing forces including wind and slope) and external sensors (used in determining speed and cadence) that are combined to provide an estimated power output. Within the study, this power meter type will be referred to as an opposing force power meter (OFPM) given the use of various sensors for determining the opposing forces that are needed to estimate power output.

The PowerPod itself contains sensors for determining air pressure/altitude (barometer), accelerometers and wind speed (Figure 3.3) and converts these inputs into opposing forces including wind forces (head, tail or side winds), road slope (grade percentage %), cyclist acceleration and other frictional drag forces (Newton 2016). The concept of using high accuracy digital sensors provide for unique ways in which to calculate opposing forces using Newton's third law of physics: opposing forces must equal applied forces. Thus if all opposing forces can be calculated and determined, power output (P) can be determined using the following formula: Power = Force (opposing forces = applied forces) x Speed.

Table 7 PowerPod Technical Specifications

Power Meter: Newton	Cost $	Stated Accuracy	Weight	Power Range (Watts)	Wireless Connectivity	Additional Notes
PowerPod	$249.00	+/- 2%	45 grams	0-2500 Watts	ANT+ (BLE Q1 2017)	$30.00 for combo mount

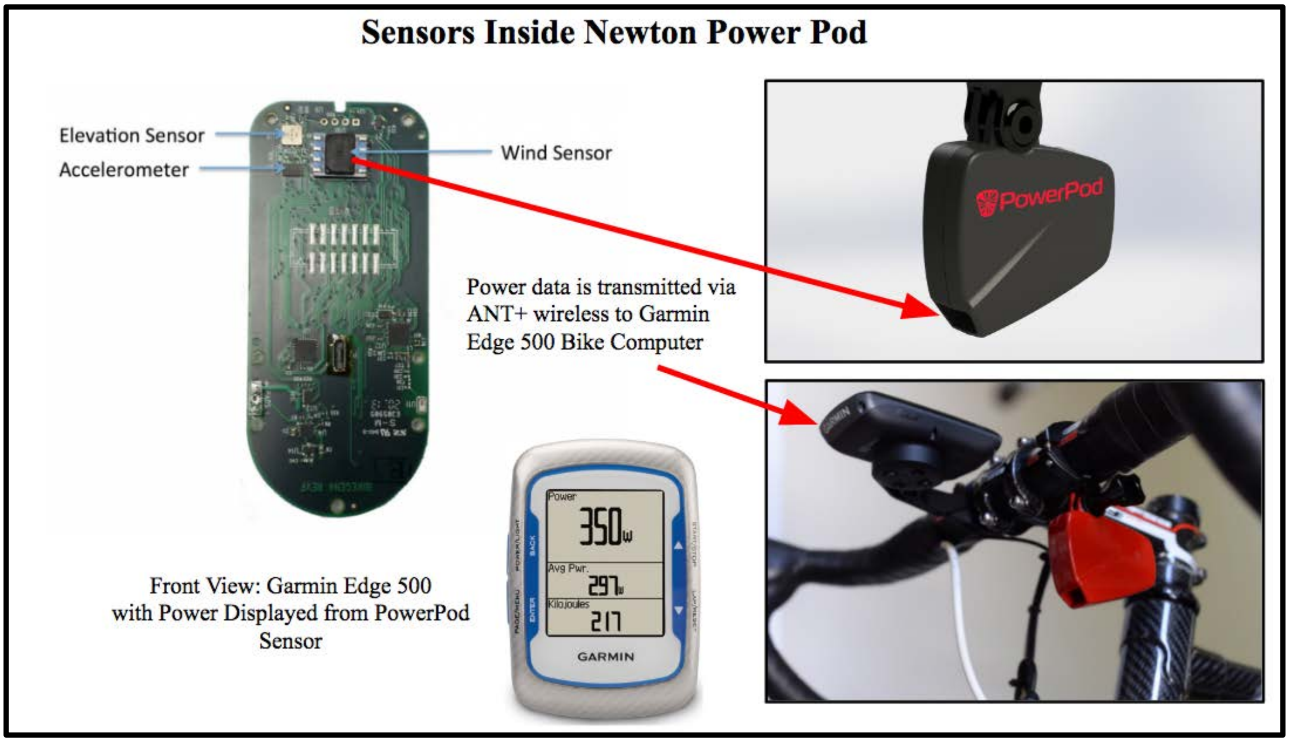

Figure 3.3 PowerPod technology with Garmin Edge 500 for power data display

In order to determine power output for the PowerPod system, the determination of speed must be captured using an external sensor (Figure 3.3.1) in additional to the PowerPod. Ground speed is determined by the number of wheel revolutions per minute (rpm) to estimate overall ground speed as shown in the below formula. Crank cadence is also measured using the same sensor (Figure 3.3.1) and measures rpm of the crank itself. Both sensors use relatively old analog sensor technology for determining the presence of a magnet passing in front of the sensor with each revolution of both the wheel and crank. The sensor must be within a few millimeters of the magnet to accurately detect the presence of the magnet passing by.

Below is the standard formula for measuring wheel rpm for calculating the speed of the cyclist, which is ultimately used within the power algorithm calculation.

1. Wheel revolutions to ground speed: one revolution is the distance equal to the circumference of the wheel traveled.
2. Distance covered in one (1) wheel revolution = (27.55 inches - diameter of a road bike tire x 3.14159) / 12 inches = 7.21 feet or 12.93 rpm = 1 mph

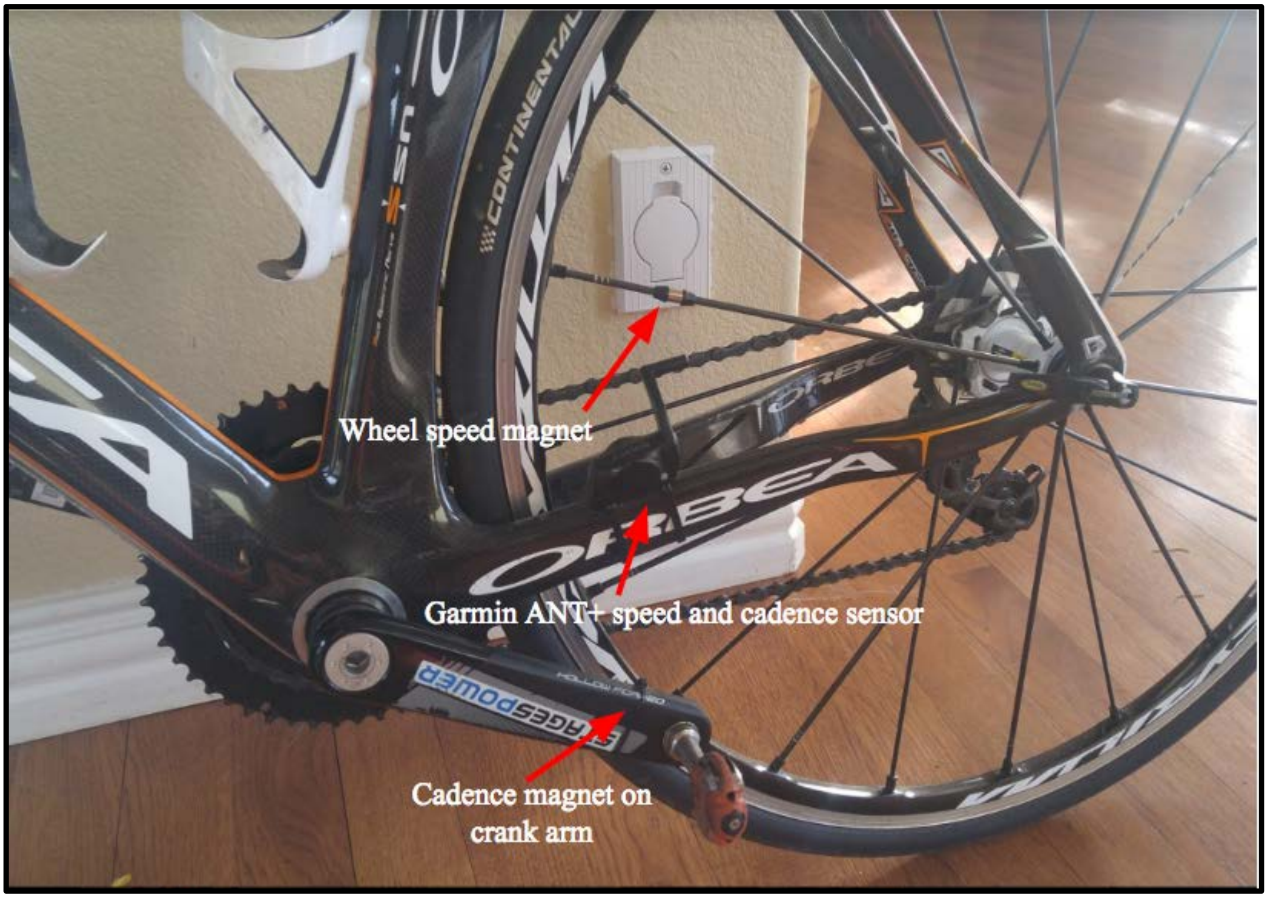

Figure 3.3.1 External Garmin sensor for determining speed and cadence for PowerPod meter

Power Pod Physics Engine for Calculating Power Output:

The PowerPod physics engine uses only speed, opposing forces and positional sensors located within the PowerPod device and the speed/cadence sensor for determining power output. Unlike the Stages Cycling Power reference system, no strain gauge technology is used in determining power output and is a critical part of the research hypothesis in determining if it is possible to accurately measure a cyclist power output using only an OFPM power measurement system.

3.4 Specifications of Innovative App Design (IAD) - Power Meter App

The Innovative App Design (IAD) power meter application is the second of the two power meter applications used in the study. The IAD system (Innovative App Designs 2016) is unique in that it leverages various location and positional sensors contained within a user's smartphone including GPS/GLONASS for speed and location (the IAD applications doesn’t use an external speed and cadence sensor like the PowerPod system). An internal barometer measures elevation change when external elevation web services are not available due to no wireless data coverage.

The IAD application also leverages external web services, accessible via a wireless data connection on the smartphone for such data inputs as wind direction, wind speed and high accuracy elevation data. High accuracy elevation calculations leverage the Google Maps Elevation API web service that provides for high resolution surface elevation data based on the highest accuracy source within the Google Maps base map infrastructure (Google Elevation API 2016). Google does not publish the quality or precision of the elevation data for various legal, technical and competitive reasons but studies have demonstrated that the elevation data is generally within the one (1) to five (5) meter range when compared to known survey markers (Google Product Forums 2016).

Additionally within the study, this power meter system is sometimes referred to as the “smartphone-based power” system as it uses only location sensors internal to the smartphone. From a cost perspective, the IAD smartphone application cost only $7.00 and makes this power meter a very affordable solution for any cyclist interested in using and training with power data.

Below are the technical specifications of the IAD power meter application (Table 3.4) that can be downloaded from either the Google Play or Apple App Store, depending on a user’s smartphone type.

Table 8 IAD Technical Specifications

Power Meter: IAD	Cost $	Stated Accuracy	Weight	Power Range (Watts)	Wireless Connectivity	Additional Notes
Power Meter App	$7.00	+/- 15%	Depends on phone type	0-2000 Watts	WWAN, BLE, ANT+	$15.00 for phone mount

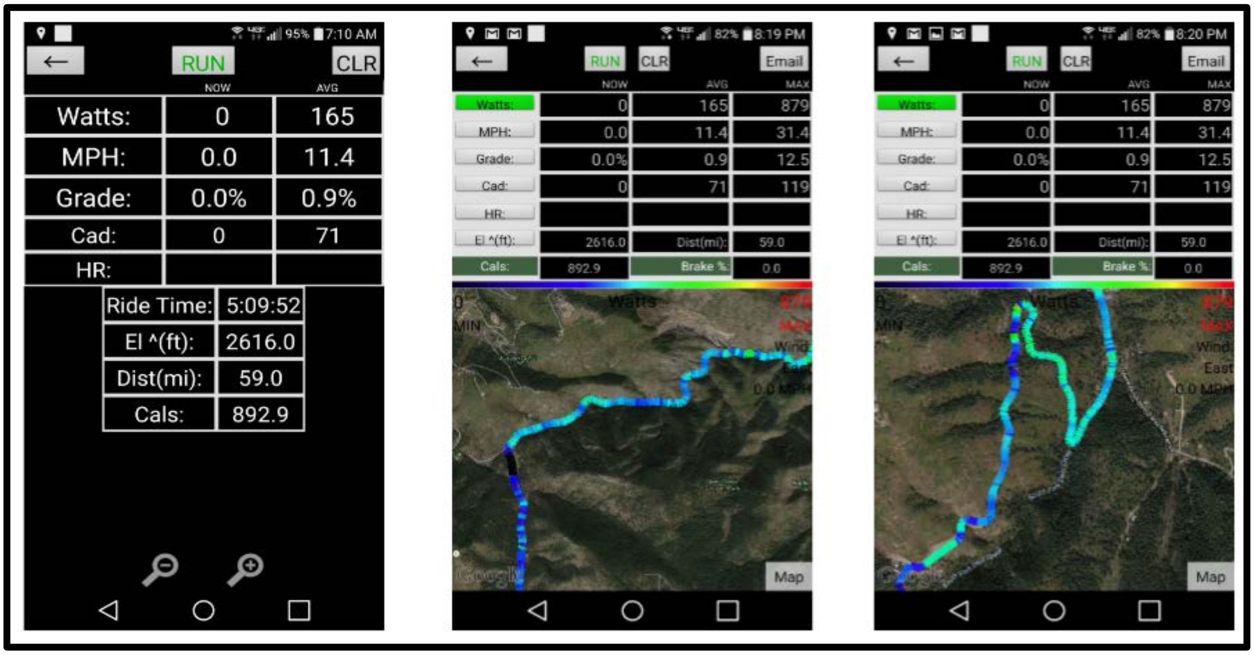

Figure 3.4 IAD application screens (L to R) - main screen, summary screens with power output overlaid on Google Maps

IAD Algorithms for Calculating Power Output:

The IAD power calculation algorithms use only GPS/GLONASS location and speed that is derived from the GNSS sensors within the LG smartphone and not via an external speed or cadence sensor. Additionally opposing wind forces from Accuweather.com and high accuracy elevation data from the Google Maps Elevation API web service (Innovative App Designs 2016) are used for calculating an implied power output. In order for the smartphone power application to have the highest accuracy, it is critical that the GPS sensors provide highly accurate position and speed data to the application in order to generate the most accurate results. Unlike the Stages Cycling Power reference system, no strain gauge technology is used in determining power output and is a key component to the research hypothesis in determining the power output accuracy based on smartphone sensors only.

3.5 Data and Methods Objectives

The end result of this research will be to showcase how the two competing power meter applications compare to the Stage Cycling reference DFPM system using field collected data while cycling three study routes. The data model will consist of collecting positional point data (latitude, longitude, altitude), speed, grade, and elevation for comparing overall power outputs as shown in Table 3.2.

Given the data volume and the need to query the data with sub-second response time by potentially hundreds of users, a GIS system like ESRI is not used given the underlying geodatabase architecture only supports legacy relational database management system (RDBMS) like Microsoft SQL Server or Postgres. RDBMS systems inherently do not scale well for web-based applications that have ever increasing data and load volumes (Kim 2016). Instead a low latency Mongo NoSQL database is used as the back end data store. The DC Rainmaker Analyzer application front end is built using an open source stack including Angular, Bootstrap, Dygraphs library and the Google Maps API (Flanagan 2016). An open source custom .fit file parser is used on the downloaded field data that has been sampled at 1Hz (one sample per second). The entire application runs on Google App Engine, Compute Engine and Google Cloud Storage. The above architecture provides the ability to provide a high performance web application using the best open source software and spatial analysis functions without the performance penalty that is common with legacy geodatabases like ESRI ArcGIS Server.

Research Design

The below data model represents the data fields (columns) that will be collected and stored within the MongoDB data store for comparing the smartphone and OFPM technologies to the reference DFPM system as shown in Figure 3.5. Location data collected in the below model is sampled at a 1 Hz rate (1 sample/row of data per second or 3600 data rows per hour) in order to have a universally synchronized time field to create a comparison database. The below data model is also updated from a “seconds from start time” and joined with a GPS clock timestamp data in which both location and power data are compared using the GPS Timestamp as a primary key. All the data collection systems (Smartphone, OFPM and DFPM systems) store data using a proprietary format (i.e. .fit and .tcx files) that can ultimately be used with both proprietary and open source tools for side-by-side comparisons as shown in Figure 3.5.1 below.

Table 9 Raw exported data exported from Garmin 520 bike computer

	Time	Distance	Power	Cadence	Speed	Altitude	Latitude	Longitude	Slope
1	00:00:00.000	0	0	15	7.5960000...	1688.2	39.549495382000003	-105.08693369	0
2	00:00:01.000	0.0028	30	31	10.0656	1688.2	39.549506446000002	-105.086972	0
3	00:00:02.000	0.0058900...	30	38	11.138400...	1688.2	39.54951793	-105.08701483	0
4	00:00:03.000	0.0093500...	20	40	12.4704	1688.2	39.549530586000003	-105.08705934	0
5	00:00:04.000	0.0131400...	100	43	13.636799...	1687.5999...	39.549542068999997	-105.08710401	-15.830500...

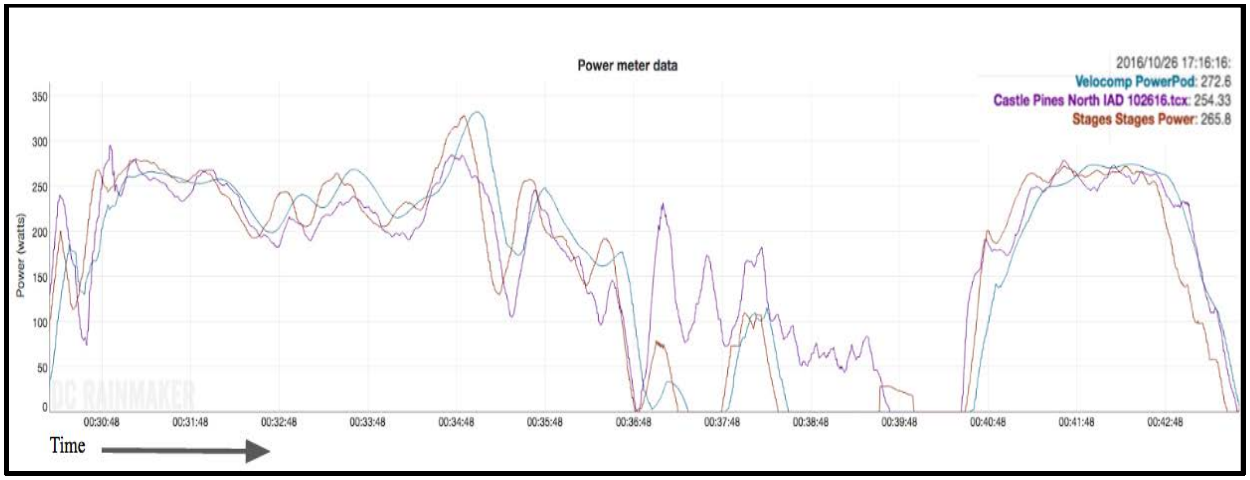

Figure 3.5 Side by side comparison of Stages Power, PowerPod and IAD power meter app

3.6 Study Routes for Power Data Collection

The study routes consist of three unique geographies and course lengths that provide insights into how each application performs under various conditions including rolling hills, mountain course climb and steep mountain climb sprint. Below are the study routes selected that includes top-level maps, elevation profiles and mileage calculations.

1. Castle Pines North (Figure 3.6 and 3.6.1) is a 17-mile loop consisting of rolling hills with 3 medium length climbs, various flat sections and several fast descents. The route geography is typical for the Douglas County area and popular with many local cyclists.

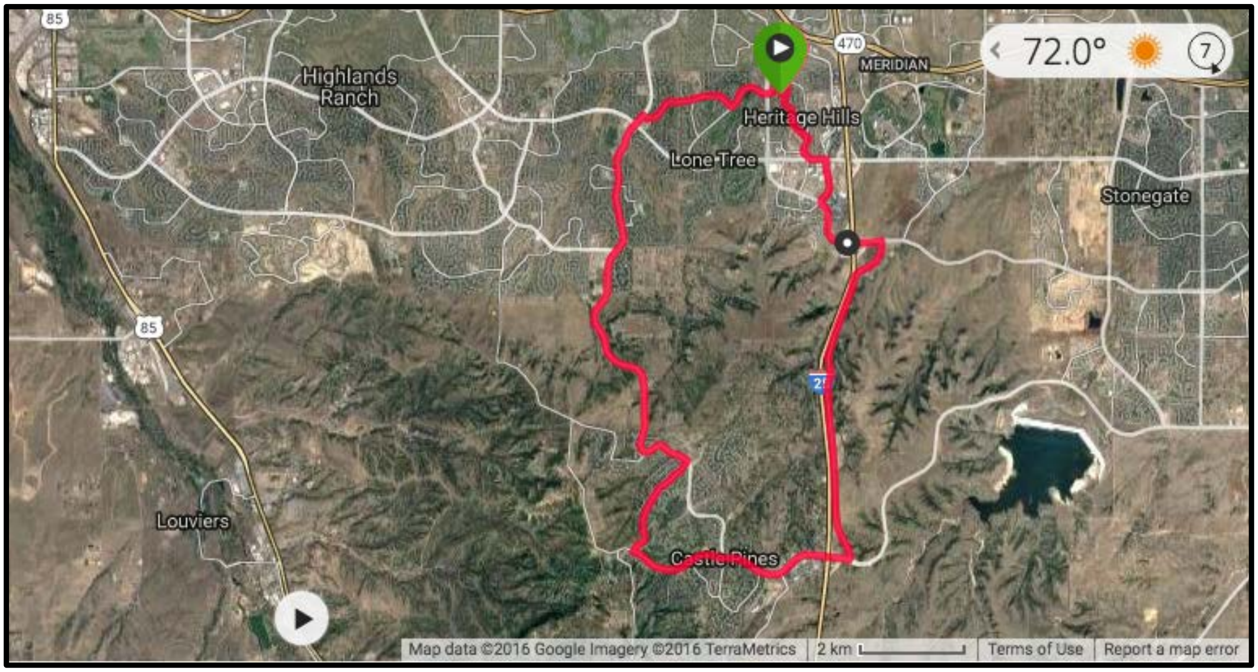

Figure 3.6 Castle Pines North loop route from home (green pin) and back

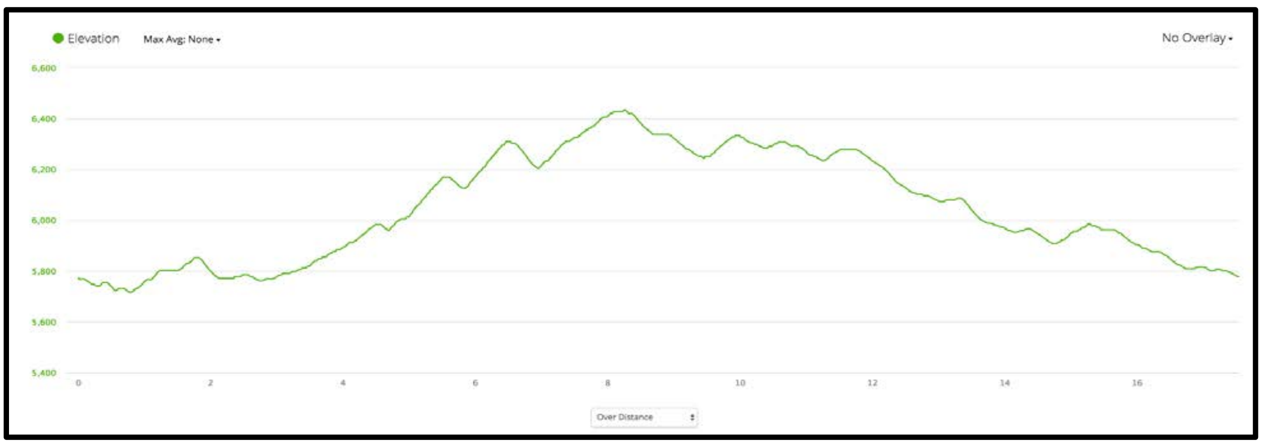

Figure 3.6.1 Elevation profile for Castle Pines North study route

2. Deer Creek Canyon (Figure 3.6.2) is a 13-mile mountain climb that starts with a rolling section and then ascends quickly at the Deer Creek Canyon entrance into a very steep, 6-12% grade climb. The beginning portion of the route is within Deer Creek Canyon before turning left and climbing High Grade Road. Portions of the route top out at 12% road grade. Power data will only be collected on the ascent and the ride is typical of a hard Colorado mountain climb.

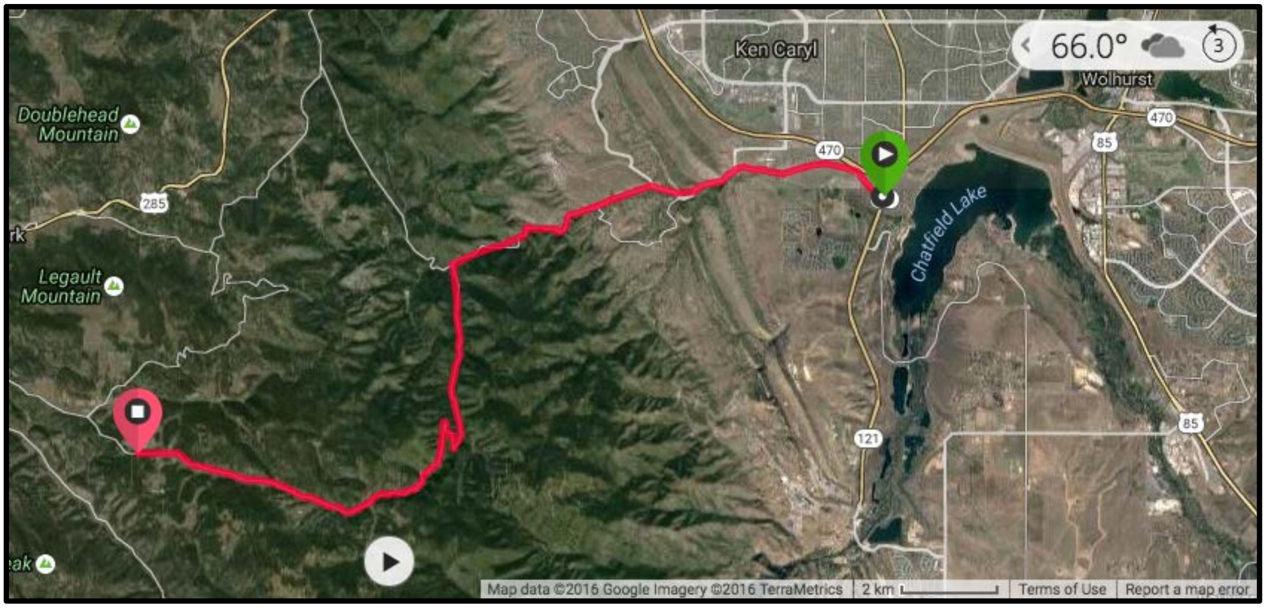

Figure 3.6.2 Deer Creek Canyon study route from West Deer Creek Canyon Road (green pin) to the top of Pleasant Park Road (red pin)

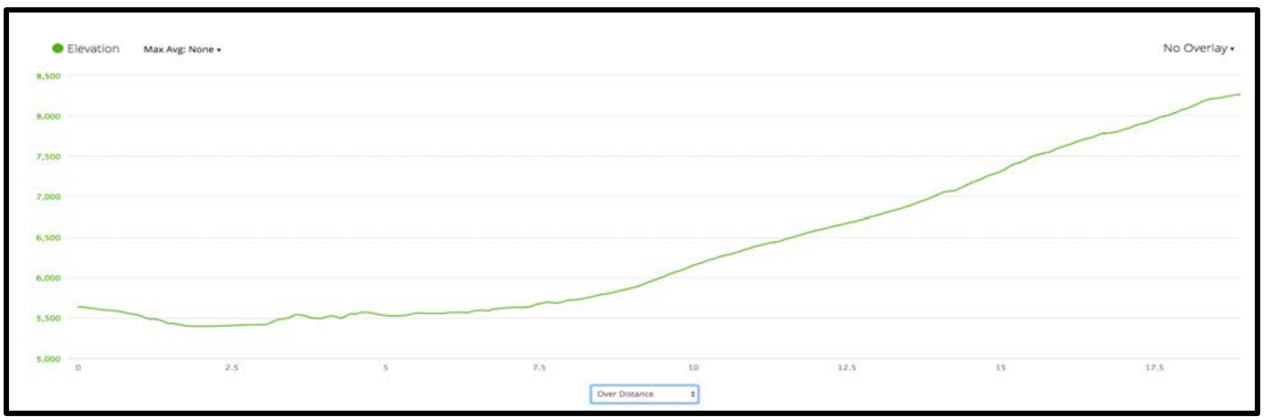

Figure 3.6.3 Elevation profile for Deer Creek Canyon route

3. Lookout Mountain Road (Figure 3.6.4) is a 4.5-mile, one-way mountain climb sprint course consisting of 5-8% road grade for the entire length. The route climbs quickly out of the City of Golden, Colorado and is a favored route by many cyclists given both the city views and challenges it presents to riders. This course is also used for time trial racing and was a featured route at the USA Pro Challenge bike race in 2014.

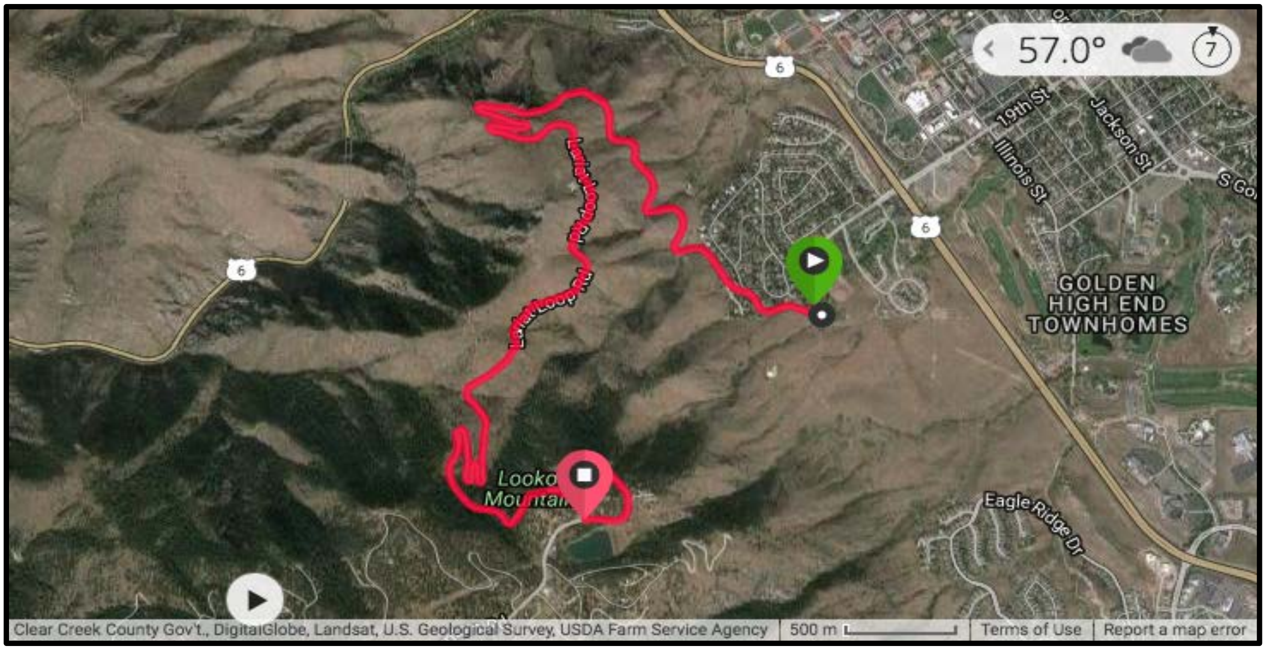

Figure 3.6.4 Lookout Mountain Road study route (green pin start and red pin finish)

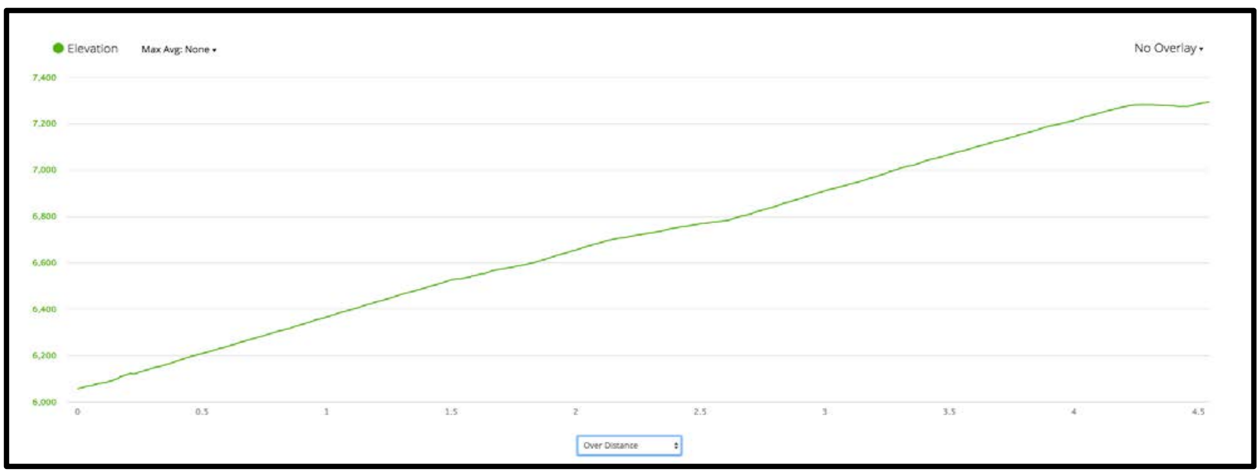

Figure 3.6.5 Elevation profile for Lookout Mountain Road study route

3.7 Data Collection Workflow

The below process flow diagram (Figure 3.7) represents the functional applications, sensors, data pipelines, databases and visualization tools that are used to reach the conclusions proposed in Chapter 1. Each step within the workflow is important to get configured correctly for the field-testing environment to reduce any possible biases that could contaminate the data with inaccurate data collections.

Below are the descriptions of each data column and how they fit into the overall field data collection process.

1. Power Meter Applications: represents the Stage Cycling Power system, which is the reference system in which the two competing applications will be measured against for accuracy. The power meter test applications consist of:
    a. Newton PowerPod (OFPM application)
    b. Innovative Application Design (IAD) smartphone application
2. Sensors: represents the various locations, positional and opposing force sensors used within the power applications in order to calculate the power output of a cyclist.
3. Data Collected: translates functional sensor type into data derived from the sensor itself. This data is typically represented as an integer value within the data field itself.
4. File Format Output: provides the file format once all the data fields have been saved into an output file format. Both .tcx and .fit (Garmin formats) will primarily be used for data comparisons.
5. Data Collection Apps: DC Rainmaker Analyzer - tool used to collect and analyze power data from many sources. Garmin Connect - tool used for collecting data from Garmin bike computers (Garmin Edge 500 and 520) and creating maps and exporting into .fit files. Google Earth provides 3D mapping application used to overlay ride data visuals.
6. Conclusions: Line graphs representing Average Power and Normalized Power. Maps showing GPS Road Network Accuracy and GPS Elevation Agreement.

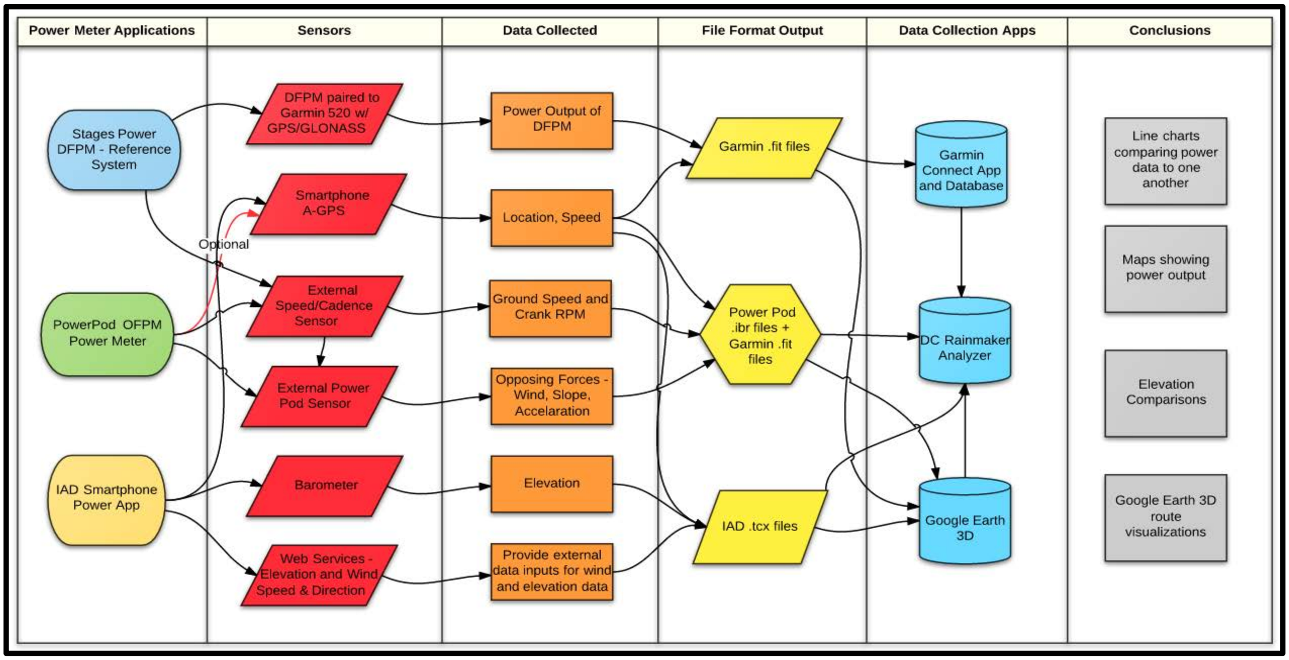

Figure 3.7 Data collection and process workflow

Table 10 Summary of ride including Average Power (AP), Normalized Power (NP), distance and cadence

Stats

Power

	IAD 082816 Final.tcx	Power Pod 0FPM 082816.tcx	Stages DFPM 082816.tcx
Average Power	186.68	216.53	225.21
Normalized Power	198.66	226.22	237.07
Max 1 sec Power	761	337	398

Heart Rate

	IAD 082816 Final.tcx	Stages DFPM 082816.tcx
Average Heart Rate	0.00	46.61

Cadence

	IAD 082816 Final.tcx	Power Pod 0FPM 082816.tcx	Stages DFPM 082816.tcx
Average Cadence	79.24	78.58	78.96

Distance

	IAD 082816 Final.tcx	Power Pod 0FPM 082816.tcx	Stages DFPM 082816.tcx
Distance	135764.26 meters	22357.27 meters	22332 meters

Chapter 4: Results

Chapter 4 details the results from the methodology outlined in chapter 3 to collect power meter readings, location, elevation data and the derived accuracies in comparison to the reference power meter over the three route study. The study is comprised of using a Stages Power Meter (used as the reference standard) to compare against the PowerPod power meter and the Innovation App Design (IAD) smartphone based power meter application. The core hypothesis of the study is to determine at what levels of accuracy do the PowerPod and IAD applications perform when compared to the Stages Power reference meter using spatial analysis. Additionally power meter cost and setup time is factored into the study results to best determine an optimal tradeoff between price, accuracy, ease of setup and customer support. Table 11 summarizes the field results using the dimensions of Average Power (AP), Normalized Power (NP), GPS-based road network accuracy, GPS elevation agreement and power difference percentages over the Stage Power reference power meter.

Though Table 11 summarizes the three study routes based on various averaging algorithms and observations, it’s important to note that averaging metrics are a deceptive and misleading measure of accuracy when taken at face value. Real time power metrics provides the most accurate picture of the level of effort exerted by the rider at any given time. For example, as a rider is pedaling at a given speed, 1-second instantaneous power measurements are visible to the rider showing the current level of exertion. Averaging techniques used in the above example would provide very little value, as the rider would be most interested in real time power measurements. This tradeoff is analogous to Chapter 2 research completed by the Kineticorp team (Neale, et al. 2016) that showed speed averaging metrics to be very misleading when comparing to specific point in time speed comparisons. However using averaging techniques does provide value within the study as both the AP and NP outputs could be used for “base lining” a riders historical power metrics that could ultimately be used to determine if a rider was improving on various fitness goals.

In order to better understand the tradeoffs between using real time power data versus averaging techniques along the three study routes, results of each route include additional drill down data analysis within the various intervals identified within a study route. The drill down analysis includes the beginning, midpoint and peak of a given route or climbs and includes power differences and data latency within the interval when compared to the Stages Power reference standard.

Table 11 Summary of three study route results

Power Meter Sensor Name	**Power Meter Sensor Type - Internal**	**Power Meter Sensor Type - External**	**Cost[1]**	**GPS Road Network Accuracy[2]**	**GPS Elevation Accuracy Agreement**	**Castle Pines North Average (AP) and Normalized Power (NP) in Watts (W)**	**Deer Creek Canyon Average and Normalized Power (NP) in Watts (W)**	**Lookout Mountain Average and Normalized Power (NP) in Watts (W)**	**3 Route Total AP and NP % Difference over Reference**
Stages Cycling DFPM[3] **(Reference Power Meter)**	Left-side crank arm only - strain gauge and accelerometer	Garmin 520 GPS/GLONASS + Speed and Cadence sensor	$530.00 to $700.00 - depends on brand of crank	Highest Accuracy - Garmin Edge 520	+/- 1 meter compared to County or USGS DEM	AP 151.74 W NP 206.12 W	AP 225.21 W NP 237.07	AP 264.53 W NP 266.65 W	AP 641.48 W NP 709.84 W
Power Pod OFPM[4]	Wind, Barometer, Accelerometer	Garmin 500 GPS + Speed and Cadence sensor	$249.00	Highly Accurate - Garmin Edge 500	+/- 3 meters compared to County or USGS DEM	AP 159.30 W NP 214.26 W	AP 216.53 W NP 226.22 W	AP 258.44 W NP 263.23 W	AP 634.27 W 1.13% higher NP 703.71 W 0.86% higher
IAD Smartphone App	A-GPS, GLONASS, Barometer, Accelerometer	Google Elevation API, Wind Speed/Direction API	$7.00	Highly accurate (with good GDOP), >2 meters (low DPOP)	+/- 1 meter compared to County or USGS DEM	AP 176.53 W NP 208.54 W	AP 186.68 W NP 198.66 W	AP 222.10 W NP 233.38 W	AP 585.31 W 9.15% lower NP 640.58 W 10.25% higher

4.1 Study Route 1: Castle Pines North - Overview

The Castle Pines North route is a 17.5-mile loop starting in the City of Lone Tree, heading south along South Quebec Street and Monarch Boulevard, east on Castle Pines Parkway and then returns north on South Havana Street into the City of Lone Tree (Figure 4.1). The route is divided by a geologic butte (Surrey Ridge) that separates the city of Lone Tree and the City of Castle

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[1] Cost does not include Garmin Edge bike computers ($300.00) used in testing to collect power meter data or Power

[2] GPS road network feature accuracy determined using Google aerial imagery with stated accuracy <70 cm in metro areas. Accuracy accessed by how close line feature was to actual bike route or road shoulder.

[3] Stages Cycling Direct Force Power Meter (DFPM) Model: FSA 386EVO Carbon/Alloy crankset.

[4] Velocomp PowerPod - Opposing Force Power Meter (OFPM)

Pines North, both located in Douglas County, Colorado. The route geography consists of rolling short hills, a long climb up Surrey Ridge and a long descent back into the City of Lone Tree. Elevation gain of the route has been estimated at 1,290 feet and is represented in Figure 4.1.1

Figure 4.1 Castle Pines North loop route starting at green flag and back

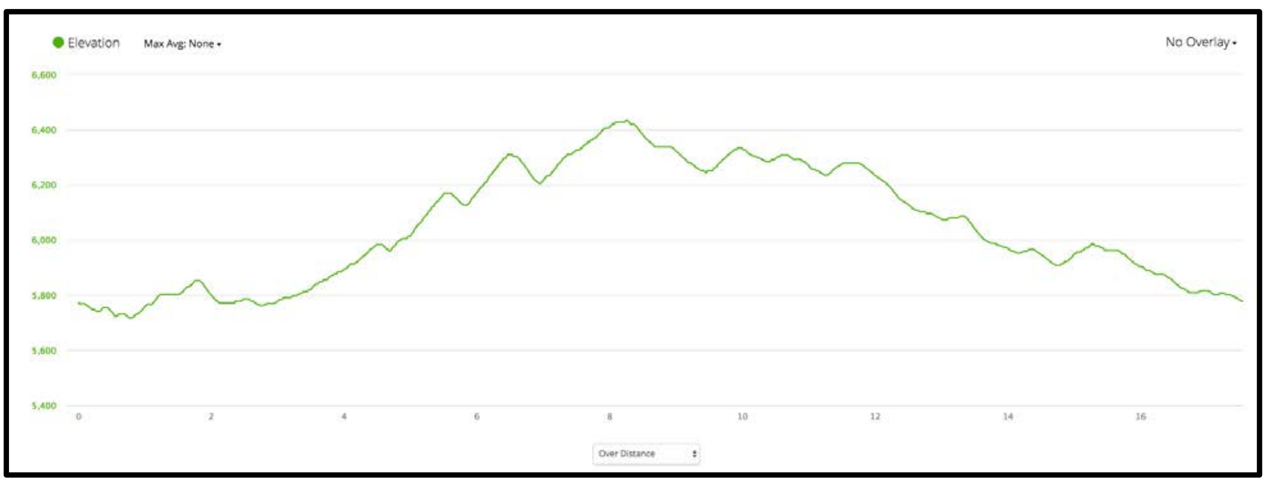

Figure 4.1.1 Castle Pines North elevation profile

4.2 Comparison of Average Power Accuracies

The Castle Pines North ride was conducted in just over an hour, completing 17.5 miles with an elevation gain of approximately 1,290 feet. From the ride, the power data has been summarized in the below Table 11 which includes Average Power (AP), Normalized Power (NP) and the percentage differences measured across the averaging metrics. When comparing the averages, the PowerPod was 5.0% above the Stages Power meter reference compared to the IAD application, which overestimated power output on average by 16.3%. But when reviewing the percentage difference using the NP averaging algorithm, surprisingly the IAD application surpasses the PowerPod meter (3.9%) at a difference of just 1.2% above the reference power meter. Upon further interrogation of the power meter data, this anomaly most likely occurred due to the accelerometer and GPS speed data being incorrect during a rapid descent in which actually no power was being generated as shown in Figure 4.2.1. When this erroneous power data is factored into the NP averaging algorithm, it actually places the averaging figure much closer to the Stages reference figure as shown in Figure 4.2 and thus not a reliable figure when using the NP metric.

Table 12 Castle Pines North Route - average and normalized power summary

Power Summary (Watts)	**Stages Power (Reference Power Meter)**	**PowerPod Power Meter**	**IAD Power Meter Application**
Average Power (Watts)	151.74 W	159.30 W	176.53 W
Normalized Power (Watts)	206.12 W	214.26 W	208.54 W
% Difference over Average Power Reference	N/A	5.0%	16.3%
% Difference over Normalized Power Reference	N/A	3.9%	1.2%

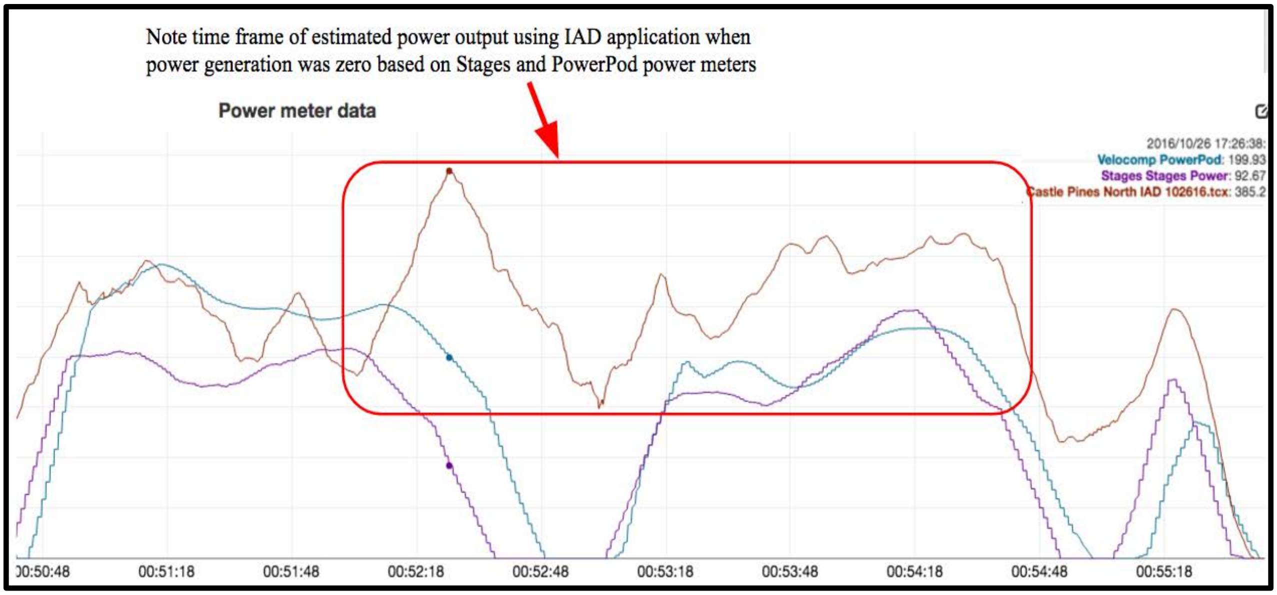

Figure 4.2 Areas in which IAD applications misrepresents power output in a rapid descent due to incorrect speed data

4.3 Comparison of Real Time Power Data Intervals within the Castle Pines North Route

In order to better understand how well both the PowerPod and IAD application performed compared to the Stages reference power meter, the study route is broken into three intervals. These intervals include the beginning of the climb, midpoint and peak of the climb. Figure 4.3 shows the power output across the entire Castle Pines North route using 30 second "power smoothing." Power smoothing takes the average of the power data that is measured in 1-second increments and averages over a user-defined period of time. Without power smoothing, the power data is visually "noisy" and difficult to visualize trends when graphed.

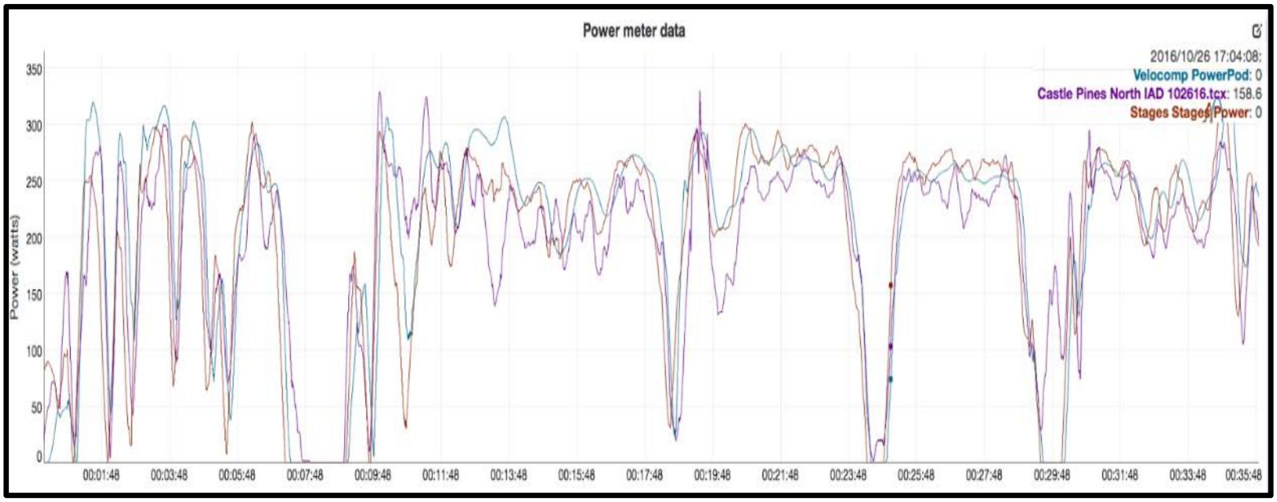

Figure 4.3 Castle Pines North study route with Stages Power meter (red line), PowerPod power meter (teal line) and IAD power meter application (purple line)

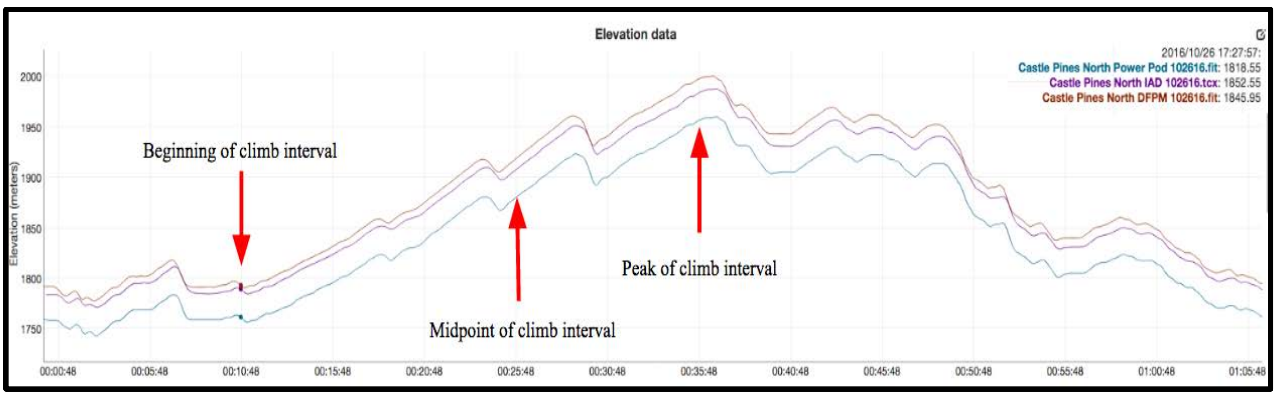

Figure 4.3.1 Castle Pines North elevation profile with identified three interval sections

Upon closer review of the power meter data at the beginning of the climb, several conclusions are derived about both the overall accuracy related to the Stages Power reference meter as well as the time needed in which the PowerPod and IAD application responds to changes in slope of the climb. Figure 4.3.3 shows the very beginning of the climb in which the Stages Power meter represented 46 watts of power being generated. The PowerPod and IAD application showed significant differences of 70 and 158 watts respectively. Twenty seconds later the PowerPod meter had caught up to the Stages Power meter and was within 4 watts and the IAD application had improved to being within 42 watts compared to the Stages power meter. Overall, the Stages and PowerPod meters had high degrees of accuracy agreement through the beginning section of the climb while the IAD application tended to show varying degrees of either over or under estimating power output as shown in Figure 4.3.4.

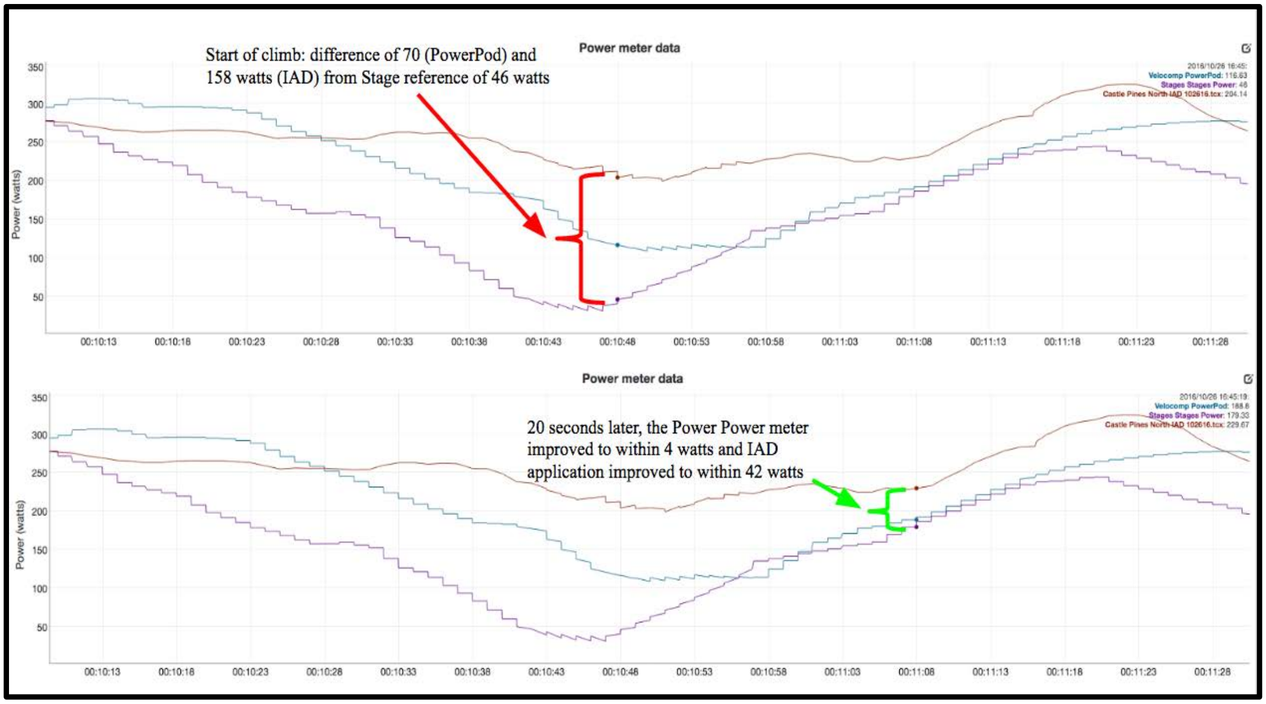

Figure 4.3.2 Castle Pines North beginning of climb with power and response time differences

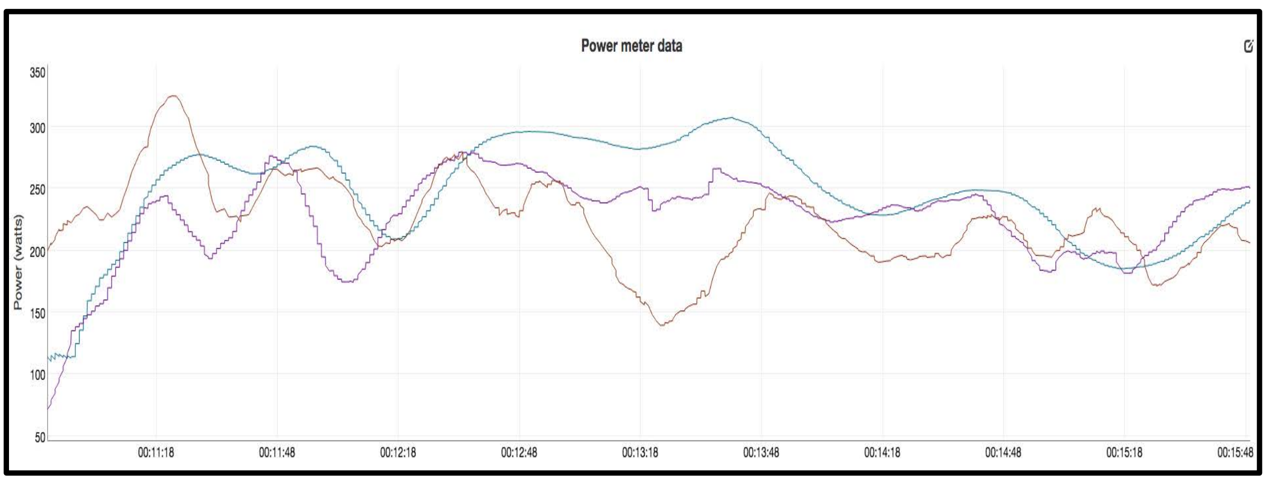

Figure 4.3.3 Castle Pines North climb over a 5-minute period (timestamp 10:48 to 15:48)

In reviewing the power data at the midpoint section of the climb, Figure 4.3.5 shows the PowerPod to be in fairly close agreement (15 watt difference) to the Stages reference meter, while the IAD application was consistently lower. As shown in Figure 4.3.5, it took approximately 5 seconds for the PowerPod to match up to the Stages meter on either side of the graph. This was also observed on the Garmin bike computers while collecting the field data in which the PowerPod seemed to exhibit data latency by three to six seconds over the Stages power meter. Based on how the PowerPod estimates power output, this observation is understandable given the Stages meter provides instantaneous power output while the PowerPod and IAD applications are providing an estimated power output based on the sensor technologies described in Chapter 3.

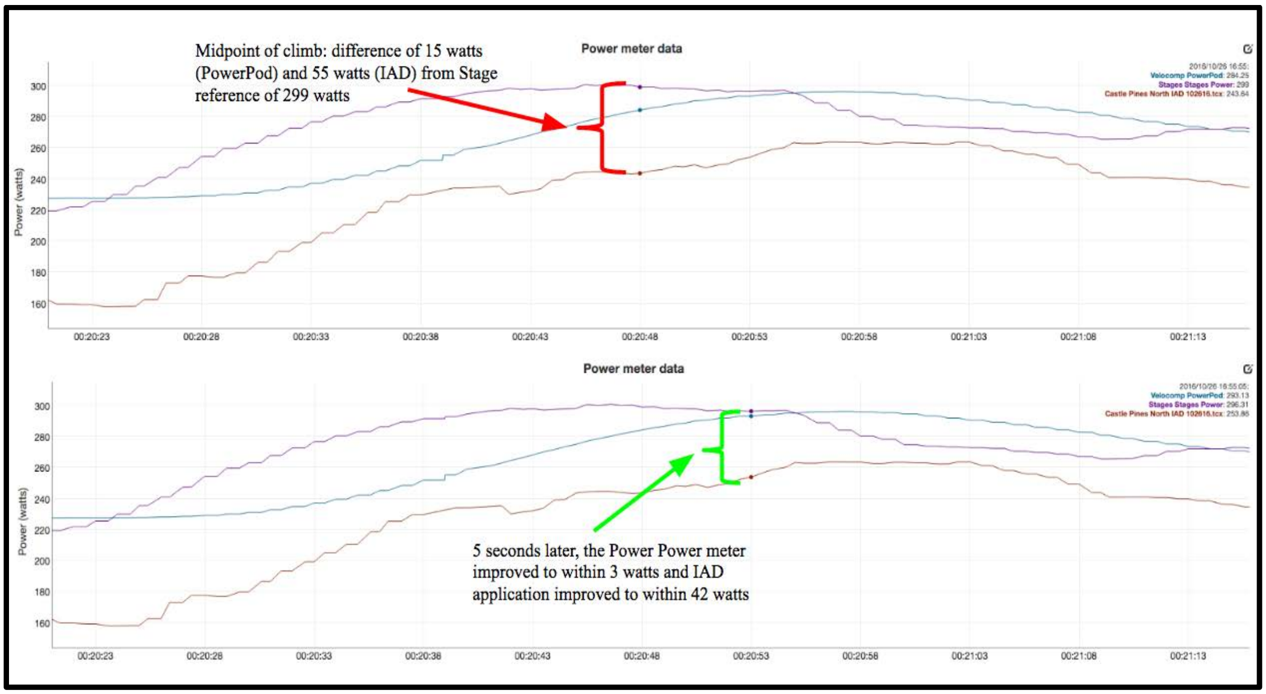

Figure 4.3.4 Castle Pines North midpoint of climb with power and response time differences

At the peak of the climb, the IAD and PowerPod meters reversed order in terms of accuracy compared to the reference meter as shown in Figure 4.3.6. The IAD application showed only a 22-watt difference from the reference meter while the PowerPod application was significantly higher at 55 watts. Interestingly, the IAD actually matched the Stages reference six seconds later and showed strong agreement of this portion of the climb.

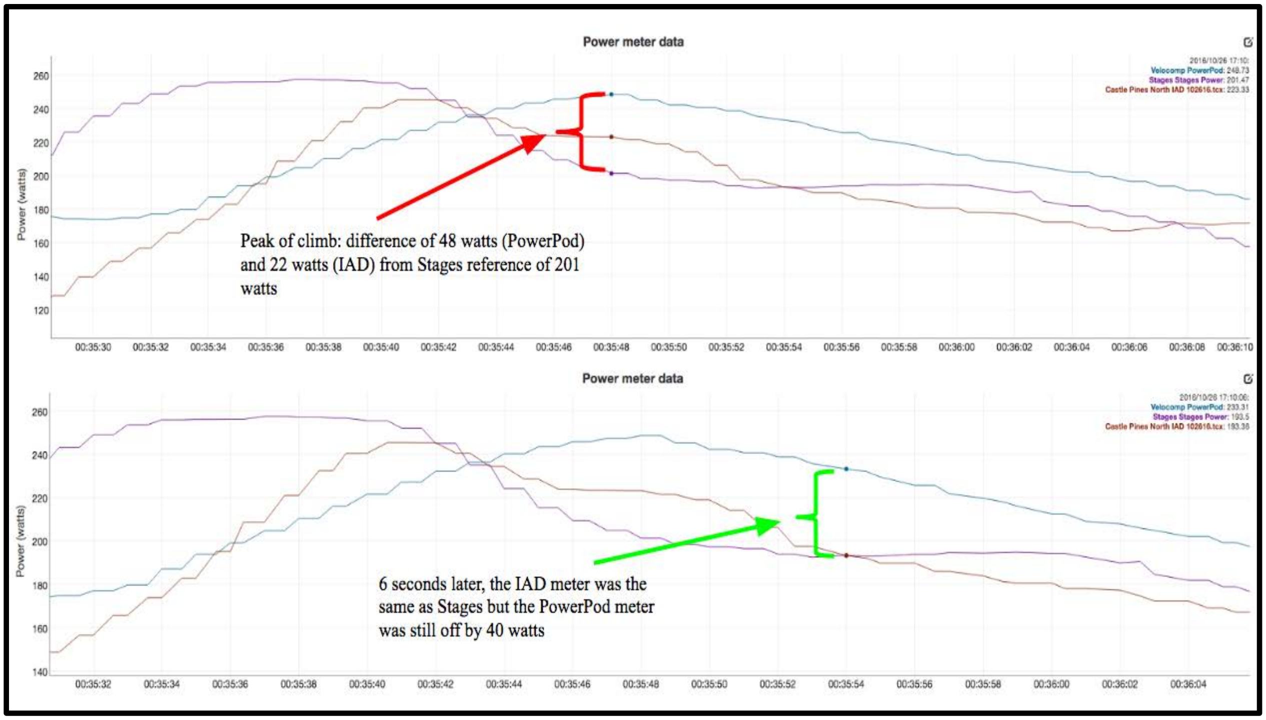

Figure 4.3.5 Castle Pines North peak of climb with power and response time differences

4.4 Comparison of GPS Road Network Accuracy

GPS accuracy provides another important data element for providing high quality inputs that is heavily used within the IAD power application for determining the cyclist speed. As part of the overall power estimation algorithm (Power = Speed * Force), the importance of sampling high quality GPS positional data for determining speed can not be overlooked. For determining overall accuracy of the positional data, satellite imagery is used to assess how close the line is to the actual ride path. If the GPS data is weak or blocked by buildings, mountains or other physical features, this can have a significant impact on the overall quality of the power data within the IAD application (Neale, et al. 2016).

In reviewing Figures 4.4 thru 4.4.1, the IAD power meter application running on an LG G4 smartphone (device uses both A-GPS and GLONASS GNSS sensors) shows a very high degree of accuracy and is representative of the actual location while riding. Though the PowerPod and Stages power meter applications do not use GPS position to determine power output, the power data is ultimately transmitted wirelessly, viewed and stored on the Garmin bike computer for downstream analysis by the rider. Within the study, both a Garmin Edge 500 and 520 are used to collect the Stages and PowerPod power data. The Garmin Edge 520 uses both GPS and

GLONASS GNSS sensors and for the most part showed slightly better positional accuracy when compared to the ground truth of the route.

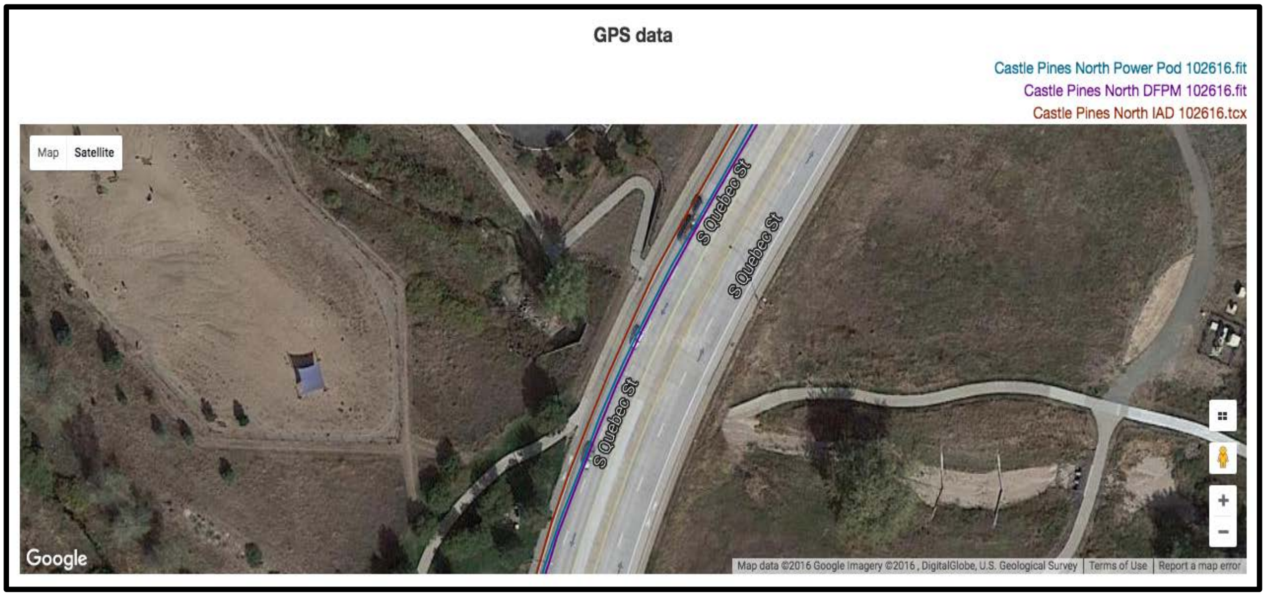

Figure 4.4 Beginning of Castle Pines North climb (timestamp 10:48) with IAD applications (red line) showing the most accurate position in the bike lane

Figure 4.4.1 Midpoint of Castle Pines North climb (timestamp 20:48) with IAD applications (red line) showing the most accurate position in the bike lane

Figure 4.4.2 Peak of Castle Pines North climb (timestamp 35:48) with all applications showing the same approximate position (+/- 3 feet to ground truth)

4.5 Comparison of GPS Elevation Accuracy Agreement

GPS elevation accuracy is another important data element for providing the most accurate representation of elevation for determining the force needed to climb a slope. As part of the overall IAD power estimation algorithm (Power = Speed * Force), the importance of sampling high quality GPS elevation data (derived using either the Google Maps Elevation API or the phone itself if wireless data coverage is weak) for determining elevation cannot be overlooked.

For determining overall accuracy of the elevation data, the Douglas County GIS Open Data (Douglas County GIS 2016) Digital Elevation Model (DEM) is referenced and used to compare against the elevation data collected by the various power meter applications as shown in Figure 4.5.1. The Douglas County DEM is a high accuracy product derived from a 2013 LiDAR data collection. Given the IAD power meter application is the only application that uses elevation data for power estimation, the accuracy of the IAD elevation compared to the actual Douglas County DEM is the most relevant data comparison. For simplicity sake, only the beginning and peak of the climb intervals are used in determining the level of general elevation accuracy.

In reviewing Figures 4.5.1 and 4.5.2, the IAD power meter application shows a very high degree of elevation accuracy when compared to the Douglas County DEM. For the start of the climb, the IAD application shows an elevation of 5881 feet compared to the DEM elevation of

5872 feet. When subtracting out the additional three feet for the sensor height on the bike, the total difference is less than five feet compared to the DEM surface elevation.

For the peak of the climb, the IAD application shows an elevation of 6553 feet compared to the DEM elevation of 6570 feet. Overall, both elevation positions show very high levels of accuracy and agreement for a positional sensor that is moving at ten to fifteen miles per hour.

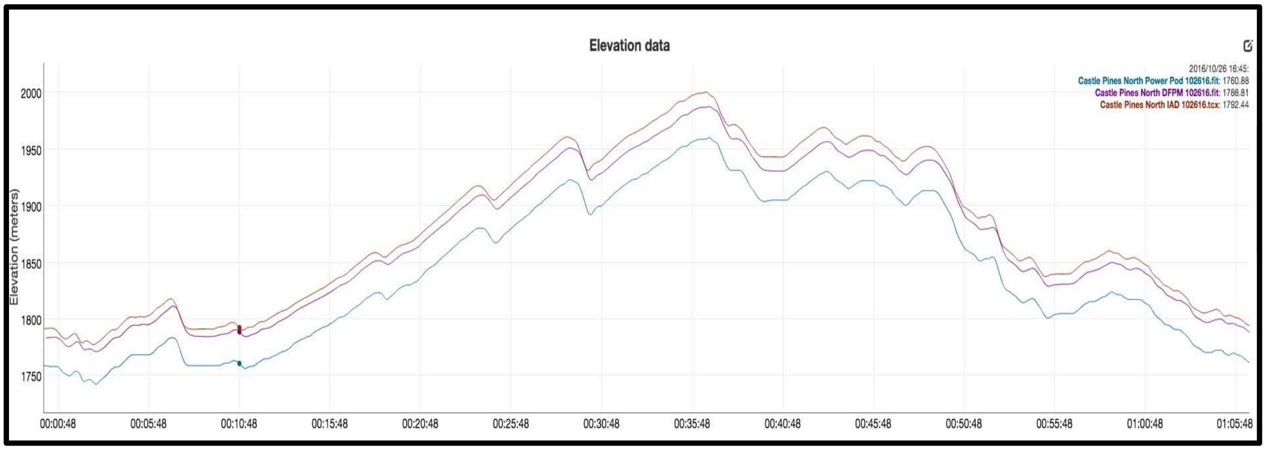

Figure 4.5.1 Castle Pines North at beginning of climb at elevations of 5881 feet (IAD - red line), 5869 feet (Stages - purple line) and 5777 feet (PowerPod - teal line)

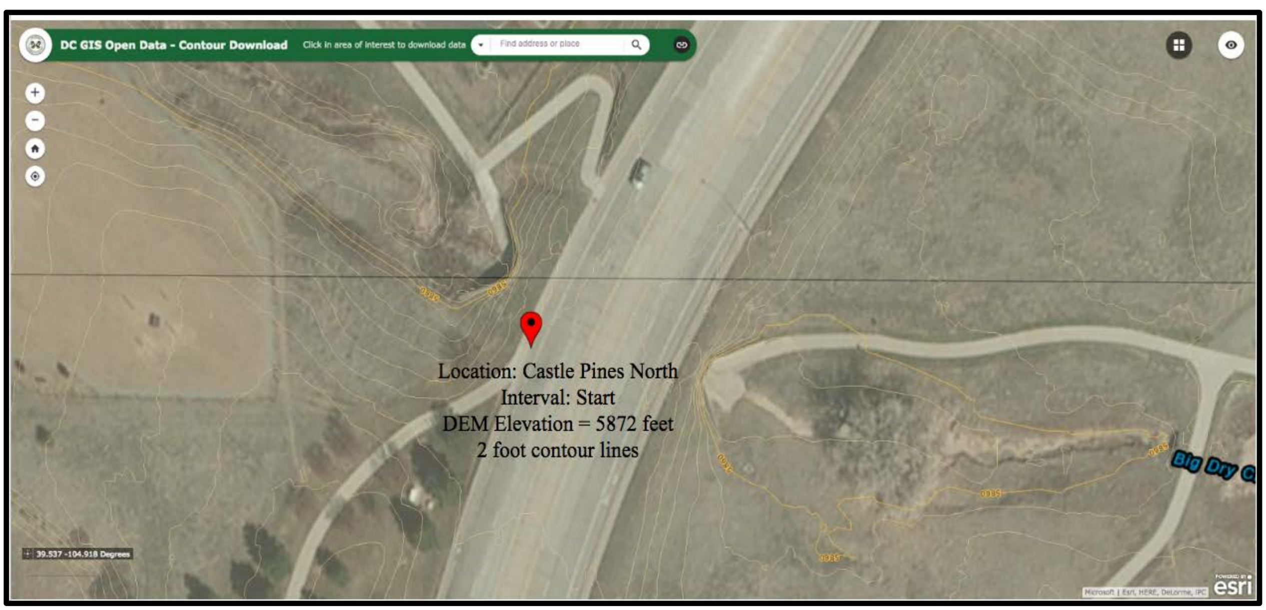

Figure 4.5.2 Castle Pines North at start of climb using Douglas County DEM showing elevation of 5872 feet.

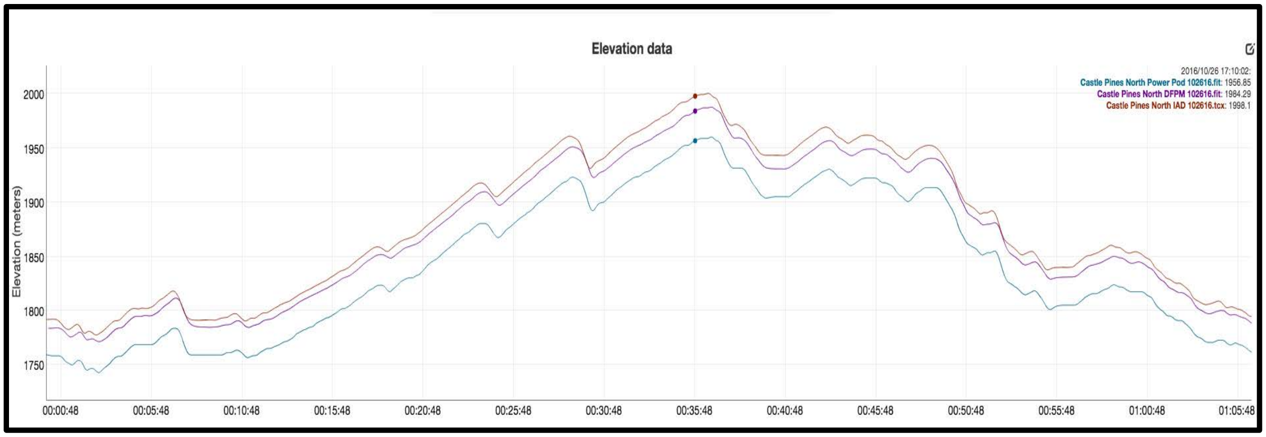

Figure 4.5.3 Castle Pines North near peak of climb at elevations of 6553 feet (IAD - red line), 6509 feet (Stages - purple line) and 6419 feet (PowerPod - teal line)

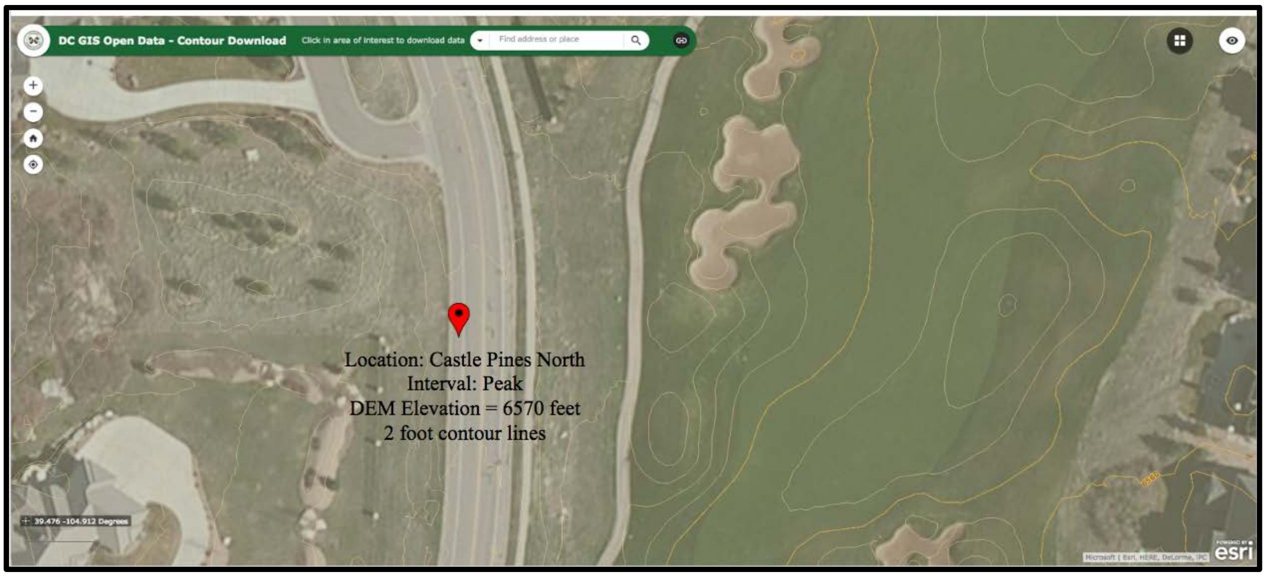

Figure 4.5.4 Castle Pines North near peak of climb using Douglas County DEM showing elevation of 6570 feet

4.6 Results Summary for Castle Pines North Route

When summarizing the results of the PowerPod power meter application to the reference power meter from Stages Cycling, the PowerPod provides measurements on average of 7.5 watts higher than the Stages reference meter and slightly above (4.86%) the +/- 2% stated accuracy on the PowerPod website (ibikesports.com). When comparing the PowerPod meters response time, the meter typically showed data latency of three to six seconds behind the Stages Power meter which was also confirmed by the power data collected and reviewed above. One additional area that the

PowerPod was challenged by was at the beginning of a fast descent in which the power data was off by more than 100 watts as showcased in the above results. Overall the PowerPod performed very well on average in comparison to the Stages meter within the Castle Pines North study area and also scores well for price to performance ratio over the Stages power meter.

When reviewing the IAD smartphone application, the average power output was 16.3% higher than the Stages power meter but respectively close to the application designers stated accuracy of +/- 15% over a traditional power meter (Innovative App Designs 2016). Similar to the PowerPod, the IAD application seemed to overstate power was during fast descents. The application had a tendency to interpret a high rate of GPS speed and pedal cadence into high rates of power output when in actuality no power was being generated due to the crank being idle. This was a consistent observation and was provided as feedback to IAD for future consideration for using a speed and cadence sensor to properly measure wheel speed (compared to GPS speed derived from the phone) and crank cadence instead of relying on accelerometers within the smartphone to estimate crank cadence. Overall the IAD application provided valuable power data for a price point that is accessible to a very large recreational cycling demographic.

4.7 Study Route 2: Deer Creek Canyon - Overview

The Deer Creek Canyon route is a 13.9-mile mountain climb starting at the base of Deer Creek Canyon Road located in Douglas County, Colorado (Figure 4.7). The route travels west along Deer Creek Canyon road for approximately seven miles and then turns left onto Deer Creek Road before turning into High Grade Road and eventually onto Pleasant Park Road near the summit of the route. This route carries the name “High Grade” by local cyclist and is indicative of the 5-12% road grade that is encountered along the route. The route geography consists of a gentle climb for 3 miles, followed by a long and steep climb up Deer Creek Canyon Road. Turning left onto Deer Creek Road, the route offers a short break in climbing before ascending a long climb up High Grade Road, which peaks with a short 12% road grade section. The route starts to plateau at Pleasant Park Road with the remaining 4 miles at a 4-5% road grade. Elevation gain of the route has been estimated at 2,800 feet as represented in Figure 4.7.1.

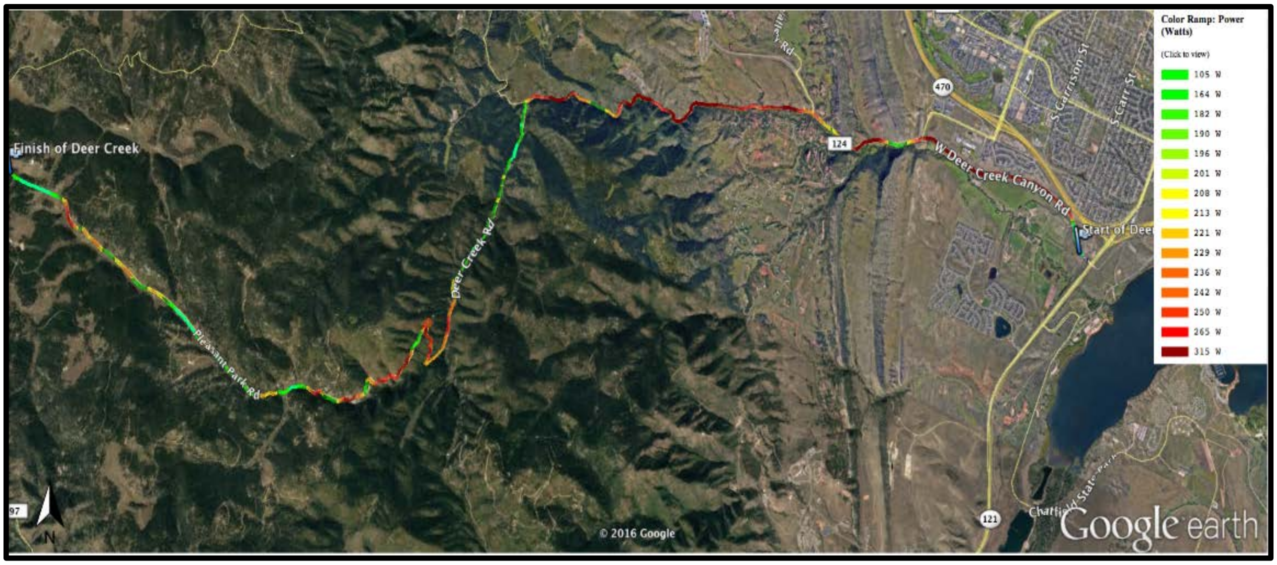

Figure 4.7 Deer Creek Canyon study route with power output scale

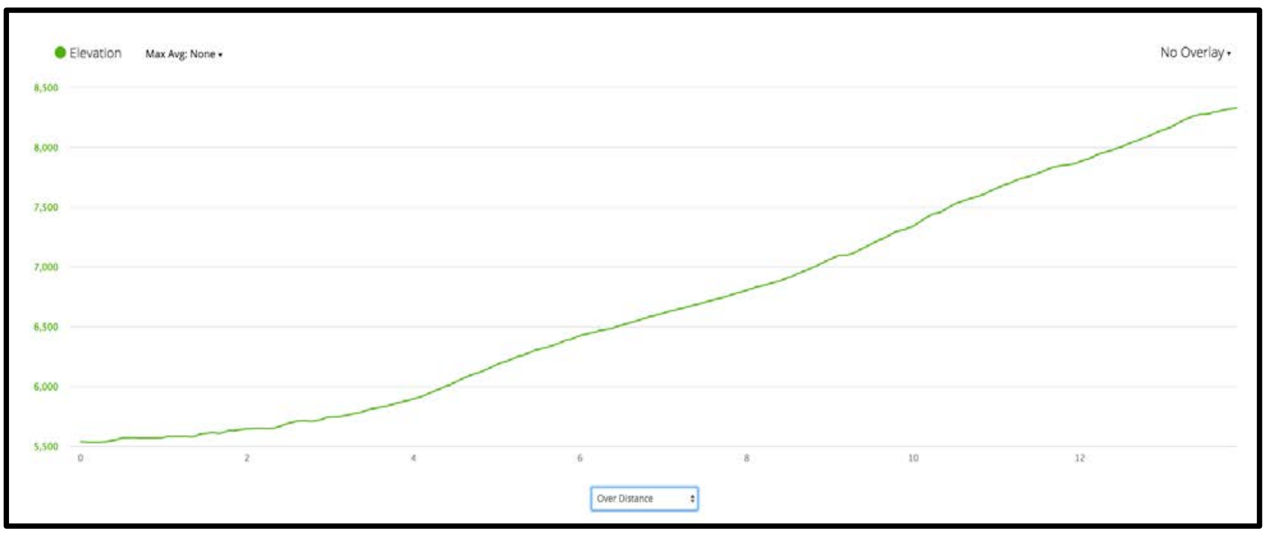

Figure 4.7.1 Deer Creek Canyon elevation profile

4.8 Comparison of Average Power Accuracies

The Deer Creek Canyon ride was conducted in one hour and fifteen minutes, covering 13.9 miles with an elevation gain of approximately 2,800 feet. From the ride, the power data has been summarized in Table 13 below which includes Average Power (AP), Normalized Power (NP) and the percentage differences between the Stages Power reference and the PowerPod and IAD power meters. When comparing the raw averages, the PowerPod is 3.9% below the Stages Power meter reference. The IAD application also underestimated power on average by 18.7%. When reviewing the percentage difference using the NP averaging algorithm, the IAD application improved slightly to 17.6% while the PowerPod meter slipped to a 4.6% below the reference power meter.

Table 13 Deer Creek Canyon Route with average and Normalized Power summary

Power Output Summary (Watts)	Stages Power (Reference Power Meter)	PowerPod Power Meter	IAD Power Meter Application
Average Power (Watts)	225.21 W	216.53 W	186.68 W
Normalized Power (Watts)	237.07 W	226.22 W	198.66 W
% Difference over Average Power Reference	N/A	3.9%	18.7%
% Difference over Normalized Power Reference	N/A	4.6%	17.6%

4.9 Comparison of real time power data intervals within the Deer Creek Canyon route

Upon further interrogation of the power meter data, several sensor anomalies seemed to have substantial impacts to the overall quality of the data collection due to a weak GPS signal used by the IAD application highlighted in Figure 4.9.1. Given the power output figures in Table 13 have been averaged with sensor data that either over or under estimates GPS speed (IAD application), further investigation is required in order to better understand areas in which a smartphone-based power meters performance is impacted by the weakening of the GPS signal due to a geometric dilution of precision (GDOP) (Langley 1999). Additional analysis will not be provided for the missing speed and cadence data for the Stage Power meter, as this will be categorized as an anomaly with an unknown cause. It should be noted as with any wireless data communications, connection loss can occur and many times not explainable.

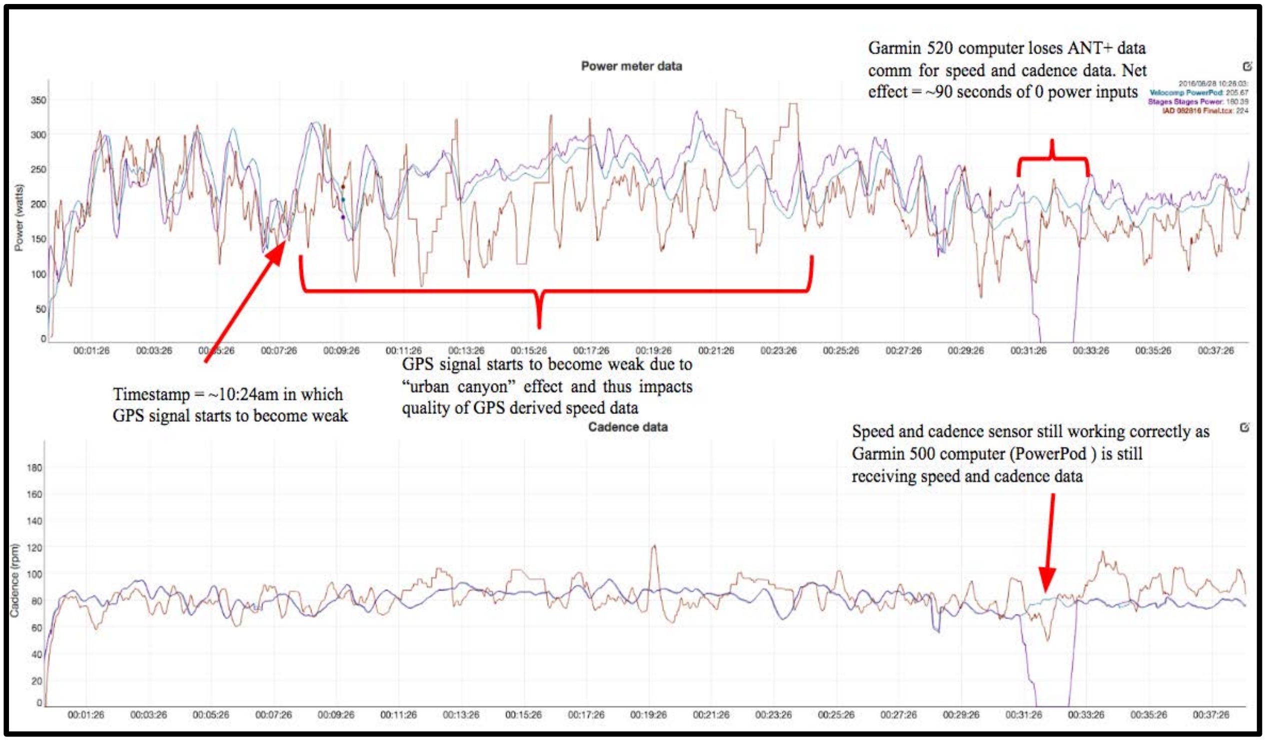

Figure 4.9 Time series data showing both GPS sensor data weakening (left side) and completely missing speed and cadence sensor data from Garmin 520 (right side)

At approximately ten minutes into the ride, the IAD application starts to behave in an inconsistent manner giving both under and over estimates of power output compared to both the Stages and PowerPod meters. Given the IAD application relies heavily on GPS data to measure ground speed in which to estimate power (Power = Force * Speed), closer inspection of the quality of the GPS data is required. When reviewing the raw GPS data overlaid on top of Google imagery (Figure 4.9.1), it becomes apparent that the steep canyon walls of Deer Creek Canyon are impacting the GPS signal being received by the LG GPS/GLONASS smartphone receiver. The irregular line vectors are typical of when a GPS receiver has a weak incoming signal that is degraded by surrounding terrain or man made features such as tall buildings. The weakening of the GPS signal is most commonly caused by a geometric dilution of precision (GDOP) and is indicative of the GPS receiver not being able to receive a strong signal from a minimum of three GPS satellites that allow for a precise position on earth.

In the case of the GPS receiver within the LG G4 smartphone, the receiver seems not well suited for delivering a consistent and high quality GPS location and subsequent speed data that is used by the IAD application. Typically smartphones such as the LG G4 rely on Assisted GPS (A-

GPS), which provides location enhancement that is augmented by the cellular network infrastructure. Given the location of the smartphone at the time of the received GPS signal, wireless data coverage and subsequent positional assistance was not available (Figure 4.9.2) and the phone defaulted to exclusively using autonomous GPS mode only. This degradation in performance was also noted in previous research conducted by Neale (Neale et al. 2016) and Zandbergen (Zandbergen 2016) regarding the impacts of trees and other geologic objects.

When compared to the excellent performance of the Garmin Edge 520 receiver accuracy (Figure 4.9.1 purple line), which also uses two GNSS receivers (GPS and GLONASS), it is difficult to determine the performance differences between the two like receivers without running additional smartphone testing applications concurrently with the IAD power meter application. These additional measurements on the phone could be used to determine satellite availability, received signal strength indicator (RSSI measured in -dBm) and signal interference that might have caused the errors within the GPS data.

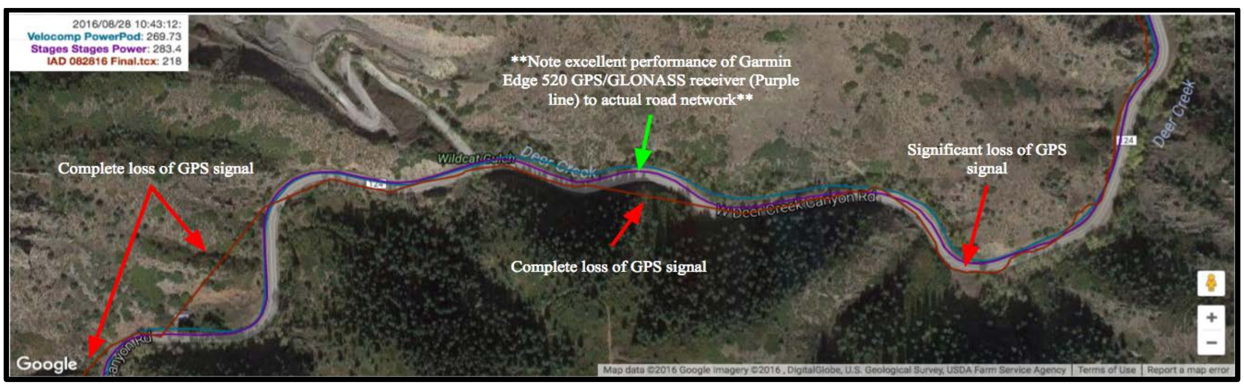

Figure 4.9.1 GPS data quality received for IAD application (Red line - GPS/GLONASS receiver in an LG G4 smartphone) compared to Garmin Edge 500 (teal line - GPS only receiver) and Garmin Edge 520 (purple line - GPS/GLONASS receiver)

Figure 4.9.2 Verizon data coverage in which A-GPS was not available for position assistance (sensorly.com)

In additional to poor GPS data and the impact on both location and speed data, the poor speed data also contributed to both under and over estimation of the power output data as shown in Figure 4.9.3. When reviewing the 3D image overlaid with the power output, a unique relationship between the canyon road and the canyon walls can be determined. For example if the road was mainly shadowed by a southern facing canyon wall, the power data consistently showed to be lower. A northern facing canyon wall had the opposite effect in overestimating the power. As the canyon walls begin to open up and allow for a higher GDOP (higher quality GPS signal) as shown in Figure 4.9.4, the IAD application performance increased with power output levels reaching closer to that of the Stages and PowerPod meters.

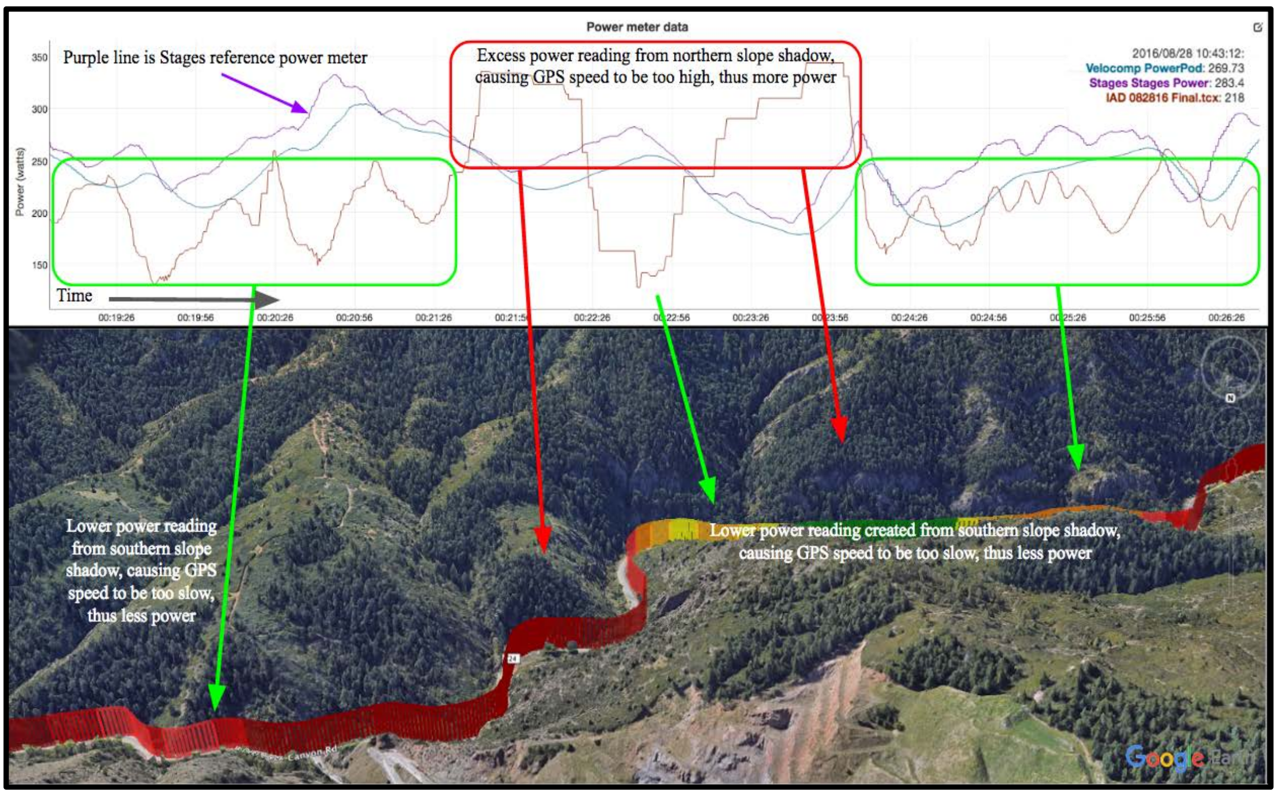

Figure 4.9.3 3D terrain view confirming weak GPS signal due to geometric dilution of precision (GDOP) within the beginning section of the climb, impacting the quality of the power output

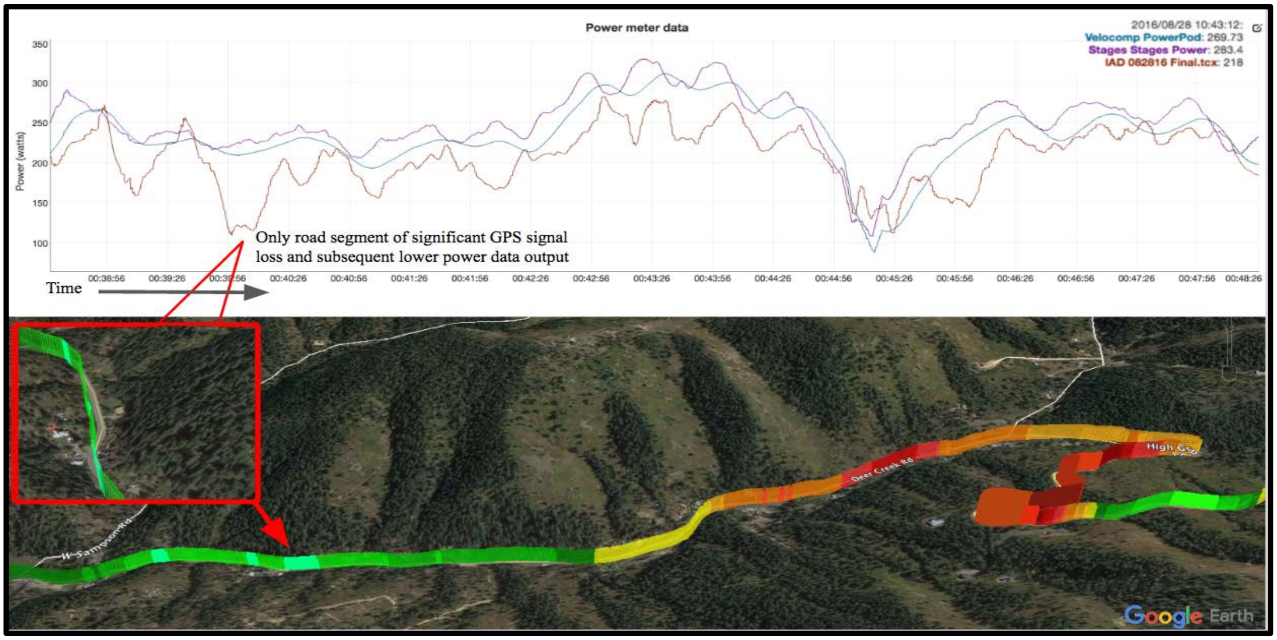

Figure 4.9.4 3D terrain view confirms higher performance for the IAD application (red line) with a higher PDOP as canyon walls open up

4.10 Comparison of GPS Road Network Accuracy

As outlined in sections 4.8 and 4.9, GPS accuracy is a very important element for providing high quality power output for the IAD power application. The PowerPod and Stage Power meters do not require GPS speed for determining power and thus the GPS road network accuracy is used only in determining the quality of the GPS receiver. As part of the overall power estimation algorithm for the IAD application (Power = Speed * Force), the importance of sampling high quality GPS positional data for determining speed can not be overlooked. For determining overall accuracy of the positional data, satellite imagery is used to assess how close the line is to the actual ride path. If the GPS data is weak or blocked by buildings, mountains or other physical features, this can have a significant impact on the overall quality of the power data. In reviewing Figures 4.10 thru 4.10.3, the IAD power meter application shows a very low degree of accuracy and is representative of the weakened GPS signal due to the canyon terrain. Also given the weak wireless data coverage as noted in Figure 4.9.2, the LG phone has difficulty in establishing a consistent and high quality position as noted below. Though the PowerPod and Stages power meter applications do not use GPS to determine power output, the power data is ultimately transmitted wirelessly, viewed and stored on a Garmin bike computer for downstream analysis by the rider. Within the study, both a Garmin Edge 500 and 520 were used to collect the Stages and PowerPod power data. The Garmin Edge 520 uses both GPS and GLONASS position sensors and for the most part shows a much better positional accuracy when compared to the both ground truth of the route as well as the LG smartphone.

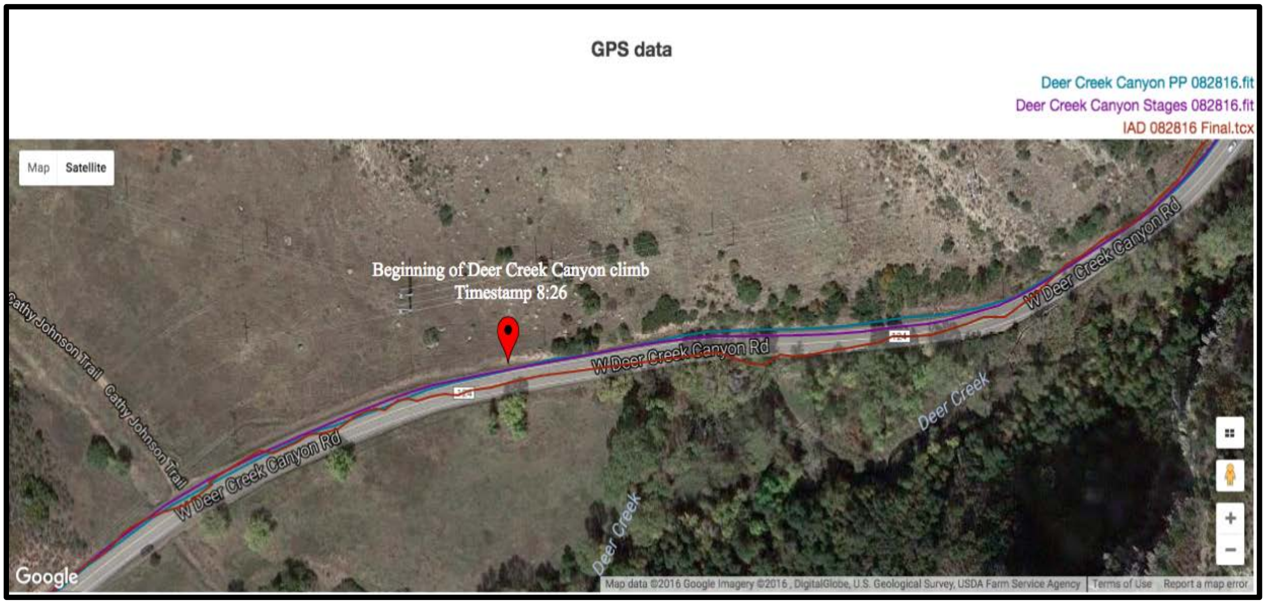

Figure 4.10 Beginning of Deer Creek Canyon climb (timestamp 8:26) with IAD applications (red line) showing the least accurate position in the bike lane and illustrates weakening of GPS signal

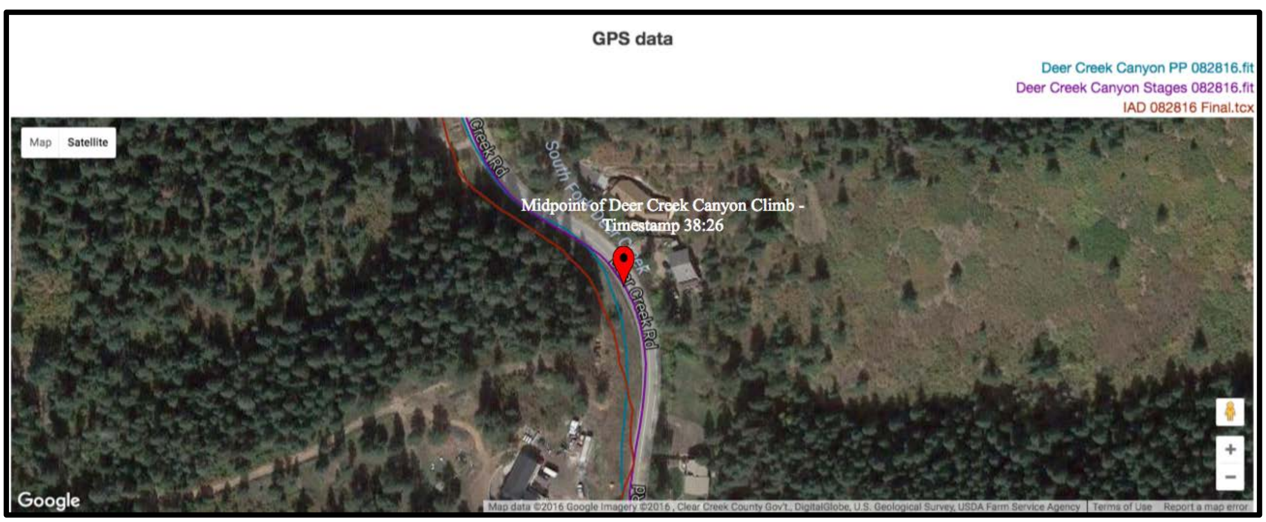

Figure 4.10.1 Midpoint of Deer Creek Canyon climb (timestamp 38:26) with IAD applications (red line) showing the most accurate position in the bike lane

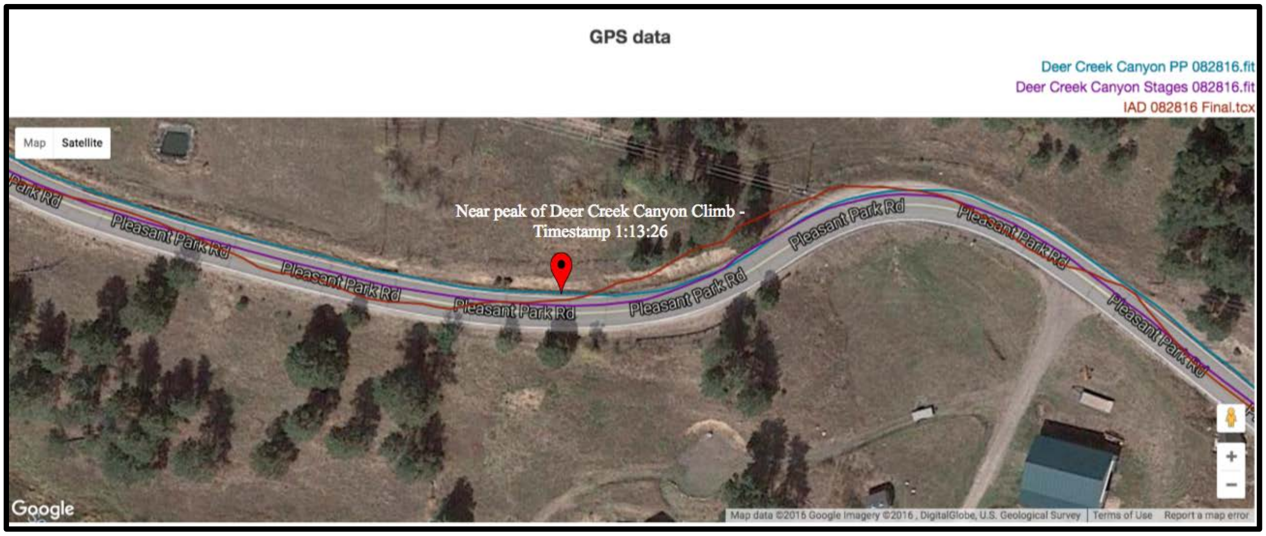

Figure 4.10.2 Near peak of Deer Creek Canyon climb (timestamp 1:13:26) with IAD (red line) showing significant GPS quality issues and Garmin Edge 520 (purple line) showing GPS drift

4.11 Comparison of GPS Elevation Accuracy Agreement

GPS elevation accuracy is another important data element for determining slope that is used in the IAD power algorithm to estimate the amount of force needed to propel the cyclist forward. As part of the overall IAD power estimation algorithm (Power = Speed * Force), the importance of sampling high quality GPS elevation data (derived using either the Google Maps Elevation API web service or the smartphone's barometer if wireless data coverage is weak) for determining elevation cannot be overlooked.

For determining overall accuracy of the elevation data, the USGS 3DEP (USGS National Map 2016) is referenced and used to compare against the elevation data collected by the various power meter applications as shown in Figure 4.11. The USGS 3DEP is a high accuracy product derived from various LiDAR collections over the last few years. Given the IAD power meter application is the only application that uses elevation for power estimation, the accuracy of the elevation data used by the IAD elevation compared to the actual USGS DEM is a very relevant data comparison over the distance of a ride. For simplicity sake in calculating total ascent, only the beginning and peak of the climb interval is used in determining the level of elevation agreement.

In reviewing Figures 4.11.1 and 4.11.2, the IAD power meter application running on the LG smartphone shows a very high degree of elevation accuracy when compared to the USGS

DEM reference. From the start of the climb, the IAD application shows an elevation of 5660 feet compared to the USGS DEM elevation of 5664 feet. Additionally the Garmin 500 (GPS only sensor) paired to the PowerPod measured 5665 feet and the Garmin 520 (GPS and GLONASS sensors) measured 5671 feet. Compared to the USGS DEM reference, all sensors had a high degree of agreement for elevation.

For the peak of the climb, the IAD application showed an elevation of 8196 feet compared to the USGS DEM elevation of 8311 feet. Additionally the Garmin 500 (GPS only sensor) paired to the PowerPod measured 8148 feet and the Garmin 520 (GPS and GLONASS sensors) measured 8156 feet. Compared to the DEM, all sensors had a lower degree of agreement for elevation accuracy with at least 115 feet of difference for the IAD application. Overall this equated to a 1.4% to 1.98% difference from the start to the near peak of the climb.

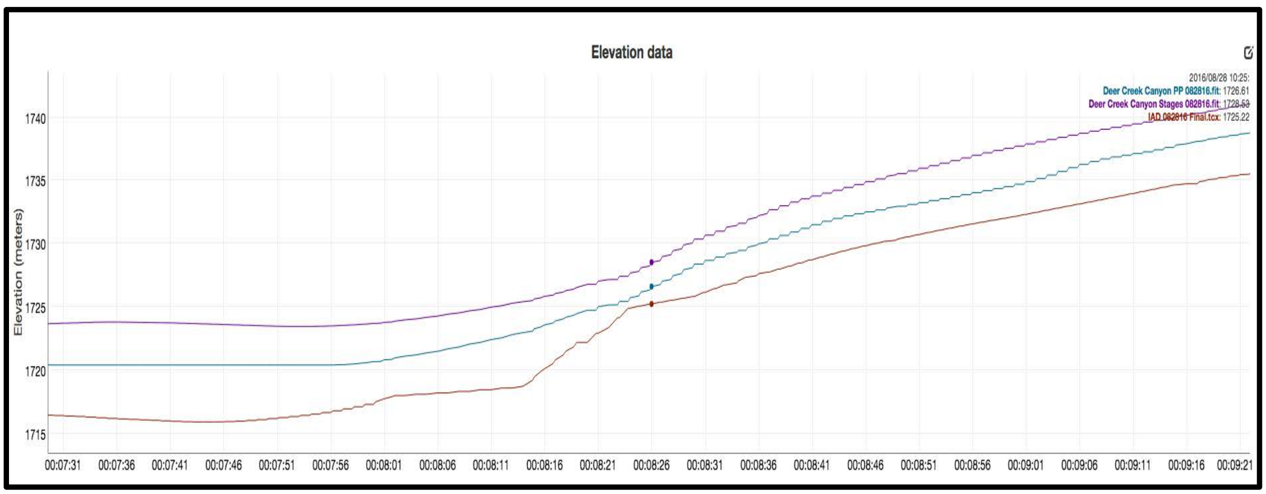

Figure 4.11 Deer Creek Canyon at beginning of climb at elevations of 5660 feet (IAD - red line), 5665 feet (PowerPod - teal line) and 5671 feet (Stages - purple line)

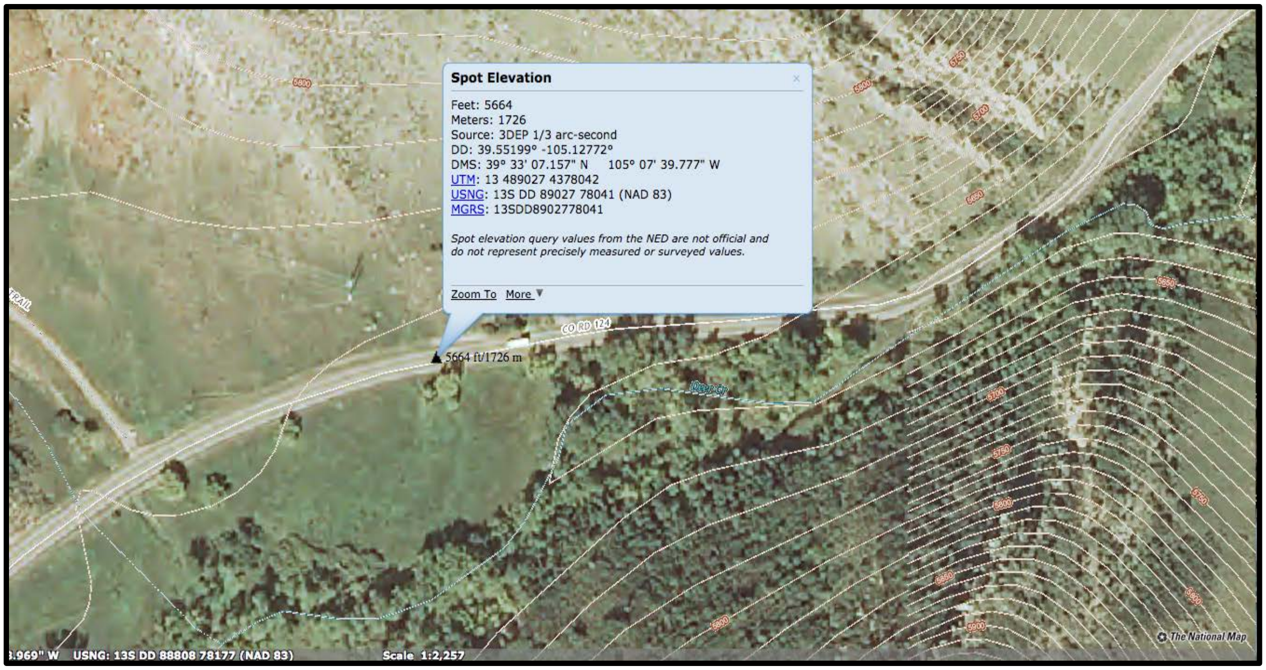

Figure 4.11.1 Deer Creek Canyon at start of climb elevation of 5664 feet using a USGS 3DEP

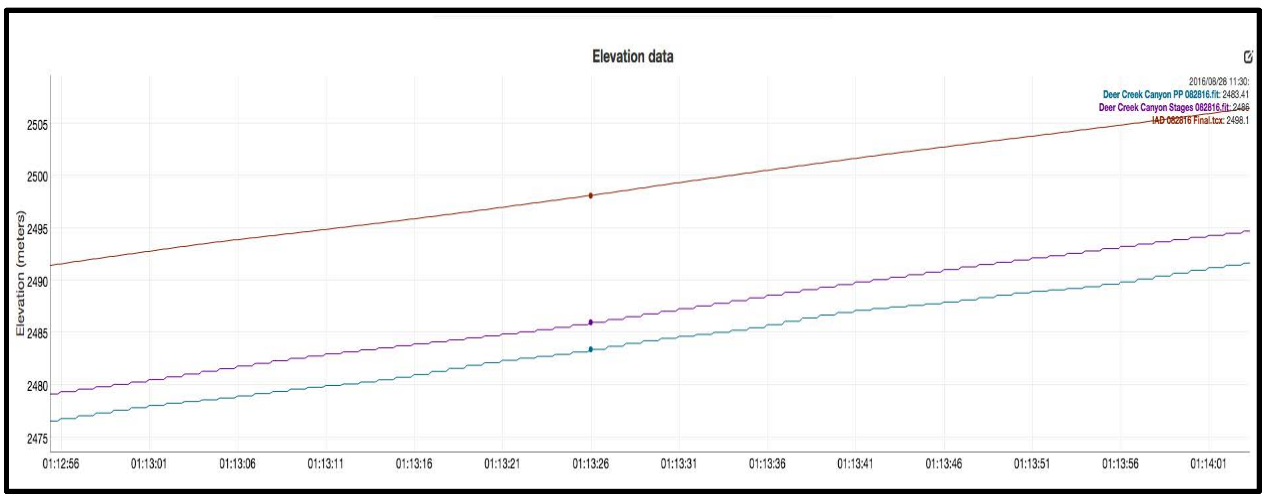

Figure 4.11.2 Deer Creek Canyon near peak of climb at elevations of 8196 feet (IAD - red line), 8156 feet (Stages - purple line) and 8148 feet (PowerPod - teal line) compared to USGS 3DEP source showing elevation of 8311 feet

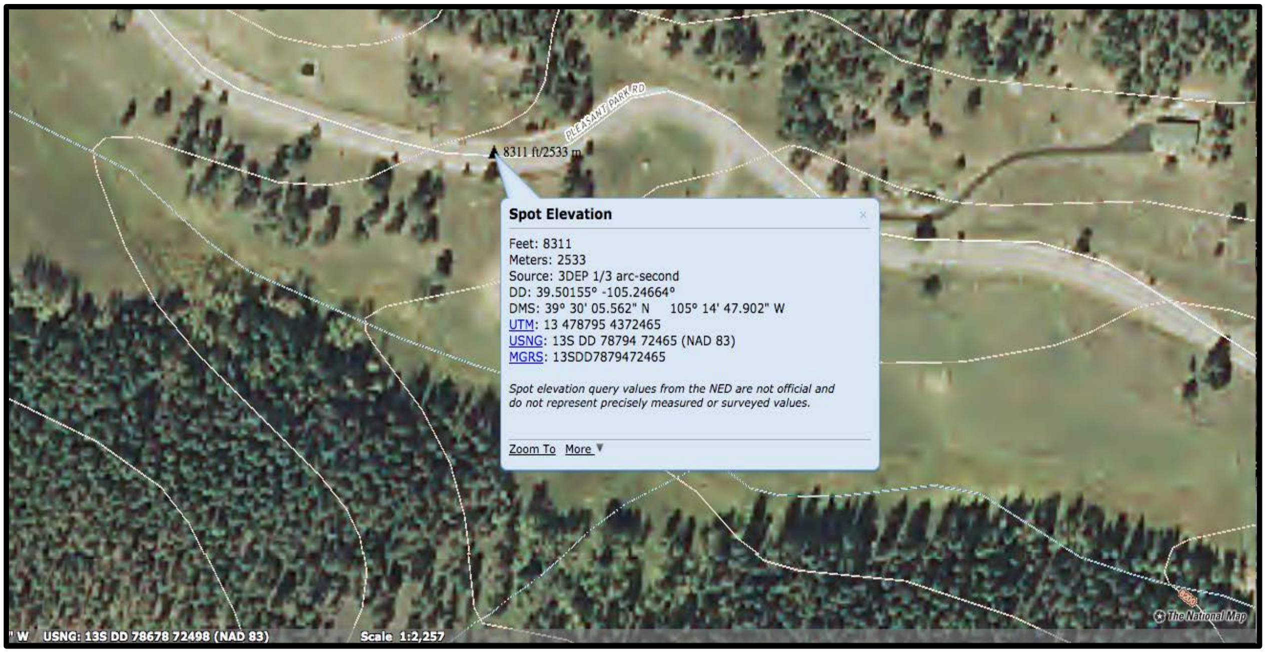

Figure 4.11.3 Deer Creek Canyon near peak of climb elevation of 8311 feet using a USGS 3DEP

4.12 Results Summary for Deer Creek Canyon route

When summarizing the results of the PowerPod power meter application to the reference power meter, the PowerPod provides measurements on average of 8.7 watts lower than the Stages reference meter and slightly above (3.92%) the +/- 2% stated accuracy (Velocomp 2016). When comparing the PowerPod meters response time to power changes, the PowerPod showed the same latency behavior as the Castle Pines North ride and typically lagged by three to six seconds in displaying a similar power output figure. Additionally the PowerPod also exhibited several excess power outputs during the descent of the climb but was outside of the study route collection. Overall, the PowerPod performed well in comparison to the Stages meter within the Deer Creek Canyon study area but was outside of the manufacturers stated accuracy metrics of +/- 2% accuracy over a DFPM power meter.

When reviewing the IAD smartphone application, the average power output over the climb was 18.7% lower than the Stages power meter. A large contributing factor was due to weak GPS signals within Deer Creek Canyon that had a large negative impact on both GPS speed and elevation data. Additionally given the route had little cellular coverage, the IAD application was unable to access elevation services via the Google Maps Elevation API or the wind speed web service used in calculating opposing wind forces. Given the Garmin 520 with GPS and

GLONASS sensors provided excellent accuracy within Deer Creek Canyon, further investigation is needed in order to better understand what attributed to the LG G4 (GPS/GLONASS sensors) shortcomings given the similarity in GNSS receiver modes. Overall the IAD application provided valuable power data for the first ten minutes of the ride until the GPS signal became too weak to provide any power output data of value.

4.13 Study Route 3: Lookout Mountain Road - Overview

The Lookout Mountain Road route is a 4.55 mile mountain climb (Figure 4.13) starting in the city of Golden, Colorado and heading west on Lookout Mountain Road (also known as Lariat Loop) as it climbs to the summit near the Buffalo Bill Memorial Museum. The route, used by many cycling enthusiast for time trialing, starts at the Lookout Mountain pillars (Figure 4.13.1) and then summits at Buffalo Bill Memorial Museum, which is used as the "finish line". The route consists of a fairly steep 5-8% road grade with an elevation gain estimated at 1,225 feet as represented in Figure 4.13.2.

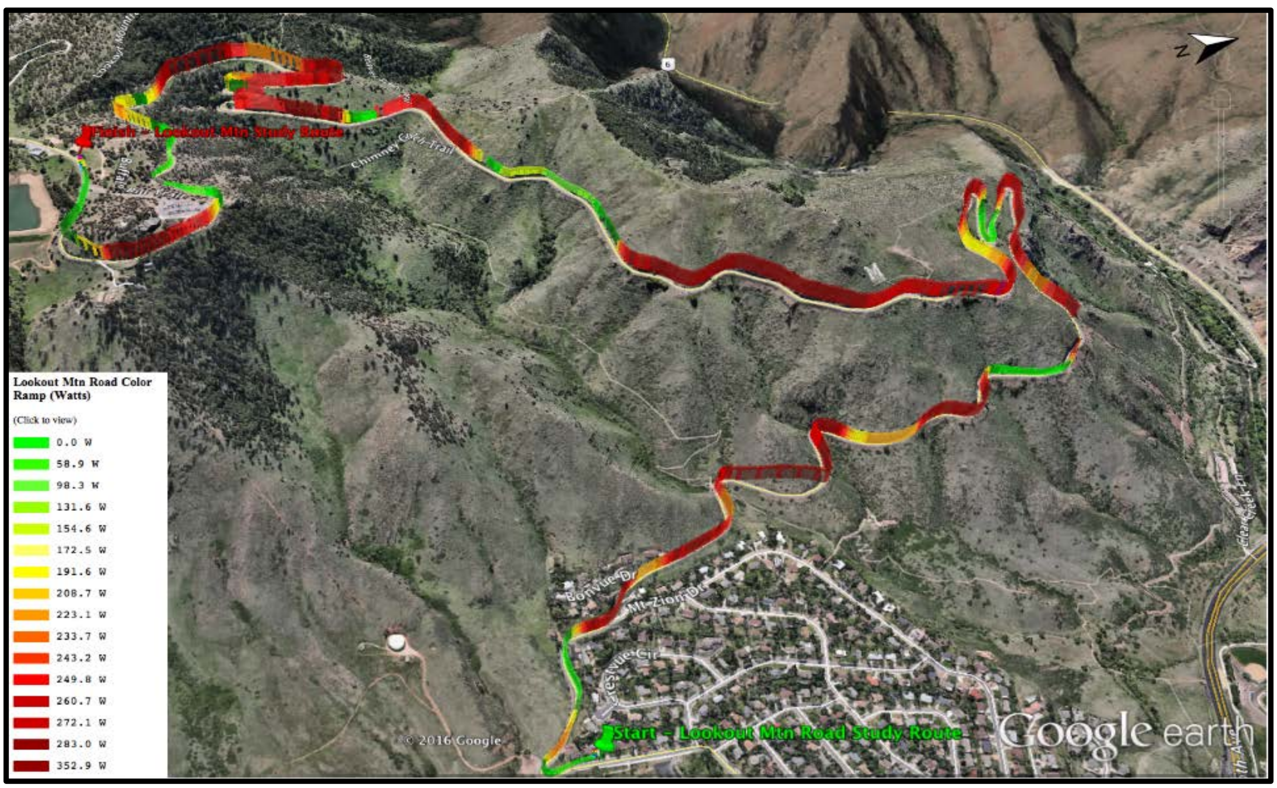

Figure 4.13 Lookout Mountain Road study route

Figure 4.13.1 Lookout Mountain Road pillar starting line for time trial (image courtesy of Pedaldancer.com)

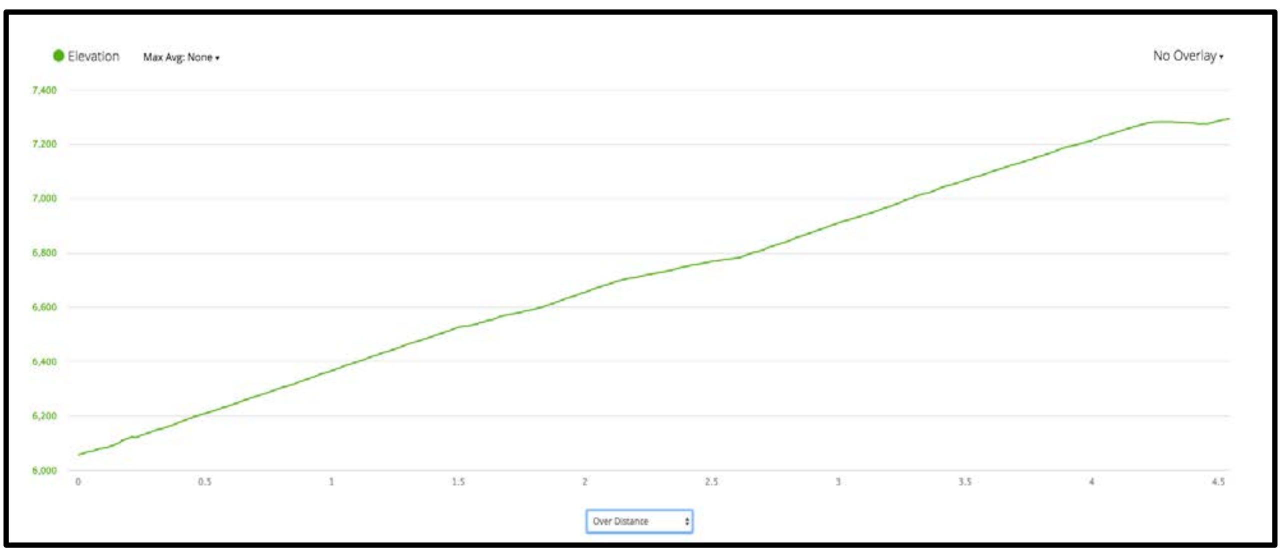

Figure 4.13.2 Lookout Mountain Road elevation profile

4.14 Comparison of Power Averages Over Reference Power Meter

The Lookout Mountain ride was conducted in twenty-seven minutes, covering 4.55 miles with an elevation gain of 1,225 feet. From the ride, the power data has been summarized in Table 14, which includes Average Power (AP), Normalized Power (NP) and the percentage differences between the Stages Power reference meter and the PowerPod and IAD power meters. When comparing the raw averages, the PowerPod is 2.3% lower than the Stages Power reference meter. The IAD application also underestimates power on average by 17.4%. When reviewing the percentage difference using the Normalized Power averaging algorithm, the PowerPod improved to just 1.3% lower than the Stages meter while the IAD application improved to 13.7%.

Table 14 Lookout Mountain Road Route - Average and Normalized Power Summary

Power Output Summary (Watts)	Stages Power - Reference Power Meter (Watts)	PowerPod Power Meter (Watts)	IAD Power Meter Application (Watts)
Average Power (Watts)	264.53 W	258.44 W	222.10 W
Normalized Power (Watts)	266.65 W	263.23 W	232.38 W
% Difference over Average Power - Reference Meter	N/A	2.3% lower	17.4% lower
% Difference over Normalized Power - Reference Meter	N/A	1.3% lower	13.7% lower

4.15 Comparison of real time power data intervals within the Lookout Mountain Road route

When reviewing the power meter data across the short distance of the route, several sections of the route seem to have also been impacted by weak GPS signals (Figure 4.15), much like what was experienced within the Deer Creek Canyon study route. Unlike the Deer Creek Canyon route, which was bound by canyons walls on both the north and south side, the Lookout Mountain route traversed various drainage area depressions that caused a lowering of GDOP. Based on the power meter readings and spatial analysis, weak GPS signals degraded the performance of the IAD application due to the shadowing effects caused by the steep east facing drainage area depressions along the route as shown in Figure 4.15.1. Given the power figures in Table 13 have been averaged with sensor data that under estimated GPS speed, a negative impact to the overall power meter performance of the IAD application was observed.

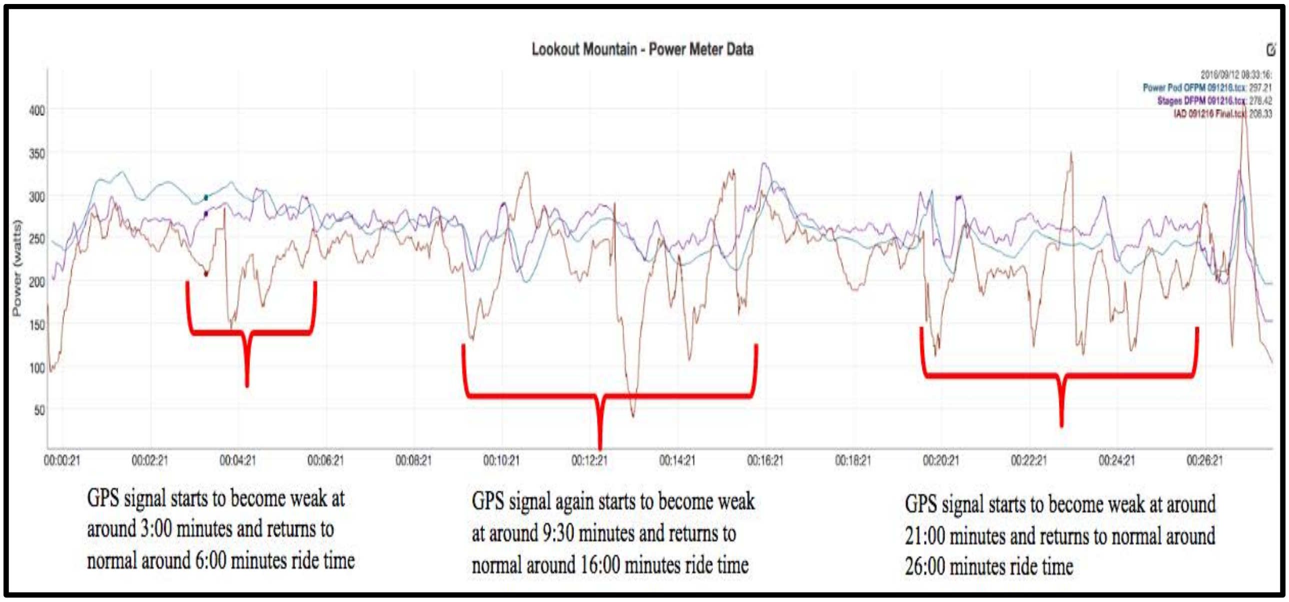

Figure 4.15 Time series data showing GPS sensor data weakening in three different sections and having a negative effect on the IAD power meter data

At approximately three minutes into the ride, the IAD application starts to behave in an inconsistent manner in which power output data is not provided to the IAD application due to a complete loss of GPS position data, thus impacting the ability to derive an accurate speed and subsequent power output. When reviewing the raw GPS data overlaid on top of Google Earth 3D imagery (Figure 4.15.1), it becomes apparent that the GPS signal being received by the LG GPS/GLONASS smartphone receiver is being impacted by the east facing canyon walls of Lookout Mountain.

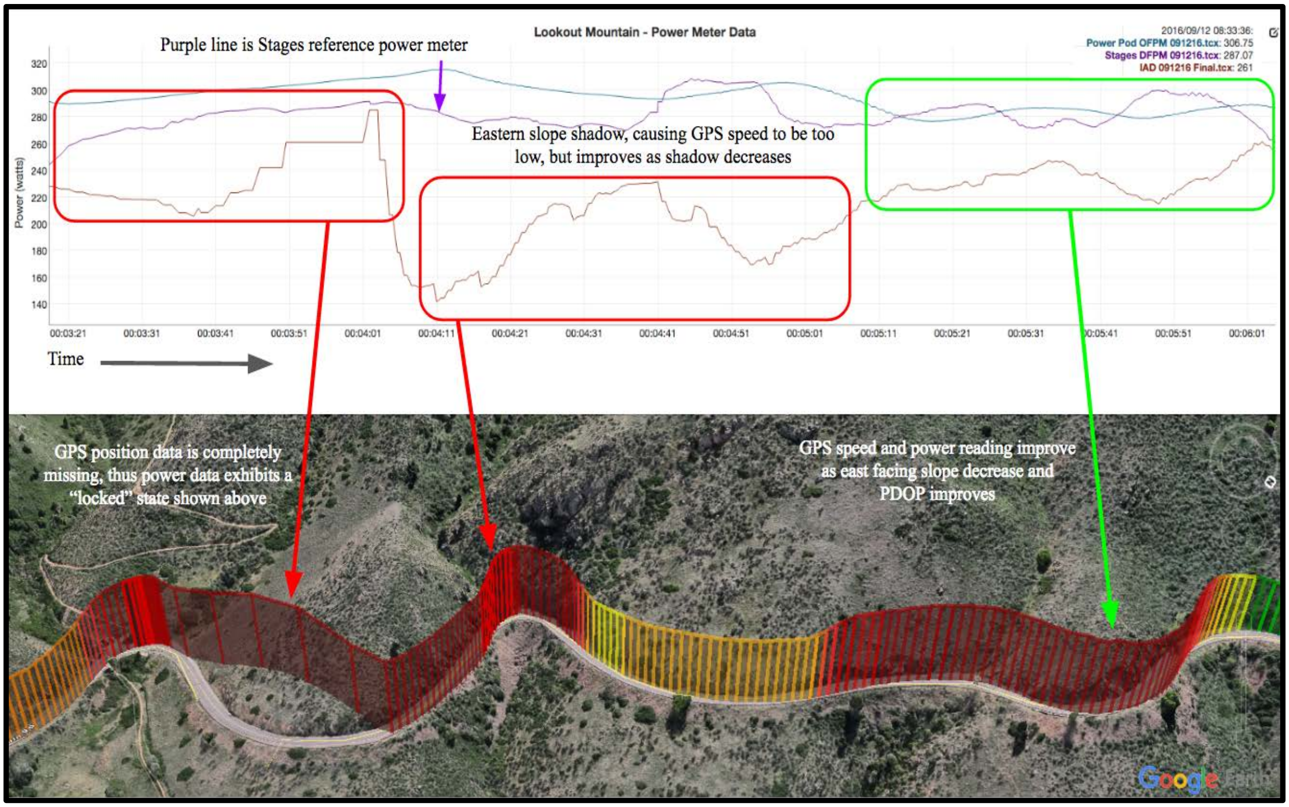

Figure 4.15.1 Lookout Mountain Road route showing impact of GPS signal loss from east facing mountain slope

In the case of the GPS receiver within the LG smartphone, the receiver seems challenged in providing a consistent and high quality GPS location using the Assisted GPS (A-GPS) capabilities that are augmented by the cellular network infrastructure. Given the location of the smartphone at the time of the received GPS signal, wireless data coverage and subsequent positional assistance was available (Figure 4.15.3) but did not seem to have an impact on improving the GPS data made available to the IAD application.

When compared to the excellent performance of the Garmin Edge 520 receiver accuracy (Figure 4.15.2 purple line) which also uses two GNSS receivers (GPS and GLONASS), it is difficult to pinpoint the performance differences between the LG and Garmin 520 receivers without running additional testing applications concurrently with the IAD power meter application. These additional measurements on the phone could be used to determine satellite availability, received signal strength indicator (RSSI measured in -dBm) and signal interference that might have caused the low GDOP readings.

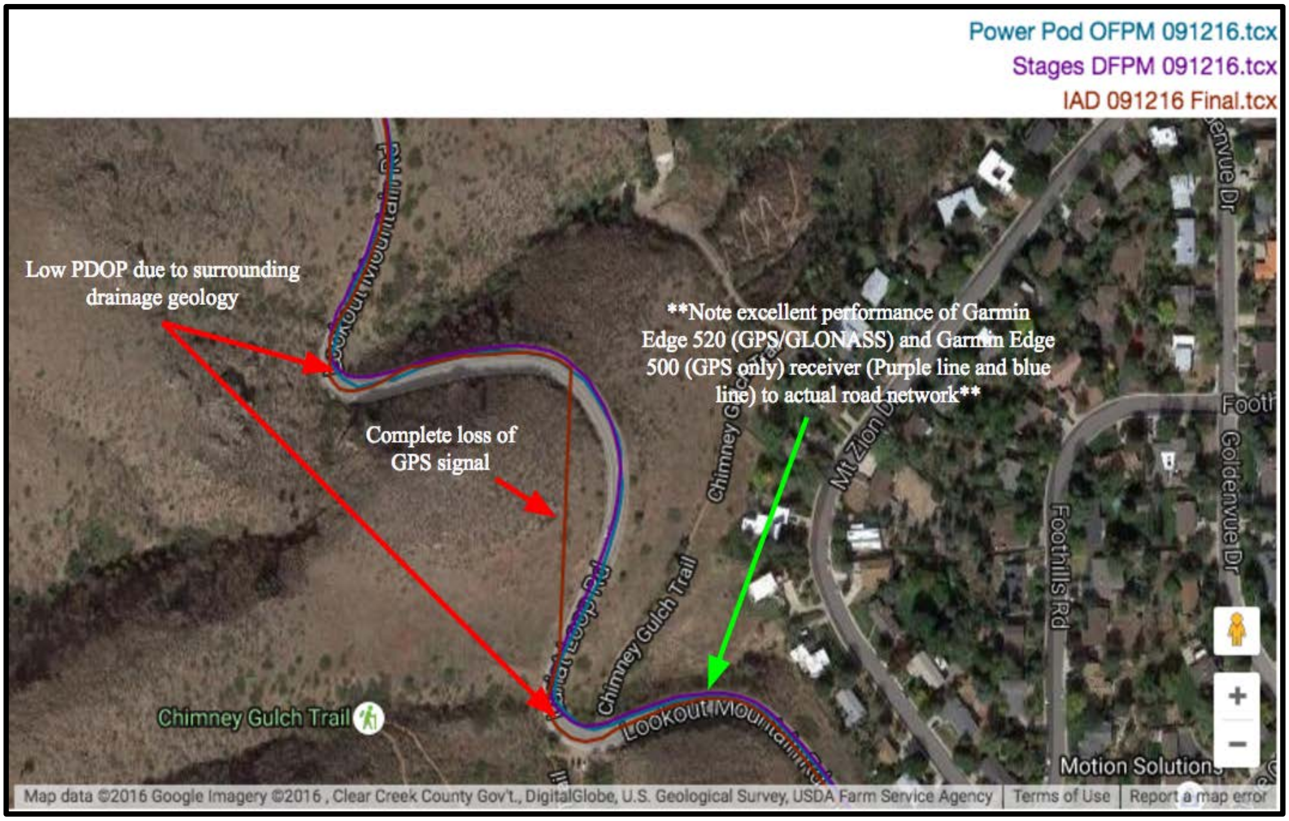

Figure 4.15.2 GPS data quality received for IAD application (Red line - GPS/GLONASS receiver in an LG G4 smartphone) compared to Garmin Edge 500 (teal line - GPS only receiver) and Garmin Edge 520 (purple line - GPS/GLONASS receiver)

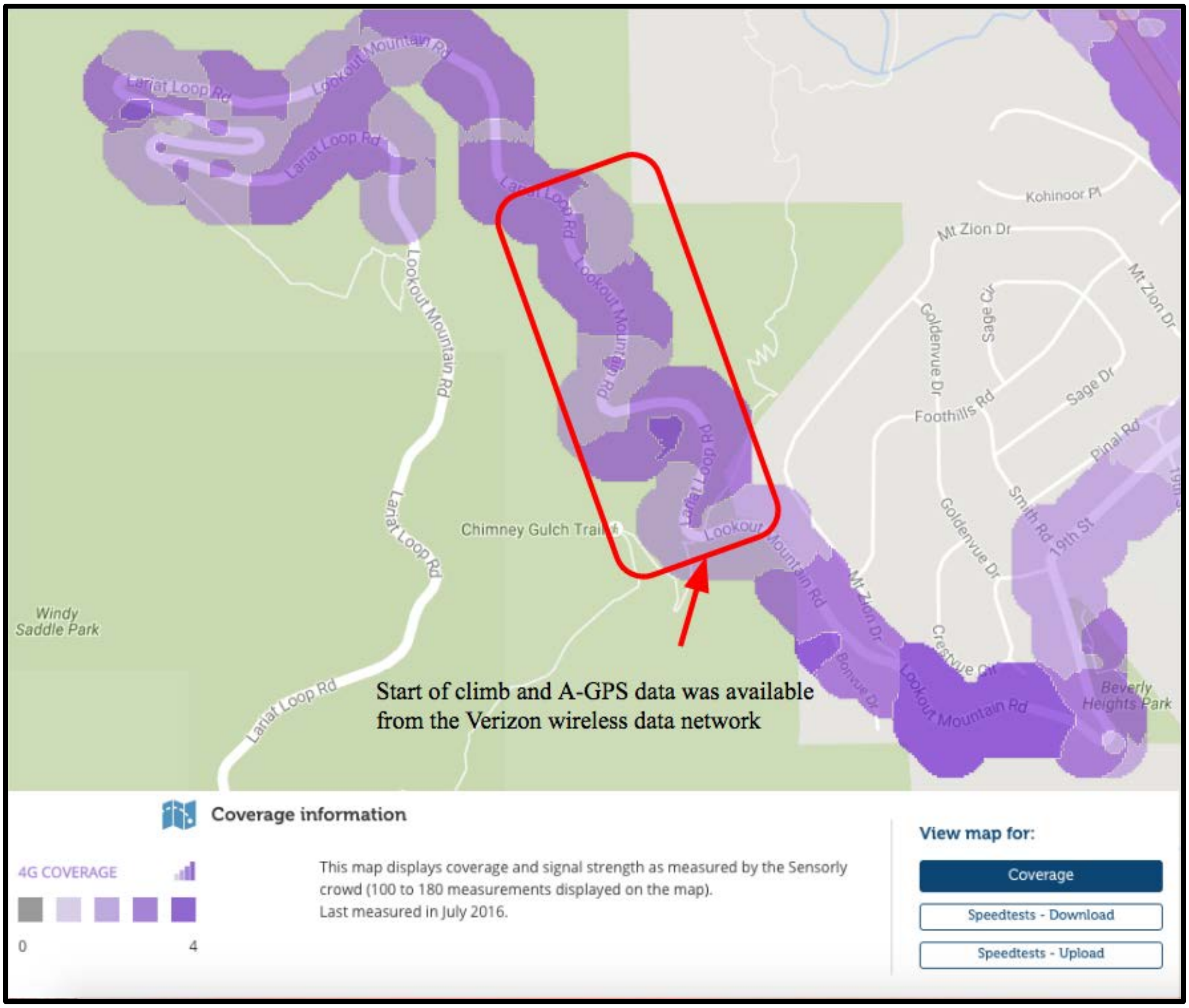

Figure 4.15.3 Verizon data coverage in which A-GPS was available for assistance but overall position data is missing for several segments (source sensorly.com)

4.16 Comparison of GPS Road Network Accuracy

As outlined in previous sections, GPS accuracy is a very important element for providing high quality power output data for the IAD power application. In reviewing Figures 4.16 thru 4.16.1, the IAD power meter application shows a very low degree of accuracy and is representative of the weakened GPS signal due to the drainage area terrain. Also given the weak wireless data coverage as noted in Figure 4.9.2, the LG phone has difficulty in establishing a consistent and high quality position as noted below.

Figure 4.16 Beginning of Lookout Mountain Road climb showing all receivers experiencing possible GDOP effects due to weak GPS signals

Figure 4.16.1 Midpoint of Lookout Mountain Road climb (timestamp 13:22) with Garmin 520 (purple line) showing the most accurate position in the bike lane with Garmin 500 and LG G4 positions >2 meters from the actual location

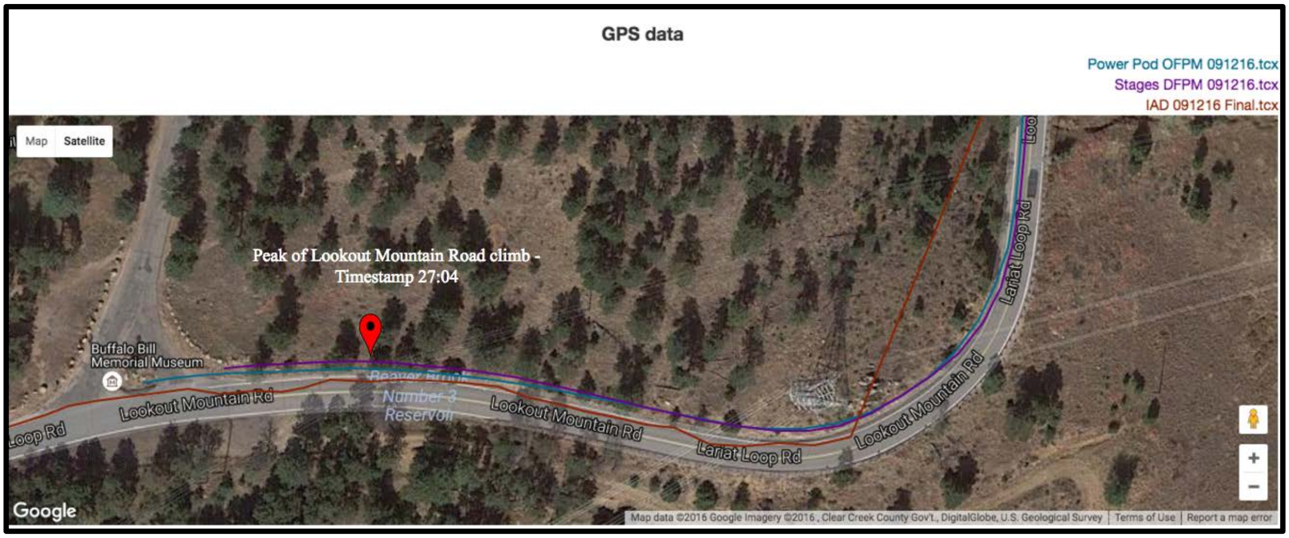

Figure 4.16.2 Peak of Lookout Mountain Road climb with LG G4 (red line) showing significant GPS quality issues and Garmin 500 (teal line) and Garmin Edge 520 (purple line) showing some level of GPS quality <3 meters

4.17 Comparison of GPS Elevation Accuracy Agreement

For determining overall accuracy and agreement of the elevation data, the USGS 3DEP is used again to compare the elevation data collected by the three power meter applications as shown in Figure 4.17. Given the IAD power meter application is the only application that uses elevation data as part of the power estimation algorithm, the accuracy of the elevation data is critical in providing an accurate power output over the distance of a ride. For simplicity sake, only the beginning and peak of the climb intervals are used in determining the level of elevation agreement and accuracy.

In reviewing the beginning of the climb at timestamp 0:36 seconds (Figures 4.17.1), the IAD power meter application (red line) and the Garmin 500 (teal line) show a very high degree of elevation agreement at 6053 feet each, with the Garmin 520 (red line) showing a higher elevation of 6069 feet. When compared to the USGS 3DEP reference of 6065 feet (Figure 4.17.2), the elevation data from the Garmin 520 is within 4 feet of the stated elevation using the USGS 3DEP and 12 feet from the IAD and PowerPod elevation estimates. Compared to the USGS DEM reference, all sensors have a high degree of agreement and accuracy given the steep slope of Lookout Mountain.

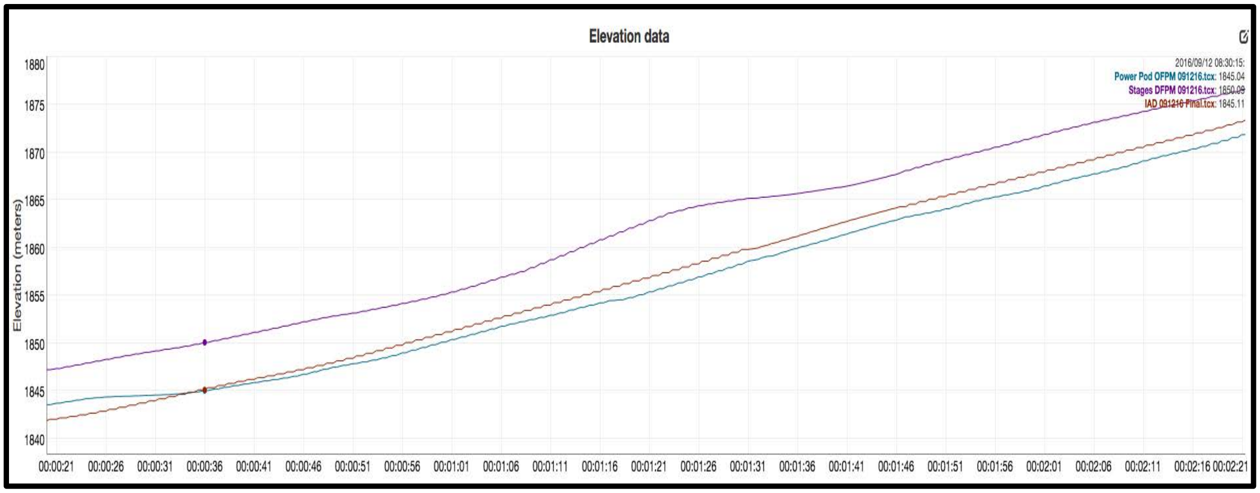

Figure 4.17 Lookout Mountain Road beginning of climb elevations of 6053 feet (IAD - red line), 6053 feet (PowerPod - teal line) and 6069 feet (Stages - purple line)

Figure 4.17.1 Lookout Mountain Road start of climb elevation of 6065 feet using a USGS 3DEP

For the peak of the Lookout Mountain Road climb, the IAD application shows an elevation of 7286 feet compared to the DEM elevation of 7307 feet. Additionally the Garmin 500 paired to the PowerPod measured 7253 feet and the Garmin 520 (GPS and GLONASS sensors) measured 7278 feet. Compared to the DEM, all sensors had a lower degree of agreement for elevation with 21 feet of difference for the IAD application. Overall this equated to a 0.28% to

0.74% difference at the peak of the climb and a high degree of accuracy given the steep relief and slope of Lookout Mountain.

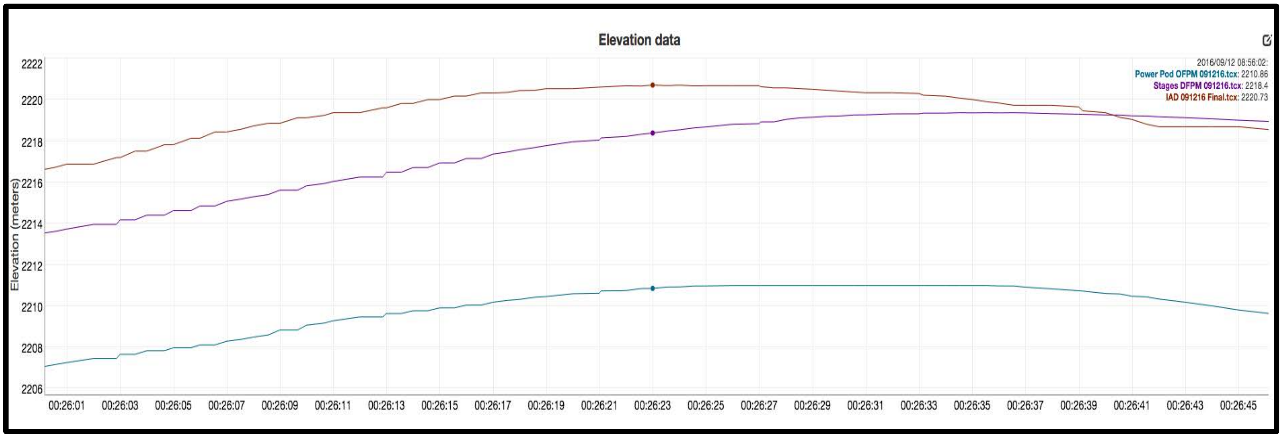

Figure 4.17.2 Lookout Mountain Road peak of climb with elevations of 7286 feet (IAD - red line), 7278 feet (Stages - purple line) and 7253 feet (PowerPod - teal line) compared to USGS 3DEP source showing elevation of 7307 feet

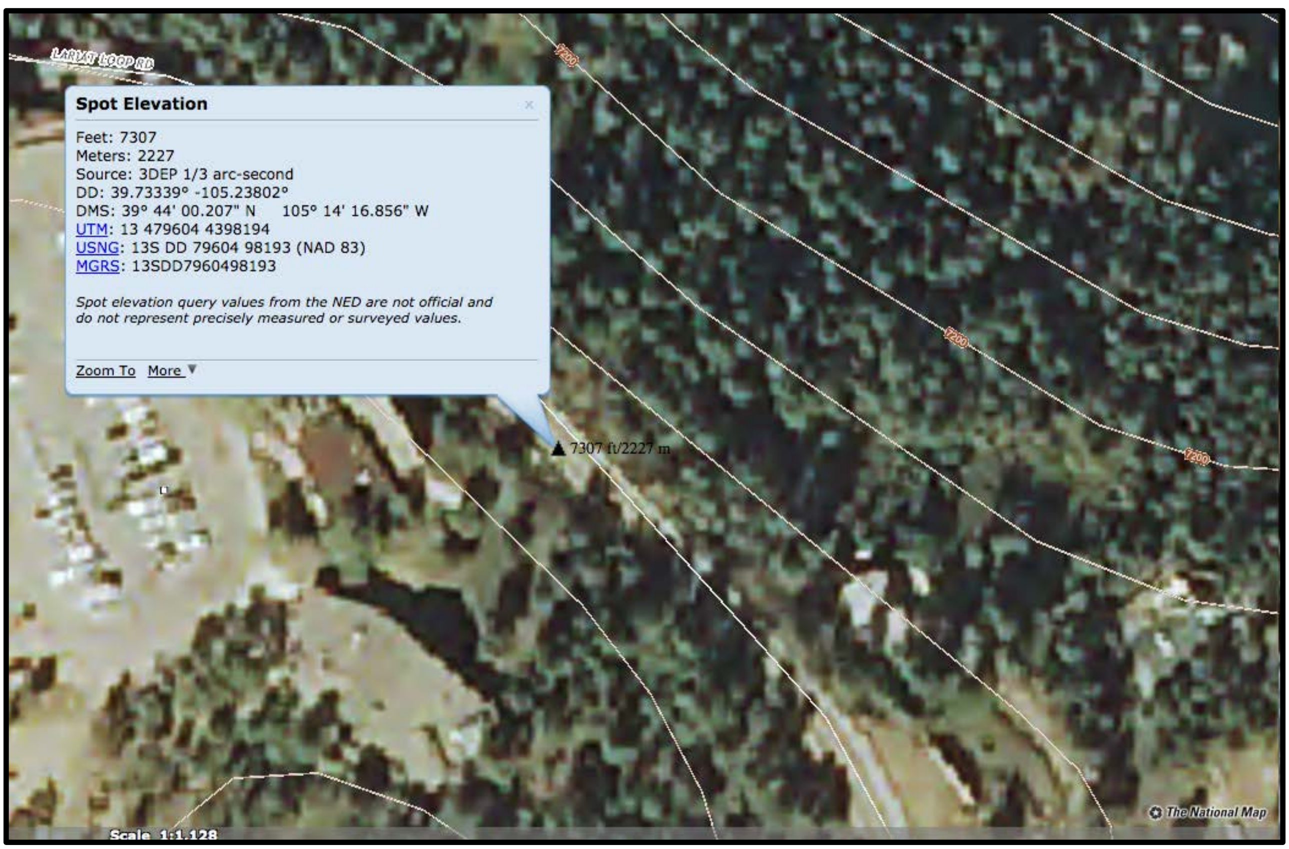

Figure 4.17.3 Lookout Mountain Road peak of climb (timestamp 26:23 min) at an elevation of 7307 feet based on the USGS 3DEP

4.18 Results Summary for Lookout Mountain Road route

When summarizing the results of the PowerPod power meter application to the reference power meter from Stages Cycling, the PowerPod provided measurements on average 6 watts lower (2.3%) than the Stages reference meter and within the product specification of +/- 2% power accuracy over a DFPM system. When comparing the PowerPod meters response time to power changes on the Stages DFPM, the PowerPod exhibited the same latency characteristics as witnessed on both the Deer Creek Canyon and Castle Pines North rides. Latency typically ranged from three to six seconds in displaying a very similar power output figure that is indicative of a DFPM system. The PowerPod also seemed to overestimate power output in the beginning interval of the climb but recovered at 4:30 minutes into the ride and performed well to the summit of Lookout Mountain Road. Overall, the PowerPod performed as expected when compared to the Stages power meter and within the manufacturer's stated accuracy metrics of +/- 2% accuracy over a DFPM power meter.

When reviewing the IAD smartphone power application, the average power output over the climb was 17.4% lower than the Stages power meter. Like the Deer Creek Canyon study route, a contributing factor to the lower power output figures was due to weak GPS signals near the drainage depressions that caused a lower GDOP as noted in Figure 4.15. This caused a negative impact on both GPS speed and elevation data. Though most of the route had wireless data coverage, the LG G4 smartphone was unable to access quality location data and thus had a negative impact on the overall performance of the IAD application. Further investigation is needed to better understand what attributed to the location shortcomings of both the LG G4 and Garmin devices. Overall, the IAD application provided accurate power data when the GPS signal was strong compared to both the Stages and PowerPod systems. Future considerations for the IAD application would be to use an external speed and cadence sensor to offset any negative impacts caused by weak GPS signals.

Chapter 5: Conclusions and Future Considerations

This chapter summarizes the results of the power meter study, as well as presents a number of different opportunities and conclusions for using smartphone and opposing force power meters (OFPM) as a potential “poor man’s” power meter for road cyclist. The findings from the field study will be discussed in the first section, followed by the successes, shortcomings and sources of error for the sensor technologies used in the study. A SWOT analysis will conclude the chapter by determining which sensors and subsequent power meter technologies are best suited for a cyclist needs with regards to accuracy, budget considerations and ease of use. The chapter will conclude with thoughts on smartphone sensor improvements, crowd sourced power data, and machine learning technologies that could ultimately displace costly DFPM systems.

5.1 Findings

The overall testing methodology used in this field study resulted in a deeper understanding and appreciation of:

1. The power accuracies that can be achieved using sensors found in everyday smartphones or via alternative approaches using opposing forces sensors for determining power output
2. The limitations of using these sensor types
3. The price/performance benefits realized with each sensor technology

When reviewing the PowerPod power data using average power (AP) across all three (3) study routes, the level of accuracy achieved was outstanding at just 1.13% higher than the Stages reference power meter. The IAD power meter also performed quite well at just 9.15% lower than the Stages power meter. Upon reviewing the power data using the Normalized Power (NP) algorithm, the PowerPod performed at an amazing 0.86% higher than the Stages power meter and 10.25% higher for the IAD application. But as discussed in Chapter 4 results section, using averaging algorithms for side-by-side comparison provides little value to cyclist using power data for understanding the “real time” level of effort being expended while riding.

When comparing against the Stage Cycling power meter, the PowerPod provided the closest real time power metrics, limited only by three to six seconds of latency from when the effort was expended to when the power data was visible on the Garmin Edge cycling computer. Additionally the PowerPod had a tendency to overestimate power output in fast and rapid descents in which little to no effort was being expended but would eventually correct the power output calculations after five to ten seconds as shown in the chapter 4 results.

The IAD application performed per the developer's specification of having a +/- 15% average difference compared to a typical DFPM power meter. When the IAD application had access to high quality GPS speed input from the LG smartphone and had wireless data coverage, the application performed better than the developer’s specification of +/- 15% accuracy over a DFPM system.

Most of the IAD’s technical challenges came from the LG smartphones GPS/GLONASS receiver that was not providing high quality position and speed data to the application. Many times within the mountain routes (Deer Creek Canyon and Lookout Mountain Road) the phone's sensors either provided a lower quality reading or did not provide a reading at all. This observation was also concluded by Zandbergen’s research regarding the positional accuracy of A-GPS from mobile phones (Zandbergen and Barbeau 2011) as outlined in chapter 2.

Overall, this significantly impacted the overall performance of the IAD application and was difficult to determine the exact reason for position data loss without having additional GPS applications running concurrently to validate GDOP and signal quality levels.

When reviewing the findings along the dimension of price/performance, the PowerPod system retailing at $249.00 is hands down the best value for any serious cyclist who rides several times per week. The PowerPod system is very affordable, provides very accurate quasi-real time performance (taking into account the three to six seconds of power display latency), portability from bike to bike and is relatively easy to setup and configure when compared to a DFPM power meter system.

The IAD power meter application also provides a great value at just $7.00 and can be downloaded to any smartphone from either the Android Play Store or Apple App Store. The application provides by far the best value for any recreational cyclist looking to train with power data, but doesn’t have the budget to spend on higher priced systems. As long as the smartphone is within wireless data coverage and in areas in which the GPS signal can’t be compromised, the overall results will provide value to any cyclist and validates the hypothesis that a smartphone can be used as a “poor man’s” power meter as contemplated in the introduction to the research.

5.2 Successes and Failures of Testing Methodology

Setting up an “end to end” power output data collection pipeline for all three power meters involved careful planning, setup, configuration, collection and analysis using a variety of different tools, many of which didn’t provide all the required analytics in one product. Setting up the test bike with all three power meters proved to be straightforward but required a bike mechanic to remove the existing crankset and replace it with the Stages Cycling power meter. After installation, the Stages crankset was paired to the Garmin Edge 520 bike computer following the YouTube instructions provided on the Stages website.

Installation of the PowerPod meter also proved to be straightforward but required an additional handlebar mount in which the sensor pod was installed underneath the Garmin Edge 500 bike computer. Pairing required establishing an ANT+ wireless data connection between the PowerPod and the Garmin speed/cadence sensor on the bike as well as pairing with the Garmin Edge 500 bike computer. The directions provided were vague and required additional emails to the Velocomp support team who eventually answered the questions. The pairing process also proved challenging and requiring several resets to establish connections and get the system working. Once paired, the PowerPod required a calibration ride that lasted for approximately ten minutes, at which time the power meter was ready for use. Overall the installation process is for the technically savvy and would prove frustrating to many users not familiar with Garmin bike computers, sensors and the ANT+ power and speed/cadence sensor pairing process.

The IAD application required very little setup effort except to download the application onto the phone and enter in the appropriate user fields including rider weight, total bike weight, drag coefficient (predefined setting of 4.0 based on bike type) and file output type (.tcx file format was selected) for post ride analysis. Once the rider profile was saved, the application was ready for use.

After completing the power meter setup on the bike, the remaining steps involved setting up user and device profiles for which the field collected data was downloaded from the Garmin Edge 500 and 520 bike computers into the Garmin Connect portal. The Garmin Connect application was primarily used for storing the ride data, mapping the start and end points of a study route, generation of elevation profiles and exporting .fit files for use in the DC Rainmaker Analyzer tool. Other analysis tools used in the data collection process included Isaac (PowerPod analysis tool) for the creation of .kml file exports for viewing the power meter data in Google

Earth as well as USGS and Douglas County GIS portals for comparing elevation accuracies to the stated elevations from the IAD app and Garmin bike computers.

The biggest challenge within the testing methodology came when the testing data either became corrupted or the application crashed while riding. Several times during the early data collection process the IAD application would crash, leaving no data from the study route and therefore could not be used. Other challenges included the amount of time it would take from data collection, download and processing in the early stages of collecting field data. Gaining early access to the DC Rainmaker Analyzer tool improved the entire data pipeline creation process from hours to just 20 minutes.

5.3 Sources of Error

During the data collection phase across all three routes, it wasn't apparent that numerous errors were being introduced into the data fields until after the data was post processed and analyzed. Listed below are the largest known sources of error uncovered during the study.

1. GPS data weakened by surrounding geology within the study route. Largest impact was reflected in the IAD power results due to various mountain canyons in which the LG GPS receiver was not well suited for. Further analysis is needed to directly understand why the LG smartphone struggled in low GDOP areas while the Garmin 520 showed exceptional position accuracy. These results also concur within the research completed by Paul Zandbergen and Sean Barbeau in 2011 that showed varying degrees of horizontal position accuracy depending on how fast an object was going or whether it was being used indoors. More recent research by Neale and team (Neale et al. 2016) also concluded that both GPS signal loss and GPS sampling rate had the highest impact on overall accuracy and performance when compared to a set of known reference standards.
2. Inaccurate cadence data estimated by accelerometers used by the IAD application. Largest impact was on the IAD application, which uses cadence rpm to estimate power output. For the Lookout Mountain Road ride, cadence rpm was underestimated. Overestimation occurred for both the Deer Creek Canyon and Castle Pines North routes. Impact to overall results can't be determined without further analysis in removing the LG accelerometer sensed cadence data and replaced with actual Garmin cadence data and the power

algorithm re-run to compute new power outputs to determine if the power output data would more closely represent that from the Stages or PowerPod system.

3. Not using dual GNSS receivers for both Garmin bike computers. The Garmin Edge 500 was limited by being a GPS receiver only, thus potentially impacting the quality of the road network accuracy.
4. Loss of Verizon wireless data network coverage for use in both A-GPS position augmentation as well as elevation and wind services. Largest impact reflected in the IAD power results but degree of accuracy impact is unknown due to the proprietary algorithms used within the IAD application.
5. Accurate elevation data for top of Deer Creek Canyon ride. USGS 3DEP DEM and IAD show a minimum of 115-foot difference. Impact to overall IAD power results unknown.

5.4 SWOT Analysis

The SWOT analysis in Table 15 provides a summary from both the observations and data captured during the two-month field data collection process. It is meant to serve as a way for cyclist to quickly understand the strengths and weaknesses of each of the power meter systems and determine if a specific system is better suited for a riders individual needs. Though the data was only collected using one rider over three study routes, the analysis and observations provided still hold true, several months after the formal data collection process concluded.

Table 15 SWOT analysis for cyclist looking to determine which power meter system best meets their needs using the results from the field study

SWOT Analysis	Stages Power Meter	PowerPod - OFPM	IAD - Smartphone App
Strengths	1. Highest level of power accuracy - thus used as the reference in the study 2. Immediate power output readings 3. Doesn’t rely on external GPS or cadence sensors 4. Many crankset options including Shimano, SRAM and FSA	1. High accuracy power data for <$250.00 investment 2. Ease of installation on handlebars 3. Portability from bike to bike 4. Isaac software provides for great post ride analysis 5. Small, lightweight pod 6. Cool technology	1. Works with any smartphone 2. Price point of $7.00 3. Provides cyclist mass market with access to power information 4. Ease of installation and user field setup
Weaknesses	1. Price point of >$530.00 for access to highest	1. Latency from effort expended to power display on bike	1. +/- 15% accuracy might not be good

	quality power data 2. Left side power only 3. Installation process 4. Not easily portable from bike to bike 5. Recalibration over time	computer (3-6 sec) 2. High power readings during quick descents 3. Pairing process to speed/cadence meter 4. Customer support - took too long to get questions answered 5. Small buttons for pairing process	enough for some cyclist 2. Viewing of power data on smartphone is difficult 3. Cadence data was too noisy and not reliable 4. No option to pair BLE heart rate monitor
Opportunities	1. Deeper integration into existing crankset components 2. Price point <$400.00 for greater market adoption	1. Support Bluetooth so pod can be set up using phone 2. Smaller form factor 3. Building awareness at grassroots level	1. Offer option to pair IAD app with BLE cadence sensor for higher quality data 2. Product awareness to the masses
Threats	1. Competitive products with lower price points <$300.00 2. If power meters become features of crankset suppliers vs aftermarket	1. DFPM meters <$300 2. Smartphone power meters get within 5-7% accuracy of PowerPod 3. Awareness of accuracy that can be achieved using PowerPod	1. Other power meter app providers with higher accuracies 2. Lack of awareness causes product to stall

5.5 Future Considerations

Much like the early days when skeptics thought a smartphone would never be able to provide turn-by-turn navigation as good as an in-vehicle navigation system, the advancements of both smartphone navigation apps and sensor technology have disrupted the need for an embedded in-vehicle navigation system. Given the accuracy and price point (free) of navigation apps like Google Maps, the market for in-vehicle navigation has collapsed and is only found today in the most expensive vehicles.

A parallel analogy can also be drawn with regards to how smartphone applications and sensor technology will continue to close the performance gap over expensive DFPM systems. Though the accuracy will always be a source of debate among the cycling elite, a real market opportunity exist with getting power meter apps into the hands of cycling's massive recreational market.

In this study, we evaluated both smartphone and OFPM based power meters and determined the areas in which improvements could be made as noted in the SWOT analysis. One clear area of improvement that will help the advancement of future power applications is improvements of position sensors that are embedded in smartphones. As shown in the field results, the IAD application (as well as other smartphone based power meters) relies heavily on accurate GPS position and speed readings in order to provide the most accurate power calculations. Future improvements in receiver sensitivity, increased sampling rates (Neale 2016), ability to handle lower GDOP signals, and other position sensor optimizations are necessary for a smartphone power meter application to perform near the level of a DFPM or OFPM system.

Other possible considerations for the IAD application would be to consider using the phone's accelerometer data in which to provide an Enhanced 911 (E911) assistance services. The application could detect large changes in both speed (going to zero) and G-forces to indicate that the rider has potentially crashed or been hit by a vehicle and the application could assist in dispatching emergency services to the last known GPS position of the rider.

Future improvements and considerations also extend from the power meter device into fitness web services that support the capture and analysis of rider/user generated content (UGC) of power data. Companies such as Strava have already started using cloud-based machine learning to provide estimations of power output based on user uploaded data. As with any machine-learning algorithm, the more subject data the algorithm as to learn from, the better the power estimations become.

In the next few years, new data driven companies are poised to monetize position, speed and elevation data into new “power meter as a service” offerings when connected to a smartphone or bike computer. As these new business and technology models develop, they hold great promise to continue the advancement of the cycling power meter market and challenge the incumbent DFPM suppliers on accuracy, price and innovation.

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