METHODS FOR THE IMPROVEMENT OF POWER RESOURCE PREDICTION AND RESIDUAL RANGE ESTIMATION FOR OFF-ROAD UNMANNED GROUND VEHICLES

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Declaration

I declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the original work of the author. The thesis has not been previously submitted to this or any other university for a degree, and does not incorporate any material already submitted for a degree.

Tom Webber, July 2016

Abstract

Unmanned Ground Vehicles (UGVs) are becoming more widespread in their deployment. Advances in technology have improved not only their reliability but also their ability to perform complex tasks. UGVs are particularly attractive for operations that are considered unsuitable for human operatives. These include dangerous operations such as explosive ordnance disarmament, as well as situations where human access is limited including planetary exploration or search and rescue missions involving physically small spaces. As technology advances, UGVs are gaining increased capabilities and consummate increased complexity, allowing them to participate in increasingly wide range of scenarios.

UGVs have limited power reserves that can restrict a UGV's mission duration and also the range of capabilities that it can deploy. As UGVs tend towards increased capabilities and complexity, extra burden is placed on the already stretched power resources. Electric drives and an increasing array of processors, sensors and effectors, all need sufficient power to operate. Accurate prediction of mission power requirements is therefore of utmost importance, especially in safety critical scenarios where the UGV must complete an atomic task or risk the creation of an unsafe environment due to failure caused by depleted power.

Live energy prediction for vehicles that traverse typical road surfaces is a well-researched topic. However, this is not sufficient for modern UGVs as they are required to traverse a wide variety of terrains that may change considerably with prevailing environmental conditions. This thesis addresses the gap by presenting a novel approach to both off and on-line energy prediction that considers the effects of weather conditions on a wide variety of terrains. The prediction is based upon non-linear polynomial regression using live sensor data to improve upon the accuracy provided by current methods.

The new approach is evaluated and compared to existing algorithms using a custom 'UGV mission power' simulation tool. The tool allows the user to test the accuracy of various mission energy prediction algorithms over a specified mission routes that include a variety of terrains and prevailing weather conditions.

A series of experiments that test and record the ‘real world’ power use of a typical small electric drive UGV are also performed. The tests are conducted for a variety of terrains and weather conditions and the empirical results are used to validate the results of the simulation tool.

The new algorithm showed a significant improvement compared with current methods, which will allow for UGVs deployed in real world scenarios where they must contend with a variety of terrains and changeable weather conditions to make accurate energy use predictions. This enables more capabilities to be deployed with a known impact on remaining mission power requirement, more efficient mission durations through avoiding the need to maintain excessive estimated power reserves and increased safety through reduced risk of aborting atomic operations in safety critical scenarios.

As supplementary contribution, this work created a power resource usage and prediction test bed UGV and resulting data-sets as well as a novel simulation tool for UGV mission energy prediction. The tool implements a UGV model with accurate power use characteristics, confirmed by an empirical test series. The tool can be used to test a wide variety of scenarios and power prediction algorithms and could be used for the development of further mission energy prediction technology or be used as a mission energy planning tool.

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List of Abbreviations

ACC	American Control Conference
AGM	Absorbed Glass Mat
AI	Artificial Intelligence
ALV	Autonomous Land Vehicle
BT	Battery Terminal Voltage
BV	Battery Voltage
CDE	Centre for Defence Enterprise
CDF	Cumulative Distribution Function
CSV	Comma Separated Values
DARPA	Defence Advanced Research Projects Agency
DPM	Dynamic Power Management
DSTL	Defence Science and Technology Laboratory
FCRAR	Florida Conference on Recent Advances in Robotics
GIS	Geographical Information Systems
GPS	Global Positioning System
HMI	Human Machine Interface
IC	Internal Combustion
ICR	Instantaneous Centres of Rotation
IED	Improvised Explosive Device
IEEE	Institute of Electrical and Electronics Engineers
IPM	Intelligent Power Management
IROS	Intelligent Robots and Systems
KG	Kilo Grams
LiPo	Lithium Polymer
Li-ion	Lithium-ion
MOD	UK Ministry of Defence
NATO	North Atlantic Treaty Organisation
NEC	Network Enabled Capability
NiCd	Nickel–Cadmium
NiMH	Nickel–Metal Hydride
NRMM	NATO Reference Mobility Model

PMS	Power Management Systems
PV	Photo Voltaic
RF	Radio Frequency
RGB	Red-Green-Blue (colour system)
RMSS	Resource Management Systems Simulation
SUGV	Super-hardened Unmanned Ground Vehicle
SWAP	Size, Weight And Power
UAV	Unmanned Aerial Vehicles
UGV	Unmanned Ground Vehicles
UK	United Kingdom
UO-FACT	Urban Operations Focus Area Collaborative Team
US	United States
USA	United States of America
VEL	Velocity
VRC	Vetronics Research Centre

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1 Introduction

Power resource management is an essential capability of military battlefield platforms. All vehicle based capability is reliant upon the storage and managed depletion of some form of exhaustible energy resource. The importance of power management has been highlighted as a key conclusion of a recent think-tank event focussed on 'robust military platforms' organised by the UK Ministry of Defence (MOD) Defence Science and Technology Laboratory (DSTL) [1] and the Vetronics Research Centre (VRC) [2]. It concluded that appropriate power management capability is of critical importance for platform survivability and subsequent mission success as it underpins almost all other capability, and as such should have considerable attention devoted to both its development and optimisation.

In the near future, the battlefield is predicted to contain an increasing number of specialised unmanned platforms with greater autonomous capability. The diverse array of platforms will be reliant upon a wide variety of energy sources and storage systems for their operation. This complexity of the challenge is further increased by the operational environment itself. Modern UGVs are required to traverse a wide variety of terrains that may change considerably with prevailing environmental conditions [3].

The ability to quickly understand the dynamic and unstructured environments encountered by military platforms is of increasing importance as is highlighted by recent Centre for Defence Enterprise competitions and funding (CDE Research Challenge 1: acquiring data for autonomous vehicles [4]). Much research has been conducted for structured and relatively static environments, in particular terrains made up of prepared road surfaces. However, the exploitation of such work is limited for military platforms and subsequently a technology gap has arisen.

Combined, these factors present a significant and increasingly complex power management problem. Existing methods of power resource management and energy prediction, ranging from human estimation to basic instrumentation approaches, represent an unfeasible power management challenge for fleet operators of the future.

As a primary contribution, this work aims to improve on current state of the art approaches to live terrain condition identification / characterisation. Novel and economical methods of terrain characterisation are developed and simulated over representative mission scenarios. The approach is based on the application of statistical analysis and prediction methods to already existing yet unexploited UGV live sensor data and its synthesis with available context data from Geographical Information Systems (GIS) and mission planners. The synthesised data sets are used to build descriptive models of the interaction between the vehicle and the terrain being traversed.

At the platform level, an improved understanding of the interaction between the terrain being traversed with the UGV platform has direct implications for its own mobility and route planning in terms of trafficability, safety, maximum speed of traversal as well as the potential for more accurate power resource prediction (the focus of this thesis). Subsequently, new knowledge regarding the terrain can now be disseminated to allow improved mission planning for all cooperating fleet land platforms, increasing the advantage gain through better understanding.

A further primary research contribution this work presents improved methods of mission energy prediction. Based upon the previously established descriptive models of vehicle/terrain interaction, predictive models that describe future interactions in terms of energy usage are now feasible. Novel algorithms that employ predictive approaches to more accurately forecast mission energy requirements for UGVs deployed on dynamic "off road" terrains in variable climatic conditions are presented and tested.

This improved prediction increases the effective deliverable capability of the platforms by maximising the use of available power reserves, improving mission planning and by enabling efficiencies to be achieved during live missions as more is learned about the environment and the prevailing climatic conditions. This is achieved at minimal cost by exploiting already available sensor and geographic data, without incurring additional financial investment or additional Size, Weight and Power (SWAP) penalties incurred through a requirement for additional sensors, equipment or processing.

1.1 Thesis Objectives

The main objective of this thesis is to improve mission energy prediction capability in military UGVs. In order to achieve this objective, the thesis has the following primary goals:

1. To develop an approach to identifying and characterising terrain using already available information sources such as basic and standard UGV sensors and available geographical information. The approach should:
    - Characterise terrain in terms of energy requirement for UGV traversal for a range of climatic conditions and UGV velocities.
    - Be implemented in a test bed UGV platform to allow for the creation of terrain reference data sets for a range of common terrains.
    - Be validated by examination and statistical analysis of the collected data sets.
    - Provide data for the stimulus and validation of an energy prediction simulation platform for use in subsequent work.
2. To develop novel mission energy prediction algorithms appropriate to the battlefield context. The algorithms should:
    - Provide live forecasts of predicted mission energy consumption.
    - Provide live prediction of mission success likelihood.
    - Provide dynamic update to address prevailing environment changes.
    - Be tested and compared to current published research efforts using a validated simulation approach.
3. Due to the unique nature of the problem space of developing and comparing novel approaches of terrain identification and mission energy prediction in a

highly dynamic and unstructured environment a new modelling and simulation tool must also be developed. The new tool should:

- Allow the user to model the vehicle / terrain interaction of a UGV over a given mission route consisting of variable terrain types.
- Enable the modelling of variable climatic conditions and the resulting effect on the terrains.
- Provide modelling of a basic and typical set of on-board UGV sensors throughout the mission.
- Provide a platform for the development and testing of mission energy prediction algorithms.

1.2 Thesis Structure

The remainder of the thesis is structured as follows:

Chapter 2 is the first background chapter.

It provides an introduction to Energy Use and Management in Unmanned Ground Vehicles. It commences with an overview of the evolution of UGV platforms for both battlefield and civilian use followed by an overview of current research focus for UGVs. Chapter 2 also examines energy storage and consumption as well as related energy management approaches in military and related fields. Finally a discussion of the aims of Intelligent Power Management systems is presented with a focus on the applicability and relevance to the modern battlefield and its current doctrines and trends.

Chapter 3 is the second background chapter.

The chapter provides specific focus on propulsion energy prediction within the context of Energy Prediction for Unmanned Ground Vehicles. It provides a review of current research work in this area and discussed is its relevance to military UGVs and any apparent shortcomings. The state of the art in terms of terrain identification, terrain characterisation and energy prediction are reviewed and discussed.

Chapter 4 is the methodology and first contribution chapter.

It presents a novel simulation tool known as Resource Management System Simulation (RMSS) that provides the facilities to simulate the performance of the proposed mission energy prediction algorithm. It allows for the modelling of an electric drive UGV platform over a variety of terrains, climatic conditions and mission plans. The tool is built using modular design principles and provides the required flexibility to allow the user to develop and experiment with energy prediction approaches as well as providing the simulation facility for direct comparison with existing approaches. The simulation tool is validated by comparison with empirical test results collected by the UGV test-bed vehicle described in chapter 5.

Chapter 5 is the second contribution chapter.

It describes the creation and use of a UGV test platform for the collection and synthesis of terrain characterisation data sets and the methodology employed to analyse those results. The chapter details the design and operation of the UGV platform and describes its operation over a series of experiments. The platform records the output from a range of typical UGV on-board sensors when subject to various terrains, climatic conditions and velocities. The resulting data sets form a reference for further investigation. The results are analysed to assess the feasibility of using empirical data to successfully predict the moisture content of terrains.

Chapter 6 is the third contribution chapter.

It presents the ultimate focus of this thesis in the form of a novel approach to mission energy prediction. The presented algorithm uses the terrain reference data sets established in chapter 5 combined with live sensor data as a basis for dynamic prediction using a polynomial (non-linear) regression approach. The algorithm is simulated over representative scenarios and is compared to existing published research approaches.

Chapter 7 is the final chapter.

It presents the findings and draws conclusions from the work presented in this thesis. It discusses the achievements, limitations and future work.

2 Energy Use and Management in Unmanned Ground Vehicles

2.1 Unmanned Ground Vehicles

The academic community usually refers to Unmanned Ground Vehicles (UGVs), especially UGVs possessing significant autonomous capabilities as mobile robots. In a broader sense, “a UGV is any piece of mechanized equipment that moves across the surface of the ground and serves as a means of carrying or transporting something, but explicitly does NOT carry a human being” [5].

UGVs are becoming more widespread in their deployment due to advances in technology regarding machine intelligence, sensing hardware and perception algorithms [6]. Typical UGV applications are surveillance, transportation, mine clearing and search and rescue. UGVs are well suited to applications that are considered dull, dirty or dangerous or in situations where it is physically impossible for humans to venture [7], such as small crevices in collapsed buildings. Removing humans out of harm’s way is one of the primary driving motivations for UGV development, as UGVs can operate in contaminated environments or in the military context can operate behind enemy lines or be tasked with highly dangerous tasks such as mine clearance.

A good example of a UGV application is that of planetary exploration where not only is the application considered highly dangerous to humans, but also the cost associated with manned space travel can be prohibitively expensive. A typical planetary UGV is significantly smaller than that of a human crew and eliminates the requirement for complicated and heavy life support systems, which drastically reduces the cost of deployment for space exploration when compared with manned space travel [5].

As technology advances, UGVs will naturally be relied upon to deliver an increased range of capabilities for a wider range of missions that require increasing persistence and endurance [8]. The missions will have varying degrees of criticality and will be executed with various levels of autonomy, all of which has significant implications for energy requirements, management and prediction.

An example of the extremities of mission types that UGVs are expected to execute is the comparison of a drone lawn mower and a UGV conducting a search and rescue mission. The mowers task would be considered non-critical, if it were to deplete its fuel prior to the task being completed, it would at worst, be considered a nuisance. Also it would not be considered critical that the mower completed its task within a certain timeframe. But the mower would be expected to have quite a high level of autonomy, i.e. it is required to complete the mowing without human intervention. The autonomy is possible for this mission type as the mower would not have to navigate a completely unstructured environment, i.e. the ground would be generally flat and any terrain or topology that is considered non-traversable would be known prior.

In contrast, the search and rescue UGV has a mission type that would be considered time critical and power depletion would likely lead to critical mission failure. However, it is likely that it would have a low level of autonomy and would be tele-operated with reliance on a human operator. One further example is that of a planetary rover. This would be expected to have a high level of autonomy as it would have to navigate an unstructured environment with little prior knowledge of the terrain it is likely to encounter. Also, the time frame for the mission would not be as critical as the economy of the stored energy, as it would be desirable for the mission to last as long as possible.

Critical mission applications of UGVs have witnessed a dramatic growth within the past decade, especially for military applications in response to the need for Improvised Explosive Device (IED) countermeasures [9]. UGVs are also increasingly used in the area of search and rescue. These two fields share a commonality where mission objectives are often critical, and mission completion is usually time dependent.

2.2 Evolution of UGVs

Although UGVs are currently being deployed in both the civilian and military arenas, historically their use was limited to military applications. One of the first realistic and successfully deployed UGV is perhaps the Russian TT-26 “Teletank” which was developed prior to the Second World War. The Teletank designs were based on manned tanks that had the addition of a wireless communication system that allowed for tele-operation of the mobility of the tank and also the operation of a number of offensive weapons such as flame throwers or machine guns. This allowed for the deployment of offensive weapons while keeping the operator out of harm's way.

In opposition to this, Germany developed the "Goliath" mini-tank which was based on a French design. The Goliath differed to the Teletank in the fact that it was purpose built, opposed to fitting tele-operation to an existing vehicle. The goliath's offensive capabilities were limited to "single use" where the vehicle was packed with explosives and driven towards a particular target and remotely detonated.

On conclusion of the Second World War, development of UGVs stagnated until the advent of "Shakey" (see Figure 2.1), in the late 1960s (and continuing into the 1970s), which was developed to serve as a test bed for DARPA (Defence Advanced Research Projects Agency) funded Artificial Intelligence research at Stanford research Institute. "Shakey" comprised a wheeled platform equipped with camera, touch sensors, range finder and an RF link for connection to a mainframe computer [5]. Shakey is an important milestone in the evolution of UGVs, due to the fact that it can be considered the first general purpose mobile robot. It could carry out such tasks as manoeuvring around a structured environment, turning lights on and off via wall switches and pushing solid objects. Also, Shakey was the first project to combine computer vision with natural language processing which allowed it to reason about its own actions.

While Shakey may have been considered at the time to be a failure due to the fact that it was never developed to the point where full autonomous operation was achieved [5], the project established base lines for functional ability and performance for mobile robots and UGVs. It also identified technological deficiencies that defined research agendas required for the further advancement of mobile robots.

Figure 2.1: Stanford Robot, Shakey [10]   Figure 2.2: Stanford Robot, the Cart [11]

Autonomous navigation of a robot was further explored with the "Stanford Cart" project during the 1970s at the Stanford University AI Lab (see Figure 2.2). The result was the ability for the cart to successfully navigate a chair filled room without the need for human intervention. However, the process of crossing the room took five hours to complete, after every 1 metre move, the cart remained stationary for up to 15 minutes while images of the surrounding environment were processed. Similar to Shakey, the processing took place off-board using a main frame computer.

Both Shakey and the Stanford cart were developed where the traversal of the ideal surface of a laboratory floor were considered, as issues such as the artificial intelligence required to navigate an unstructured environment were focused on for research purposes. For any UGV to be deployed for military missions (and for the majority of civilian missions) the first research project that explored the possibility of typical terrain (off-road) traversal was the DARPA developed "Autonomous Land Vehicle" (ALV).

The ALV was an 8 wheeled vehicle platform developed with the aim of autonomous navigation over off-road terrain between two given points. It differs from previous attempts of unmanned operation as all required processing was performed on-board. The sensor suite included a full colour video camera and laser scanner, which were complemented by video and range data processing modules to produce road edge information and capability to generate a model of the scene ahead [5]. Goal seeker and navigation modules allowed for high level reasoning and combined with a pilot module provided path planning and steering. Towards the end of the 1980s, the ALV was demonstrating successful traversal (including route planning) of an off-road course that consisted of obstacles such as trees ditches and rocks.

The early 1990s witnessed the first deployment of a modern military UGV during the first gulf war, by the US army, primarily for mine-clearing applications. M-60 tanks and bulldozers were equipped with mine-clearing and remote-control equipment to open breaches in mined areas. Due to their successful deployment, other countries started to develop similar systems such as the French AMX30B2-DT Mine Clearing Tank for example (see Figure 2.3). It is interesting to note that these systems were modified, manned armoured vehicles with the addition of equipment that allowed for tele-operation similar in principle to the “Teletank”.

Figure 2.3: AMX30B2-DT, Unmanned mine clearing tank [12]

The success of the mine-clearance applications of the deployed UGVs encouraged the financing of research into other possible operational interests for UGVs (reconnaissance, medical assistance, ordinance disposal) and to develop the current basic technologies (sensors, image computing, autonomous navigation) to improve a UGV’s situational awareness.

Recent conflicts have highlighted the requirement for the development of small robust and agile UGVs that can navigate an urban environment, and counteract the growing use of Improvised Explosive Devices (IEDs) or survey building environments to increase situational awareness of building occupancy. This requirement has led to the development of purpose built UGVs such as the PackBot (developed by iRobot, see Figure 2.4), opposed to the utilization of a manned vehicle.

The PackBot has been successfully deployed in large numbers in recent conflicts and is man deployable, its versatility has been proven as it has been successfully used in a number of variants that allow for missions such as surveillance, IED disposal, and situational awareness of buildings. These military requirements are similar to the requirements for land search and rescue missions that require the traversal of collapsed buildings or dangerous environments. This was demonstrated during the Fukushima nuclear plant where packBots were the first UGVs to be deployed.

Figure 2.4: Packbot UGV [13]

Figure 2.5: Foster Miller Talon UGV [14]

Another example that highlights the success of small UGVs in the military environment is the Foster-Miller Talon (see Figure 2.5), which has the ability to traverse a wide variety of terrain (sand, water, snow etc.) and has the capability to traverse stairs. Similar to the packBot, the Talon has been deployed in a variety of configurations allowing for a variety of mission types, including explosive ordnance disposal, reconnaissance and hazard detection. Again, similar to the packBot, the Talon has successfully been deployed in search and rescue missions. These examples are designed to provide general functionality with flexibility regarding the mission type, opposed to a system that is limited to a single task.

2.3 UGV Research and Development

Further to the previously discussed advantage of reduction of risk to human health, UGVs create significant advantage due to the fact that they are not required to support a human crew and associated design limitations are removed. However, this also introduces a disadvantage as mechanisms are now required to replace human judgment in operating the vehicle. Although the UGV maybe tele-operated, a large range of additional sensors, processors and software are required to effect mobility [15].

Due to the wide range of applications (all with differing required complexity) that UGVs are required to support, many branches of research currently exist, all at varying levels of development. The range of researched applications has yielded a wide variety of UGV systems that boast a variety of characteristics. This makes the taxonomy of UGVs a difficult task. Gage suggests the need for an organising principle and lists characteristics that define the research fields as [5]:

- The purpose of the development effort (often, but not always, the performance of some application-specific mission).
- The specific reasons for choosing a UGV solution for the application (e.g., hazardous environment, strength or endurance requirements, or deployment method that introduces a size limitation).
- The "long term" technological challenges, in terms of functionality, performance, or cost, posed by the required application.
- The system's intended operating area, for example, indoor environments with ideal running surfaces, prepared road surfaces, or general off-road terrain.

- The vehicle's mode of locomotion (e.g., wheels, tracks, or legs);
- How the vehicle's path is determined (i.e. control and navigation techniques employed).

Historically, UGV research has been focussed upon the autonomy of UGVs and improving both their capabilities, and situational awareness. A classic application that has received much focus is the ability to plan routes and navigate long distances through highly dynamic environments [6] requiring object avoidance methods etc. and to achieve missions where a level of uncertainty is present to further stretch the possibilities of UGV missions.

This requires an increasing array of hardware, for example sensors for object and terrain recognition, GPS and inertial sensors for navigation assistance and subsequently more processing power to control the additional equipment. The resulting increased demand on energy requirements means that the research into intelligent power management is becoming increasingly important.

2.4 Energy Resources

Increased equipment, longer duration and increased complexity within UGV missions puts an extra burden on the already stretched power resources available to UGVs.

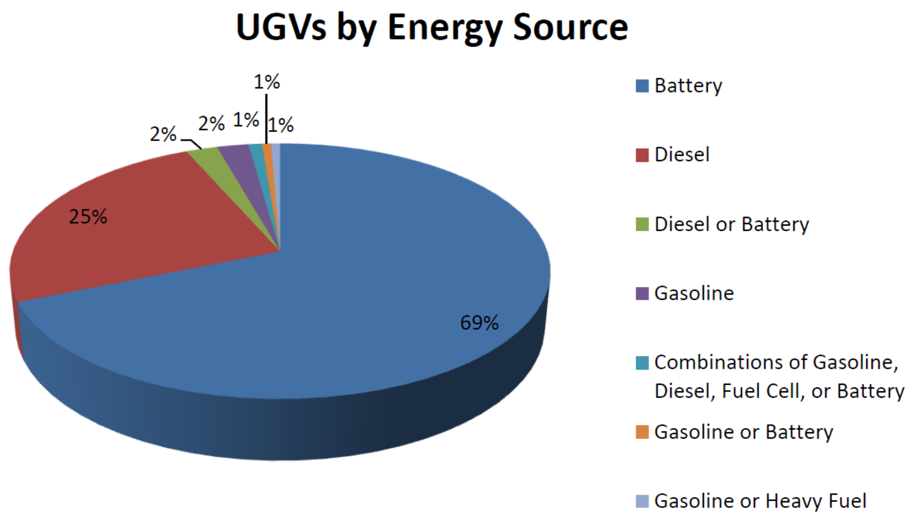


Figure 2.6: Percentage of energy sources of deployed UGVs [16]

The vast majority of small/medium UGVs (see Figure 2.6) are fitted with power sources with limited reserves such as battery packs with minimal facilities for recharging during mission time.

This energy reserve limitation can be both a restricting factor to the future abilities of UGVs and limit their flexibility to cope with various mission types. An example is limited mission duration, where a UGV operational period is directly affected by remaining power reserves. In military applications (but not limited to) it is typical that mission plans change dynamically during mission time and remaining resources will influence the possibilities available to mission planners and could restrict the likelihood of mission success. In safety critical operations, such as UGVs deployed by emergency services for search and rescue, it is of utmost importance that a UGV has enough power reserve to complete a task rather than creation of an unsafe environment through mission abortion due to depleted power.

Two main challenges exist with the current technology concerning batteries utilised as energy stores, increasing the density to allow for improved weight/power ratio and the estimation of current state of charge and how this may equate to remaining energy stored.

2.4.1 Energy Storage

As already noted, the primary energy store for the majority of UGVs are rechargeable batteries, which offer well researched, reliable and scalable sources of power. For military applications a further advantage is presented as a lower thermal signature can be obtained when compared to other propulsion methods (such as combustion engines) allowing for stealth operation and silent watch. The power density (that translates to useful energy storage capacity) is currently one of the most important challenges for UGV development [17].

Many different battery technologies that differ in cell chemistry exist, including Lead Acid (which is available in wet, gel or Absorbed Glass Mat (AGM) format), Nickel–Metal Hydride (NiMH), Nickel–Cadmium (NiCd), Lithium Polymer (LiPo) and Lithium-ion (Li-ion). All offer differing power density performance.

While it would appear that the decision for selection of best technology would be solely based on power density there are other factors that are taken into consideration and a trade-off exists between density and other factors such as cost, charging times, reliability and flexibility of operating environments.

By far the most well researched and mature technology is Lead-acid wet cell batteries which are ubiquitous in many vehicle systems. They are comparatively cheap to manufacture and are available in a large range of capacities. However, they are rarely used in modern UGVs (even though they are exceptionally cost effective) as they are physically large and heavy with a low power density, also any stored energy is lost during periods of inactivity.

Nickel Cadmium cells are generally small in size and are capable of low current capability compared to lead-acid batteries, but offer increased energy density. Regarding their use with UGVs, a drawback is that they are unable to operate in parallel without intelligent control circuitry, so may be limited to the current delivery rate of a single cell, and therefore are hampered by not being scalable as power requirements increase.

Nickel-metal hydride improve on the cadmium by offering a much improved power density but still present the drawback of requiring intelligent control when used in a parallel configuration. Further to this they have comparatively small maximum charge capacity and tend to overheat when used in large batteries.

The most recent development in battery technology is the implementation of Lithium in the cell chemistry. Lithium-ion polymer batteries are generally not rigid but are produced in a bag or pouch, thus they are slightly flexible and with no casing they are significantly lighter than other cells, and allows for the cells to be manufactured in a variety of shapes.

Lithium-ion cells yield the highest charge density when compared to the previously considered technologies. However, as the density is much increased it is considered more volatile, raising a concern for fire or explosion. For this reason, these cells are not usually used where an explosive atmosphere is present (which can be the case in search and rescue missions). However, the risk is usually mitigated by packaging the cell in a suitable material and the addition of external (to the cell) control circuitry.

The rate of increase of Power demand for UGVs is outpacing battery technology improvement. Other technologies exist but are still in the research stages and are as yet not fully deployed as a singular source of energy storage. However, such technologies as fuel cells and ultra-capacitors currently offer a possibility for a hybrid method of energy storage.

One limiting factor with the use of batteries is that current densities limit a fast response to power demands that are greater than average, ultra-capacitors have the ability to provide very high power but with low energy density, so when connected in parallel with a battery a hybrid configuration can be obtained, and has shown to provide a more effective solution than simply over-sizing batteries to compensate for momentary power demands.

2.4.2 Energy Replenishment

It is also possible for a UGV to incorporate a method for power resource replenishment, for example a Photo Voltaic (PV) solar panel based charging system for systems where a battery is employed as the primary means of power storage. However, when considering that the majority of missions that are carried out by a UGV have to be completed within a certain timeframe, the time required to replenish the power via PV represents a limiting factor on possible mission types where this approach is appropriate. Even so, in the right circumstances it suits long duration and time unbounded applications, such as planetary exploration.

Immediate replenishment in the case of a UGV that is powered by battery packs would mean pack replacement, which is not possible for UGV missions that are not accessible to human operators. One possibility to address this is the inclusion of an internal combustion engine that combined with batteries and a generator can provide a hybrid system that can rely on the engine to recharge the batteries during convenient phases of a mission. This method is currently employed, but is only suitable for medium sized UGVs, as suitable combustion engines are not available commercially at smaller scale.

Also consider that UGVs that are required to operate in a stealth mode would be limited to periods during a mission where the engine could be used (discussed further in section 2.5.2).

2.5 Energy Consumption

As discussed previously, the diverse applications and increasing mission complexity that are required from UGVs has resulted in the addition of extra sensors and related equipment to effect reliability and improve likelihood of mission success. All of which puts an extra burden of available energy, which results in limited endurance for a UGV.

A UGVs energy consumption generally falls into two major categories, electrical (energy consumed by the on-board computer/control system) and mechanical (propulsion motors and actuators) [18]. Apart from component selection, conserving energy for the electrical category is generally focused on efficient algorithms or off-line data analysis to reduce processing time.

2.5.1 Drives and Propulsion

Propulsion energy requirements for UGVs are increasing due to increases in size, weight and complexity of UGVs, and longer mission durations, as the UGV is expected to carry more equipment for a longer duration. The majority of UGV power is used by the propulsion system (except perhaps for the smallest of systems), although this can be mission dependent. However, design considerations relating to the efficiency of the propulsion system are rarely taken into account, in favour for the UGVs ability to traverse the environment of its intended operating area.

2.5.2 Methods of Propulsion

Figure 2.6 shows that 95 percent of deployed UGVs rely on either electric motors or diesel engines (or a combination of both) to provide for the propulsion source. The advantages of the use of diesel engines are proven reliability, high power, and a compact configuration. In addition to this, they are relatively lightweight when compared to other alternatives.

The main disadvantages of using a diesel (or other fuel type) internal combustion (IC) engine are the emissions produced, noise generated, and its relatively low thermal efficiency. Also, the scaling characteristics of combustion engines results in a lower efficiency as the engine sizes decreases, making their deployment on small UGVs unfeasible (although research is ongoing into producing miniature combustion engines that have an improved efficiency).

Due to the scaling issue of combustion engines, the vast majority of small UGVs predominantly rely on electric motors for the propulsion source. This method has the operating advantage of silent operation and low thermal signature. The primary disadvantage is that they suffer from limited operational range as they generally rely on battery packs for energy.

When comparing the combustion engine with electric motors another advantage is apparent with the utilisation of the electric motor. With IC engines the method of transferring power to the wheels is traditionally via a gearbox, prop shaft, differential and drive shafts, all of which introduce weight and losses, and subsequent lower efficiency of the overall system. Further to this, it is often necessary to design the UGV around the drive train as the highly mechanical system tends to be inflexible regarding positioning of components.

The electric motor only requires cabling (opposed to mechanical drive shafts etc.), as a connection to the power source and control system, which allows for a far more flexible system, where the platform may be designed with greater consideration for factors such as payload positioning and terrain trafficability.

A hybrid option exists that combines the use of both electric motor and IC engine. The configuration of the drives allows for two main types of configuration, series and Parallel. This combination allows for additional mission duration, flexibility and silent watch operations. The parallel approach involves the wheels being driven by both the IC engine and the electric motor (with the use of a power source such as batteries), although this system increases reliability as it allows for redundancy it requires mechanical linkage from the IC engine, so incurs the design issues described above.

In the series configuration only the electric motor drives the wheels and the IC engine provides electrical energy via a suitable generator or alternator and power electronics, it is also possible for the IC engine to recharge battery packs that can be relied upon for silent running. This method of configuration allows for greater scope when considering the placement of components so takes advantage of the design flexibility described above.

However, during complete depletion of the batteries, both systems have to rely on the use of the IC engine, with this in mind careful consideration is required for mission planning so that resources such as energy stored in the batteries are used to their best effect. These configurations are generally used on UGVs that are medium sized or above due to the scaling issue discussed earlier.

2.5.3 Ground Locomotion

Early research into UGVs and mobile robots focused on mobility in structured man-made (indoor) environments that allowed designers not to concern themselves with the difficulties of mobility over unstructured environments [5]. Also, the majority of manned vehicles are designed to traverse man-made surfaces where the terrain surface is designed to suit the vehicle and focuses on efficiency. In situations where robots are already put to use in industrial applications the surface that the robot has to traverse is designed with the mobility of the robot in mind.

For these applications the wheel is by far the preferred choice for locomotion by designers, as it is superior in providing a smooth and energy efficient ride with fewer stability issues over relatively even surfaces with shallow inclines. For the indoor robot to be considered for other uses than industrial or indoor applications, designers are required to explore further locomotion methods to cope with the challenges presented by unforgiving terrain.

The three primary methods that are available to UGV designers for locomotion are:

- Rolling. This system is based on the endless rotation of either wheels or crawler tracks.

- Ambulatory. Legged systems that are generally separated into two classes, static stability (at least 3 feet are firmly in contact with the terrain surface) and dynamic stability (for vehicles that comprise less than three feet).
- Articulated. As the name suggests this method relies on articulated body segments that are linked, locomotion is achieved by the coordinated motion of the segments.

Further to the above some examples of hybrid locomotion systems exist that incorporate two or more of the above. The reason for the diversity in techniques and technologies for robot mobility is apparent, each method has its own advantages and disadvantages. Since the number of possible applications and uses of UGVs is large, not one single method can be described as the universally optimum solution. The main driving force for the selection of locomotion methods is the nature of the terrain that has to be traversed. However, the type of locomotion also impacts on the efficiency of the UGV and should also be taken into consideration during design and procurement. The two main terrain properties that influence the locomotion method are [19]:

- Geometric properties. These determine the form of the surface, such as its roughness and inclination. This includes obstacles such as steps, ruts, and ditches.
- Material properties. Which include the ground consistency, strength, friction, cohesion, moisture content, density, plasticity index etc. This affects the sinkage and slipping of the vehicle.

A number of Locomotion failures are generated by the different terrain types a UGV has to contend with. Geometric properties can cause clearance failures if a part of the UGV chassis comes into contact with the ground, component failure can occur due to excessive vibration and stability failure when traversing excessively rough terrain. Material properties may cause traction failures due to loss of friction or clearance failure due to excessive sinkage. As can be seen in Figure 2.7 the vast majority of current UGVs rely on tracked or wheeled methods for locomotion so only these methods will be discussed further in this section.

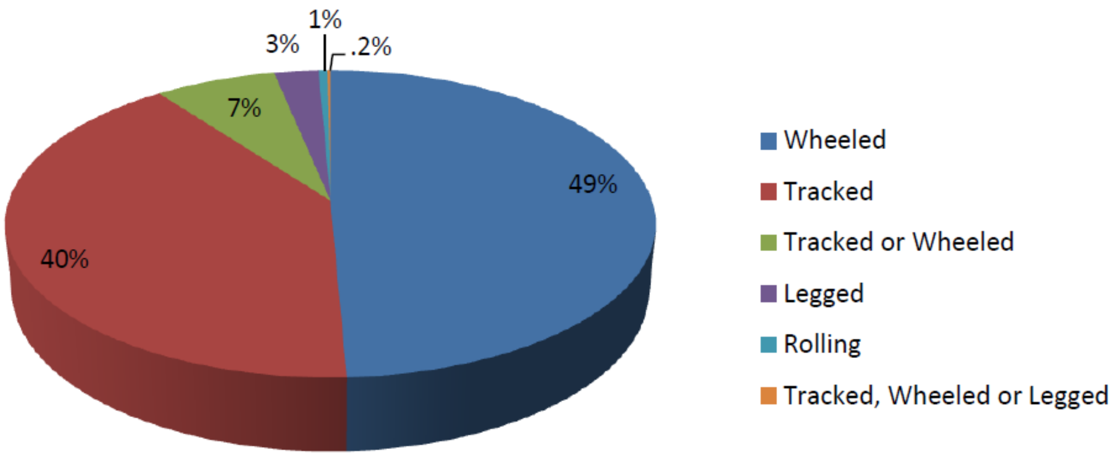


Figure 2.7: Percentage of UGVs by propulsion type [16]

2.5.3.1 Wheeled Locomotion

As previously mentioned, wheeled locomotion is best suited to prepared surfaces, however, due to its simplicity and versatility it is also widely used for unprepared surfaces as it offers high load capacity and high tolerance to surface irregularities [20] (with the complement of other techniques such as suitable tire tread).

The simplest layout for a wheeled UGV is a three wheeled "differential drive/differential wheel" configuration where independently driven wheels fixed on a common horizontal axis are complemented with a single roller ball or a castor attached to maintain balance. This 'tricycle' system has the advantage that all wheels will maintain contact with the terrain surface regardless of its roughness. Although this would appear as an advantage on rough terrain it is of importance to note that this configuration suffers from the fact that the centre of gravity must be within the three points of contact made by the wheels, this largely impacts on the loading of the UGV and results in an unstable configuration for rough terrain use.

The more familiar configuration of four wheels laid out in a rectangle formation offers much improved stability compared to the tricycle arrangement, but to ensure that contact by all four wheels (to maintain traction and reduce wheel slip) is maintained when traversing rough terrain a suspension system is required (where a fixed chassis design is implemented). Over rough terrain this can induce an impact in energy use as heat is produced in the suspension system.

By adding more wheels the surface contact area is increased, improving mobility on terrains that cause wheel slip, which, in turn, effects energy consumption. However, over rough terrain the necessity of having all wheels in contact with the surface is exaggerated, and any improvement that may be gained regarding maintaining traction with the terrain surface is lost. This problem can be addressed by having the chassis designed in a dynamic fashion where contact by all wheels with the terrain is ensured.

Regardless of the wheel configuration the ability of any UGV to traverse unprepared terrains is largely due to the tyre design. On hard surfaces the most energy efficient design is one where the tyre is rigid and thin as possible while providing adequate traction [21] (taking into consideration required traction), this configuration on hard surfaces results in the most energy efficient method of UGV locomotion. Unprepared terrains are often soft and deformable, and UGVs with wheeled configurations that navigate off-road terrains cannot take advantage of the energy efficient design. In order for the tyres to provide reliable traction the surface area needs to be increased, either by making the tyres wider or deformable (low inflation) in order to increase surface area.

Where UGVs carry out missions over varying terrain types, the large surface area of the tyre can yield both advantages and disadvantages. If the mission consists of terrains that comprise both prepared and soft surfaces, then although a large surface area of a tyre provides good traction on the soft surfaces, it provides poor economic properties when traversing the hard surfaces. Odedra [22] proposes a solution to this issue where the inflation pressure of the tyre is changed dynamically to suit the current terrain type, giving a good example of reconfiguration to suit differing terrain types.

2.5.3.2 Tracked Locomotion

An improvement to the traction of wheeled locomotion is track laying systems. This is due to the fact that tracked systems can offer an exceptionally large contact area with the terrain surface. Also, it is possible for a UGV to traverse holes and ditches (dependent on the span of the tracks), and a smoother locomotion can be obtained as peaks and troughs in the terrain can effectively be filtered out. Tracked systems also offer increased payload capacity compared to wheeled equivalents.

The advantages of a tracked propulsion system stated above come at a cost and are offset by increased friction and consummate increased energy consumption [23].

In order for a tracked system to effect turns it is required that a skid steer system is employed. Where two tracks are used for propulsion (as is the usual case) the angular velocities of the drive wheels operating the tracks are varied, resulting in one track pulling the vehicle and the other pushing it. The degree of difference of angular velocities results in the tightness of the turn (see Figure 2.8), dependent on the tightness of the turn, a resulting turning torque is applied. This also results in lateral slip, because of these effects power consumption due to track-terrain interaction becomes relevant.

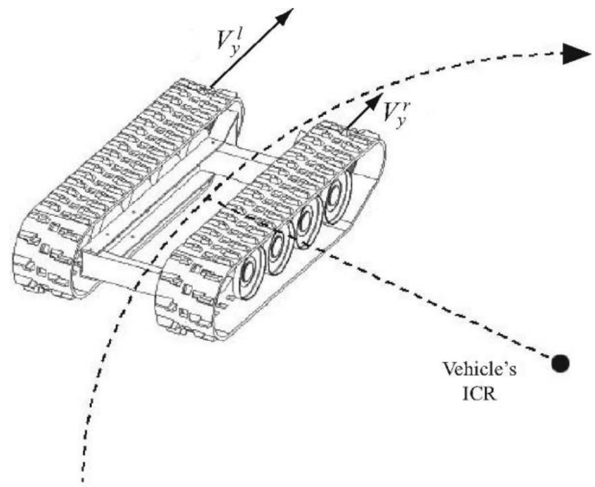


Figure 2.8: Skid steer mechanism

2.5.4 Rolling Resistance and Terrain

The rate of energy consumption for a given UGV propulsion is dependent on the velocity, the grade (incline) of the terrain being traversed, the rolling resistance coefficient (*f*) of the terrain and air resistance encountered. The rolling resistance is due to the interaction of the vehicle with the terrain through wheel/terrain interaction

(Figure 2.9). It has a more significant effect on consumption when a vehicle is traversing off-road with unforgiving terrain compared to typical road surfaces, which is the likely case for military missions [24].

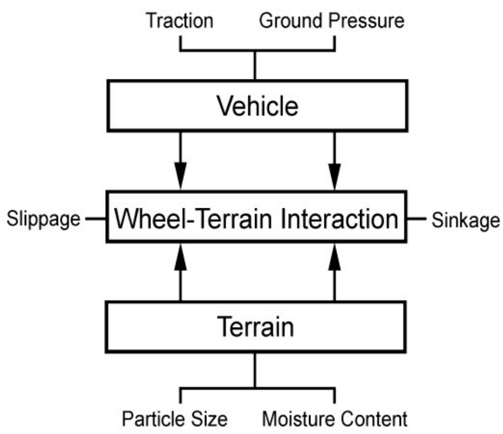


Figure 2.9: Combined Elements of terrain vehicle interaction [25]

UGVs are increasingly being employed in missions comprising rough unforgiving terrain (especially in the military context) [24], and a continual demand exists for UGVs to offer greater mobility over a wider range of terrains in all weather conditions [26].

Much research effort has been directed at the study of rolling resistance for vehicles traversing prepared surfaces (concrete, macadam etc.) where energy use is primarily effected by the deformation of the tyre [27], and changes little over most prepared surfaces. As a result, the average values of resistance when considering road vehicles are well documented [28]. Unfortunately this is not the case for off-road vehicles such as the UGVs studied here.

Compared to prepared surfaces, the additional effect of most importance when traversing unprepared terrain is the deformation of the terrain surface [28]. The resistance coefficient (*f*) impacts not only energy consumption but also the maximum permissible velocity of a UGV while traversing a certain terrain. Therefore the accurate prediction of "*f*" is equally important when the cost of route traversal is defined by both time and energy. It also may be the case that if a particular terrain type becomes influenced by a certain weather condition then it may be un-navigable by a UGV which further highlights the benefits of accurate rolling resistance prediction. The calculation or measurement of resistance coefficients for a particular UGV over varying terrains has not been fully explored [29].

Terrain deformation has two factors, vertical and horizontal. Vertical deformation is due to a realignment of the surface to support the vehicle's weight (sinkage). Extra energy is expended in this case because the vehicle has to continually "climb" out of the hole it creates (see Figure 2.10). Horizontal deformation appears as wheel slip and is due to the reconfiguration of the surface to provide a sufficient reaction against the force of the traction effort.

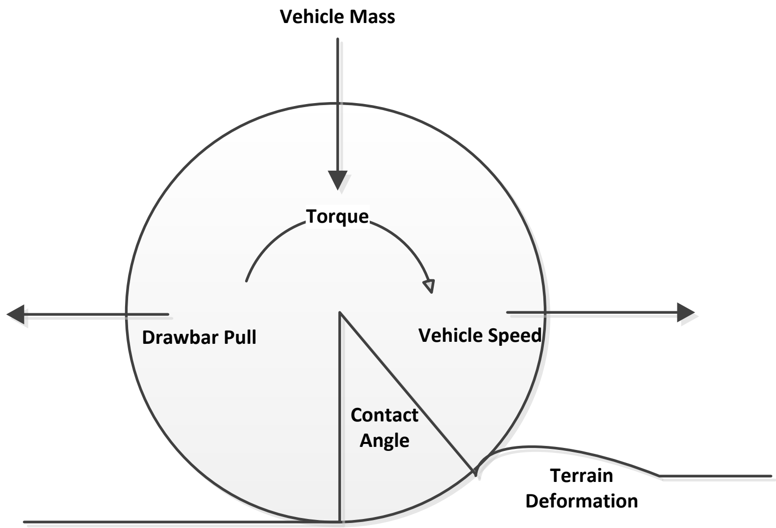


Figure 2.10: Terrain deformation due to rigid wheel interaction

Horizontal terrain deformation can be modelled as surface shear displacement versus the shear stress and is dependent on the normal load on the surface (vehicle weight), cohesion and internal friction angle of the soil (slip). Additionally, the surface may be multi-layered adding extra complexity to the model; an example of this is a waterlogged surface where displacement of the upper layers of water adds significant resistance in the form of drag at the wheels[29].

Where particle size can be considered static moisture content can be variable over a short period. It is also important to note that moisture retention is also variable dependent on the terrain type. Not only does moisture effect drag on the wheels it also effects the cohesion of the particles.

Due to the fact that prepared road surfaces and current tyre technology significantly mitigates most of the variables discussed above, it is clear that the interaction with terrain is more important for off-road vehicles from both a navigable and energy consumption approach.

2.6 Energy Management

Considering the constraining nature of typical UGV power supplies and the limitations of energy replenishment it is of great interest to designers to manage energy usage wherever possible in order to make best use of available energy resources [30]. Several energy management techniques may be employed both before and during missions, depending on mission requirements.

At a basic level where mission duration is not a concern, a typical energy management policy might be to simply carry out every task in the most energy efficient manner regardless of time taken. Using the simple example of a UGV traversing from point A to B this would mean restricting the speed of the UGV based on the current gradient being traversed in order to achieve the optimum energy consumption for incline, however, this approach is not suitable for the majority of UGV missions that have time constraints that are required to be met in order to effect mission success.

2.6.1 Consumption Management

Regardless of the size of UGV or mission type, energy conservation should be given consideration as it offers improved mission survivability. It has been shown that by applying well proven, mature techniques from other technologies, gains can be made in the area of energy conservation.

In order to address electronic systems consumption, Yonggu [31] proposes utilising a "Dynamic Power Management" (DPM) technique which was initially developed for embedded computer systems. DPM can be beneficial for energy conservation by dynamically adjusting power states of components based on current mission tasks.

This is possible as many components have multiple, selectable power states, an example being microprocessors that can run at several frequencies.

For DPM to be efficient some form of prediction algorithm is necessary considering that many components may consume more energy when being frequently switched between states, so merely powering down components during periods of inactivity is likely not to be suitable. Another possibility is to utilise the technique of "dynamic voltage scaling" where both supply voltage and frequency of a processor are reduced (where the processor is not being fully utilised) resulting in a reduction of power used.

It is important to note that the processing overhead that is required for DPM will increase the energy used during a mission and will therefore need to be factored in to any energy saving calculation.

Yonggu's study [31] suggests that the mechanical energy required for UGV motion accounts for less than 50% of total power consumption and that consumption of an embedded computer can be greater than 50%. However, this is for a relatively small UGV, as the size/weight of the UGV increases then the energy required for motion will account for greater than 50%. This will be increased further with consideration given to UGVs that have to traverse unforgiving terrain, resulting in gains from DPM not being as significant when compared to smaller UGVs traversing forgiving terrains such as asphalt.

2.6.2 Route Planning

A component of energy management is route planning. As discussed, the majority of energy consumed by all but the smallest UGVs is via the propulsion system. One method of managing energy is therefore to improve the propulsion consumption using route planning techniques that consider efficient traversal.

When consideration is given for a given route of a particular mission it appears that there are two main route definitions:

- Area coverage. This is typical for search and rescue missions. The path for the UGV to follow is usually decided by a trade-off between the most efficient methods of covering an open space with that of the shortest time.

- Path Traversal. This typically involves the UGV traversing a given path following a set of way points, where further tasks are carried out at certain waypoints. Typical missions would be Surveillance, where a UGV travels to a given location to carry out surveillance then returns to the route starting point.

By planning the route in advance an approximate forecast of energy use can be generated. The forecast is however limited in accuracy as changing environmental conditions or deviations from the planned route will introduce errors in forecasting.

The drive motors are the dominant consumers of energy for all but the smallest UGVs [32]. Therefore path planning becomes significant in improving efficiency and increasing possible mission durations. It is a well-documented fact that vehicle fuel efficiency drops dramatically at high velocities [33]. So the most obvious solution would be to select the most efficient velocity based on velocity profiles of a given UGV. However, other factors need to be taken into consideration that would impact noticeably on consumption are:

- Acceleration/deceleration
- Turning angles (More significant on skid-steer or tracked vehicles.)
- Wheel slip
- Terrain Inclines

Without consideration of power conservation UGV route planning is usually driven by a need to traverse a space with consideration to one or more of the following:

- Shortest
- Safest
- Quickest
- Most economic

It is important to note that in the recent energy minimisation research, effort has focused on shortening path length while not actually addressing actual power consumption[34]. But when considering realistic military missions the shortest route is not necessarily going to yield preferable gains in terms of time and economy when you consider the fluctuating resistances of off-road surfaces that can impact on energy consumption. The most favourable route for energy conservation may be the one that avoids unfavourable terrain, at the cost of increased distance.

Further consideration needs to be given to the amount and accuracy of pre-mission information that is available as this will impact on selected routes, if consideration is given to economy then the following attributes are to be taken into consideration:

- Inclines
- Terrain type (effects rolling resistance)
- Distance
- Prevailing weather conditions

Many UGV applications/missions require an element of area coverage, typical examples being search and rescue or reconnaissance [35] where a UGV has to sweep every point in a given region. In the case of search and rescue after a natural disaster, chances of survival diminishes rapidly after 24 hours [33], so time constraints are in competition with energy constraints and to further complicate the matter they generally have conflicting optimisation goals.

Much research into area coverage focuses on offline algorithms to generate paths that either ignore energy limitations or time constraints or considers them separately [35]. However, when considering the example mission above (search and rescue) it is critical to consider both constraints together.

Yonggue [18] proposes a technique that yields up to a 51 % saving by selecting energy efficient motors and then selecting a traversal method (with three differing coverage schemes, scan lines, spiral or square spiral) to suit the size of area to be covered along with best velocities. This work looks at the energy limitation in isolation. It also uses a mission where the terrain type is constant for the whole mission and no consideration is given to inclines. It is of importance to note that most search and rescue missions would involve consideration for both these factors.

It is also of importance to note that some of the experiments carried out used a traversal coverage method that requires a wheeled UGV to follow a spiral. Depending on the steering type of the UGV this may involve the UGV missing certain areas depending on the minimum turning radius of the UGV. Consideration should also be given to skid steer UGVs, where the impact on energy consumption is increased when many turns are effected (the spiral traversal being a good example).

The research presented above considers missions where an amount or area coverage is required. The research also assumes that the UGV has free reign to traverse where it chooses within a given area with little hindrance, e.g. indoor applications, or external locations with no obstacles, inclines or variances in terrains.

As previously mentioned, the majority of military UGV missions (and many search and rescue missions) require route traversal over unstructured domains that are made up of varying terrains including grass, dirt, sand, manufactured road surfaces (asphalt, concrete and macadam) etc. [36] each with varying inclines and rolling resistance values where consideration is given to terrain moisture content caused by prevailing weather conditions.

Compared to traditional route planning which has typically focused on either the shortest or quickest path traversal, extra complexity is added when energy management goals are also considered. On ideal surfaces the shortest route would obviously yield the most economic route, however, for the vast majority of UGV missions this would be unrealistic as complexity is introduced by dynamic environments that UGVs are required to operate in.

2.6.3 Control Method Implications

The method of UGV control is an important consideration for any energy management scheme. As the design of a Power Resource Management system is simplified for autonomous systems as operator needs and requirements do not need to be considered.

The majority of UGVs in military use have a human in the loop for operation, usually referred to as “tele-operated”. These systems tend to use a mixture of control (to varying degrees) between a human operator and parts of the system which are controlled automatically/autonomously. This mixture of control is termed as “mixed initiative interaction". This interaction can then be divided into two distinct categories[37]:

- Remote interaction. The operator and UGV are not collocated and are separated spatially. The operator is usually reliant upon sensor data for operation.
- Proximate interaction. The operator and UGV are collocated, usually the operator remains in view of the UGV.

In both the military and search and rescue context it is obvious that remote interaction is of most interest as the "human in the loop" would either be removed from the field of operation for safety reasons or due to physical limitations of the terrain during search and rescue (a collapsed building, for example).

Remote interaction adds complexity for the human operator as he/she is now completely reliant on sensor data for control. Much research is focussed on the autonomous control of UGVs, which, in theory, eliminates the use of the human operator. However, there is much confusion as to what "autonomous" actually means, Goodrich [37] points out that even with robots that are considered fully autonomous some form of interaction is required (see Figure 2.11). An example is given where a fully autonomous robot relies on the human providing mission goals and the robot maintaining knowledge of the surrounding environment and situational awareness.

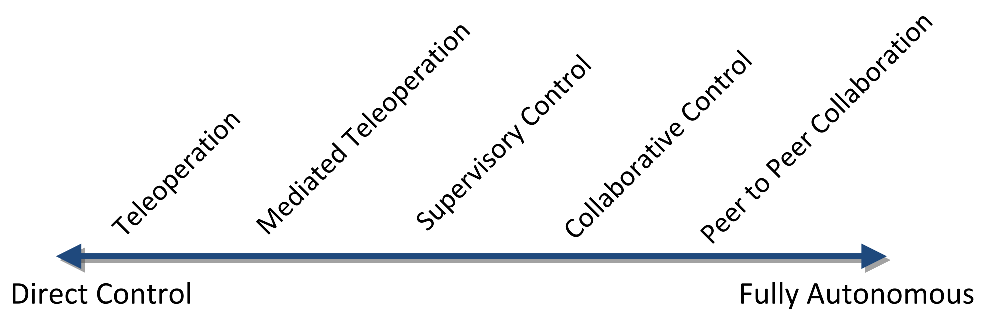


Figure 2.11: Levels of autonomy

This “mixed interaction” is an important issue when considering Power Resource management. In the example of a UGV traversing a route between points A to B it would be feasible for the UGV to automatically select the most efficient velocity based on incline of terrain being traversed in order to conserve resources and for the operator to manage all other aspects of control. However, this would impact on the time taken for the mission to be completed and may not be the most desirable solution for the operator/mission planner, and has the potential to lower the chances of mission success.

This highlights the requirement to consider “human-robot interaction” for any mixed initiative control. An approach for the example may be “supervisory control” where the machine gives the operator several options for the operator to select. But for this to be effective cognitive loading on the operator has to be considered. Where “fully autonomous” control presents a myriad of challenges it is important to note that both “mixed initiative” and supervisory control presents as many issues.

It is also important to note that although “mixed initiative control” presents many design problems, typical UGV missions tend to be quite complex and if completely reliant on a human operator, then this could be a limiting factor on the flexibility of possible mission types. Blackburn [38] highlights that during assessment of a typical fully tele-operated vehicle (in this case the human is providing all necessary intelligence) challenges were observed such as operator fatigue. It is also noted that tele-operation requires significant training, experience and practise. It was also discovered that the optimum level of supervisory control was dependent on how taxed an operator may be at any given time, an example in the military context is when under fire.

Another issue for mixed interaction is presented by Durfee [39] who notes that not only are operators put under fatigue due to the complexities of tele-operation but also due to the fact that while operators may understand the UGV application, they may not necessarily know the physical details of a particular UGV. This is partly due to the fact that in a military mission, a UGV will likely not be placed under the control not of robotic expert, but a soldier who is commanding a variety of human and mechanized systems. Another challenge highlighted by Durfee is that an operator may only be sporadically available due to uncertain wireless communication and cannot be completely depended upon for supervision.

Durfree addresses the above issues regarding mixed initiative interaction by the insertion of an agent technology layer between the UGV and operator, suggesting that the issues can be mitigated by replacing the traditional method of from a “man-must be-in-the-loop” to a “man-can-be-in-the-loop” strategy as long as the system has current knowledge of the operator requirements.

Relying on the operator for effective power management would add to the issue of fatiguing the operator. On the most basic level, reliance on the operator for power management would require them to have an understanding of the residual range available based on current energy reserves and power requirements for the remainder of the mission.

It has already been noted that allowing an integrated power management system to have partial control of energy consumers to effect conservation can lead to a detrimental effect on a particular mission. A suitable trade-off between full automatic power management and human power management may be to give the operator information regarding residual range based on desired velocities for mission, an indication could be given to allow for the operator to utilise remaining resources to their best effect.

2.6.4 Intelligent Power Management

Where missions are deemed to be critical (military applications, search and rescue etc.) it is of paramount importance that prior to the mission starting enough power resources are available for the mission to be completed within a certain time frame, and that the resources are distributed, when necessary to critical consumers during the mission length. The previously discussed variability of UGV missions and unforgiving deployment environments means this is not a trivial task to address. Furthermore, not all mission attributes may be known as a priory. Also, in both the military and search and rescue fields, missions tend to be highly dynamic and are subject to change due to unforeseen circumstances.

It has previously been noted that simply scheduling resources in their most efficient manner without regard for mission factors is not acceptable, and therefore a more intelligent approach is required. Intelligent Power Management (IPM) can be broadly summed up as "a capability which can mediate between the requirements of uninhabited vehicle subsystems and to operate them in accordance with the requirements of a mission plan" [40].

It is of importance to note that for any IPM to be effective the remaining resource requirements of a mission are required to be known (perhaps not in their entirety), and a prediction to be made on the required energy to complete the mission.

In the absence of an intelligent power management system the two main methods that are currently adopted to address mission failure due to depleting resources are:

1. Overprovision by the utilisation of larger power source(s). Impacting on both weight and size of UGV [41].
2. Mitigation of power demand by restricting UGV capability. Typically effected by restricting mission duration or limiting performance capabilities [42].

When consideration is given to UGVs that are involved in military applications there is a requirement for UGVs to develop and evolve within the Ministry of Defence's "Network Enabled Capability" (NEC) frame work which outlines a methodology for "the coherent integration of sensors, decision makers, weapons systems and support capabilities to achieve the desired effect". The two current methods stated above fall far short of the Military aspirations [43] that influence the NEC themes:

- Robustness – remain effective in the face of depleting resources.
- Broadness – Ability to operate effectively over a variety of missions.
- Flexible – Capable of achieving effects in multiple ways.
- Adaptable – Learning from operating environment and acting accordingly.

It is clear that for an IPM to address the above points, prediction of energy requirements is a fundamental element of the management process, which, without the military aspirations would be hard to meet.

Early work in defining non-functional system requirements for a typical IPM to meet user expectations was carried out by Morley [8], one of three levels of compliance (mandatory, desirable and optional) were allocated to each requirement, these are summarised as follows:

Mandatory, an IPM shall:

- Increase the amount of available energy for a UGV when compared to that of a UGV with no IPM.
- Not impact on any safety critical aspects of a UGV.
- Not cause a UGV to fail any mission objectives which it may have otherwise completed.
- Not impact adversely on the reliability of the UGV.

Desirable, an IPM should:

- Monitor the complete system to identify any faults which reduce the amount of energy available.
- Increase a UGV’s capability to perform a particular mission given the initial energy available.
- Increase a UGV’s mission duration capabilities.
- Provide the mission planner with information regarding energy requirements for the remainder of a particular mission.

Optional, an IPM may:

- Reduce its “carbon footprint”.
- Predict the power requirements of particular sensors or systems in order to turn off, components during periods of inactivity.

Satisfaction of the mandatory requirements should ensure that power consumption is managed in an intelligent manner to ensure that overall mission goals are satisfied without compromising the safety and integrity of the system allowing for the allocation of power to be effective and efficient. It is important to note that the role of the IPM system is becoming more of a necessity as UGV missions are increasing in complexity and that the “mandatory” requirements should be extended. Stranjak identifies the most important objectives of a power management system for a UGV as [40]:

1. Adherence to mission goals – manage power autonomously such that overall mission goals are satisfied.
2. Optimisation of power consumption – allocate power efficiently to improve the capability and operational life of platform.
3. Adaptively allocate power – dynamically change power allocation policy (or operational ‘mode’) to best satisfy the requirements of current context, longer-term goals, and unforeseen critical events.

Most current management systems use reactive control to respond to power demands, where the system will attempt to fulfil the energy requirement at the present moment in time [44], where no consideration is given to future power requirements of the mission.

In addition, current systems do not consider the benefits and motivators that the successful implementation of an IPM could provide and would go some way to satisfying the previously discussed NEC themes, the benefits and motivators are as follows [45-47]:

- The desire for increased efficiency in mission execution, with a consequent reduction in the cost of logistical support and over-provisioning of assets
- Increased longevity.
- An anticipated increase in system complexity: increasing numbers of subsystems and components drawing on multiple power resources.
- Greater intelligence in power distribution and resource scheduling.
- Maximisation of mission lifetime.

- Increased UGV range.
- Increased mission flexibility.
- Reduction in logistical footprint of deployed system (fewer components needed due to improved endurance).

Two key challenges for the implementation of the above are highlighted by Morley [8] and are summed up as:

- Development of Algorithms for the prediction of the future energy requirement for the platform.
- Algorithms for the optimisation of generation, storage and release of available energy.

For the prediction of future energy requirements some prior mission information would be required for an estimation to be made on required resources. Further to this, with the likelihood of changes to the mission plan during execution and possible inaccuracies with prior information, live recalculations and estimations of required power resources would be required throughout the mission.

IPM is a two stage process where initially power requirements are assessed during mission planning using available prior knowledge, and then constantly reassessed during mission execution. It is important to note that due to the complexity of the power management problem an IPM has the scope to impact on mission success due to inappropriate decisions being concluded. This concern is currently perceived to add risk to the reliability and robustness of the platform [8]. However, the above assumes that most platforms are autonomous by nature. It is important to highlight that an IPM can be implemented on a tele-operated platform, and be implemented as a guide for the human in the loop operator as discussed in the previous section.

2.7 Conclusions

The applications and deployment of UGVs has increased widely in recent years and many of the advantages they present have been realised. This increase is largely due to rapid advances in technology that has improved the capabilities, robustness and reliability of deployed UGVs. The majority of research relating to UGVs has been focused on the exploitation of these virtues through increasing the versatility of UGVs and the improvement of autonomous control.

This increased functionality has put extra demands on available UGV energy resources and has introduced a limiting factor to the further expansion of UGV capability due to over stretched energy resources, especially where these can lead to mission failure or the limitation of mission length and the traditional methods of addressing this issue have reached maturity. While areas of research concerning the autonomy and flexibility of UGVs have been vibrant since the introduction of UGVs, research concerning the availability and management of available resources (until the recent past) has been somewhat wanting.

Current methods of energy management such as dynamically conserving power and route planning yields some improvement, however, they don't consider the fact that many missions will be time dependent and will require traversal over off-road terrains. Further to this, energy management is limited to the current context of a mission without considering the future mission requirements and also ignore the dynamic nature of unstructured environments.

For critical missions that require completion within a given time frame, which is typical of military and search and rescue missions, successful power management can only be fully realised with the employment of a methodology that is capable of predicting energy requirements of a complete dynamic mission. This is discussed by the work of Morley [8] who highlights that energy requirements for the remainder of the mission should be taken into consideration by the IPM and, further by Stranjak [40] who states that along with the current longer term mission goals should be considered by the IPM for power allocation.

In order to allow for the further evolution of UGV flexibility and capability without undermining mission survivability due to depletion of stored energy, there is a requirement to improve on current methods of intelligent power management.

Therefore the focus of this thesis is the prediction of total mission energy as part of a resource management system for UGVs, as discussed in the next chapter.

3 Energy Prediction in Unmanned Ground Vehicles

As previously discussed, energy prediction is a key component of all but the most basic energy management system. For any system to be effective it is important to estimate the remaining mission power and power requirements as accurately as possible. This allows the system to effectively distribute power to consumers in a manner that ensures that the mission is completed within necessary parameters if possible, or failing this provide critical information, either to a human operator in the case of a tele-operated platform, or the autonomous system about any shortfall in mission energy requirements.

In the absence of mission energy prediction there is a tendency to over-provide energy storage, usually by providing larger and heavier batteries. This increases the size and mass of the UGV [8], which will in turn effect its operational performance in terms of speed and manoeuvrability. The performance degradation is compounded as the rate of energy consumption is increased by the extra weight of additional energy storage.

Energy prediction therefore enables efficiency in the application of energy resources to ensure the achievement of mission aims. At a basic level, all available remaining energy can be applied to the achievement of mission goals without the need for excessive overhead safety margin or over specification of energy storage. Missions can also be adapted as the prevailing energy situation is revealed. This might involve selection or re-ordering mission goals, routes or velocities in order to more efficiently apply available energy to the overall mission aim. It may also include selection or rejection of new opportunities as they arise.

Prediction also provides the critical function of determining whether a mission can be completed at all with the available energy resources. For safety critical missions, being able to accurately forecast power reserves/requirements allows safe completion of atomic operations, where partial completion would result in an unsafe situation.

Any mechanism that would increase the effective available energy resources and the subsequent utility of a UGV, without adding size, weight or limiting functionality, would be highly beneficial. It would effectively increase the performance of UGVs and allow for an increase of mission types and durations [48]. But consideration should be given to the fact that appropriate implementation of energy prediction is somewhat dependent on both the UGV and mission type.

Currently, many UGVs do not employ Energy or Power Management Systems (E/PMS) that incorporate the capability to perform predictions on future mission power requirements (or no PMS at all) and this ability is considered only desirable as opposed to mandatory [8]. Furthermore, the systems that do employ a level of power prediction fail to include consideration of factors such as the platforms dynamic environment and specific mission requirements.

3.1 Propulsion Energy Prediction

As previously discussed [2.5.1 and 2.5.4], propulsion energy for a particular mission can account for 90% of the required total mission energy due to the resistances that propulsion systems must overcome. Therefore the primary focus of a mission energy prediction system in all but the smallest UGVs is prediction of propulsion energy use.

Focussing on propulsion energy requirements the mission energy prediction problem can be likened to residual range estimations made by hybrid or electric vehicles that are used primarily on highways. However these types of vehicles generally travel on asphalt surfaces which have ideal frictional properties and little rolling resistive change throughout a vehicles journey making energy prediction relatively straight forward and variances of prediction usually focus on driver style as this is the most prominent varying factor[49].

At its most basic level mission energy prediction could be considered the prediction of the energy required for a UGV to traverse a predetermined route (from A to B) at a fixed velocity, where energy consumption for a certain velocity is known as a priory. However, this assumes that the consumption to be constant as long as the velocity remains constant. In reality UGVs have to traverse a wide variety of terrains, especially when consideration is given to the use of UGVs in military and search and rescue applications. These applications result in the seemingly simple task of traversing from A to B very complex where environments are unstructured and terrain types vary widely [50].

Therefore, a primary complexity of prediction of propulsion energy requirements is that resistance forces will vary drastically dependent on the mission and terrain type [51]. For accurate energy prediction information about the current and future terrain in terms of energy required by the propulsion system to traverse must be accurately estimated.

Prediction is especially challenging for off-road vehicles when considering that resistance coefficients for terrain types can change (more dramatically) due to influences of weather (moisture content being the most prevalent), that have a large effect on resistance and subsequent power consumption. Propulsion energy requirement is therefore harder to predict for their future mission requirements opposed to other UGV consumers (cameras, sensors etc.) where external forces have less varying effect on consumption. The problem can be divided into three distinct processes, terrain identification, characterisation and finally energy prediction.

3.2 Terrain Identification

As terrain characteristics play a critical role in propulsion energy prediction, the ability of a prediction system to identify the terrain that UGV traverses, both in the present and in the future, should be considered of paramount importance for ensuring mission success.

3.2.1 Offline Terrain Identification

Terrain identification using offline methods has received significant attention over the past 40 years, these methods commonly involve human intervention, an example being the “Cone penetrometer” (in its simplest form a tool with a conical tip manually pushed into a terrain) where on implementation a parameter known as a the “cone index” is obtained. The limiting factor of the “cone index” is that it represents both “slip” and “sinkage” and they cannot be readily differentiated. The use of the penetrometer to “identify terrain characteristics from the vehicle mobility or terrain trafficability viewpoint remains controversial” [26]. Its original intended use is to give an indication of vehicle mobility on a “go/no go” basis.

The “Bevameter” method can be seen as an improvement on the above as it comprises of two separate tests. One being a “plate penetration” test designed to measure the predicted vertical deformation of the terrain (sink) due to the vehicles weight. The other being a “shear test” that gives indication to horizontal deformation of the terrain (see Figure 3.1).

Figure 3.1: Bevemeter used for both penetration, and shear tests

The relatively new subject of terramechanics (founded by Bekker [52] and furthered by Wong [26]), whose basic principles include the modelling of terrain behaviour, measurement and characterisation of the mechanical properties of terrain pertinent to vehicle mobility, and the mechanics of vehicle–terrain interaction attempts to address the terrain-vehicle interaction issue in order to provide guiding principles for the development, design, and evaluation of off-road vehicles [26]. It is important to note that the subject of Terramechanics makes no attempt at terrain classification or identification.

Although there are many different terrain types, all with their own unique vehicle interaction properties, no standard method for classification currently exists. Many researchers have their own method of classification for terrain types, Odedra’s attempt would appear to be the most comprehensive and this by no means covers every terrain (see Table 1). It does highlight the many variables involved when weather influences are taken into consideration for terrain resistance.

Terrain type	General surface properties	Sun	Rain	Snow/ice
Sand	sinkage, slippage	hot	hydrocolloid	n/a
Mud	sinkage, slippage	soft	liquefaction	hard
Clay	slippage, sinkage	hard	liquefaction	slippage
Rocks	uneven, hard	dry, hot	slippage	slippage
Forest	long grass, foliage,	dazzle	marsh	hard
Short grass	can get tangled	$\mu = 0.35$	$\mu = 0.2$	$\mu = 0.15$
Gravel	loose, uneven, slippage	dry, hot	slippage	slippage
Dirt track	dusty, level	dry	liquefaction	slippage
Paved road	gaps, flat, high friction	$\mu = 0.7$	$\mu = 0.5$	$\mu = 0.08$
Asphalt	flat, high friction	$\mu = 0.8$	$\mu = 0.4$	$\mu = 0.06$

Table 1: Terrain types and their properties [50]

Error! Reference source not found. also highlights the effects weather has on terrains. Factors effecting terrain properties are particle size and the elements that fill the voids in between particles, which contains air, water or ice. These factors greatly affect the terrains' properties, sand for example, has very small particles and has very different properties when wet compared to when dry, which in turn affects the ability of that terrain to support a vehicle, and the vehicles performance, therefore the key elements that dictate terrain properties are particle size and the percentage of water content [22].

3.2.2 Online Terrain Identification

The previously discussed methods of terrain characterisation require human intervention, (or in the case of the Bevameter approach, cumbersome mechanical equipment to be fitted to the vehicle) and are not suitable for operation during most mission types. Alternative methods of terrain identification using live on-board sensor data are being researched and developed [53, 54] but the topic is still considered to be is in its infancy. Wheel-terrain interaction analysis and vision based systems are the two primary methods that are currently being researched.

In the commercial field when considering skid steer UGVs very little information is available regarding remaining endurance [9]. Morales et al [34], while not addressing energy prediction in its full context, addresses the little explored area of modelling power consumption for tracked vehicles. The approach uses the power losses which are modelled from two different perspectives, the power drawn by the rigid terrain and the power supplied to the drive motors. Experiments carried out were over differing terrain types but not of the type associated with off-road vehicles but the relevance of dynamic friction losses with respect to total power consumption were confirmed.

Pentzer et al [9], highlights the two areas of research effecting skid steer endurance. These are battery models that accurately determine remaining energy, and methods for accurately estimating energy required for completing a mission. Pentzer notes that a successfully applied method for wheel/track slip estimation uses the instantaneous centres of rotation (ICRs) of the tracks or wheels of a skid-steer that provides accurate motion and power use estimation. However previous work required terrain parameters relating to power usage to be learned through post mission optimisation.

Pentzer's work builds on the previous work relating to ICR, by identifying ICR locations and power model parameters during operation of the UGV. A Karman Filter is used to estimate the locations of the ICR which are then combined with on-board sensor data to provide a model of the UGV movement (via a least squares recursive algorithm). The result is an estimate of power model parameters relating to friction between the tracks and terrain surface and rolling resistance. Pentzer furthers the work by demonstrating that the algorithm had the capacity to learn that power modelling coefficients for varying terrains assuming a method is in place for detecting the terrain change.

It is important to note that if terrain classification/identification methods are employed, then any additional sensors and computational time will impact on overall power consumption. It is obviously of interest, where possible to utilise existing sensors for data gathering. Iagnemma's work [55] suggests a method (using wheel-terrain interaction analysis) for online estimation of two key terrain parameters, "cohesion" (c) and "internal friction angle" (σ). The method is computationally efficient so processing overhead would be at a minimum.

The shear properties of the terrain are often described in terms of the horizontal stress vs. shear displacement. Figure 3.2 shows a typical relationship between torque applied and displacement of the top terrain layer.

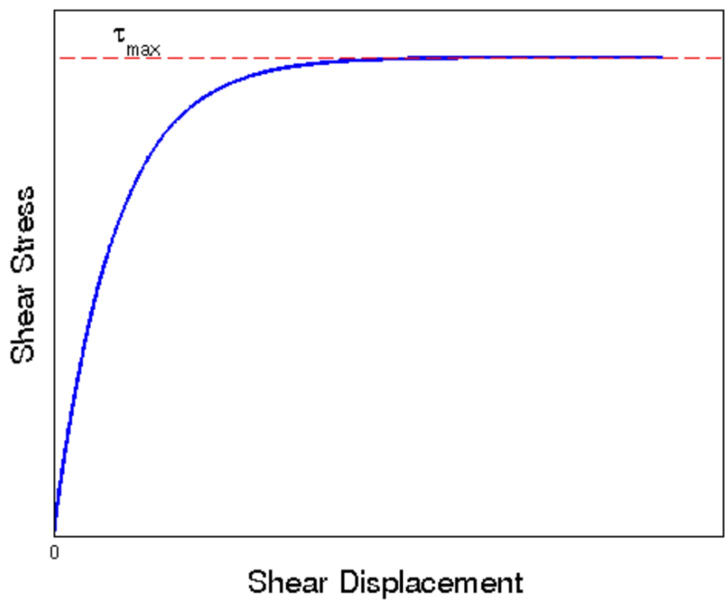


Figure 3.2: Shear Stress vs Shear Displacement of Wheel Terrain Interaction

Janosi et al [56] suggests that this can be described by an exponential function for most applications as:

$$\tau = (c + \sigma \tan\varphi)\left(1 - e^{-\frac{j}{K}}\right) \tag{1}$$

Where j is shear displacement, K is shear deformation modulus, σ is normal stress, φ is the internal friction angle of the soil and c is cohesion of the soil.

The field of terramechanics often simplify to the Coulomb-Mohr soil failure criterion exploiting the fact that the value of τ_{max} is critical rather than the behaviour of the wheel in transition from traction to slip for a range of τ values. τ_{max} is the ultimate maximum value of torque that can be applied to the terrain before slip occurs. Therefore the soil failure to support the applied torque (slip) can be described as:

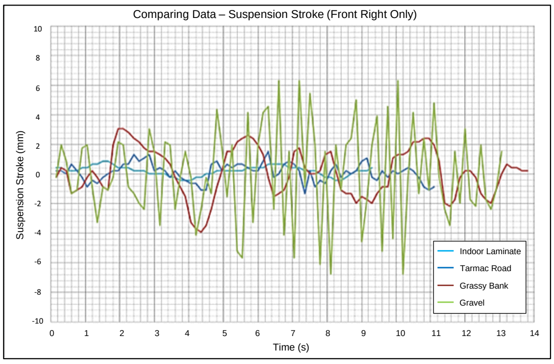
$$\tau_{max} = c + \sigma_{max} tan\phi \tag{2}$$

Where c is cohesion of the soil, σ_{max} is maximum normal stress at wheel terrain interaction interface, φ the internal friction angle of the soil, and σ_{max} the stress applied to the soil which has a direct relation to the vehicle mass and contact area with the ground.

Iagnemma [55] implements (2) and a least squares estimator to compute the two parameters in real time. The maximum shear (slip) terrain strength (τ) can be calculated, also the two parameters can be used to determine the terrain type. This method showed promise for sensing maximum shear. However, when these two parameters are used without any other data, terrain classification would be difficult when consideration is given to moisture content of terrains.

Further examination of Table 1 highlights this problem further, i.e. as to what terrain properties will show a distinct difference in all weather conditions? This is due to the fact that it will be harder to independently class terrain and label each one because of the number of variations and changes in them. Odedra [22] proposes that to sense the terrain, the system must use on-board sensors to take measurements of the drive systems' slippage and sinkage, which are the main conditions of the wheel-terrain interface.

The work of Reina [57] proposes a methodology to address monitoring and accurately measuring both slippage and sinkage to reduce odometric errors and improve energy consumption. It is important to note that slippage in the longitudinal plane is addressed in this work. The condition where all wheels are simultaneously slipping is addressed. The proposed methodology for slip measurement required no extra hardware in the form of sensors, as data was collected from standard UGV sensors. By comparing data from wheel encoders with data from a gyroscope, and with current sensors it was shown that the majority of wheel slippages were detected on sandy non flat terrain. The method suggested for sinkage utilised a vision based algorithm and required extra hardware in the form of a camera mounted on the UGV body. The results proved promising in terms of accuracy and very robust in terms of disturbances and varying light levels.



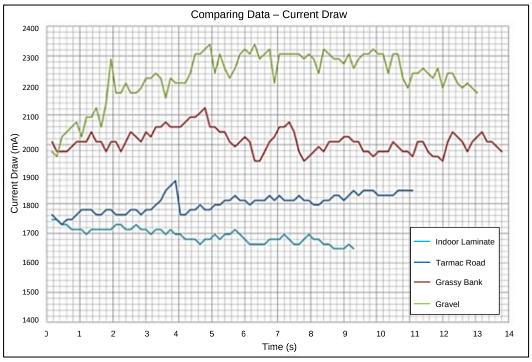


Figure 3.3: Results showing suspension stroke and current draw for varying terrains [50]

Odedera's [50] method of utilising wheel-terrain interaction analysis for terrain classification uses a basic approach. Sensors used for data gathering were a current sensor used to measure the vehicles power consumption which related to the rolling resistance, linear potentiometers were installed at each wheel to measure the frequency of the suspension which gave a measure of the terrains' roughness, and the suspension stroke was also measured using the linear potentiometers to measure the terrain topology. The graphs shown in Figure 3.3 clearly show that terrain type can be detected using the sensor data stated.

However, the samples for the graph were taken at a constant speed, and it relies on the rolling resistance being calculated from measured current. It would assume that the rolling resistance is linear with velocity. This tends to only be the case where the driving conditions are favourable and the resistance describes only the losses due to friction in the tires when rolling on prepared surfaces [29]. It is also important to note that no consideration is given to weather effects on the terrain types either. The work highlights the complexities and difficulties with terrain classification. It can be noted from Figure 3.3 that there is notable suspension travel on the "grassy bank" terrain, when examining Table 1, it may be necessary to include another dimension for roughness.

Ojeda [53] proposes a method of wheel-terrain interaction analysis for terrain characterisation that requires little overhead regarding extra sensors (data is collected from sensors that are typically installed to UGVs, i.e. motor current sensors and gyros), but is limited to skid/steer vehicles. Due to the difficulties of extracting the internal friction angle (ϕ) and the cohesion parameter (c) (see (2)) from a single shear stress/displacement curve, Ojeda raises the interesting proposition of utilising the slip effect of a skid/steer UGV while effecting a turn to replace the "shear plate" of the "bevameter" method (discussed earlier). This is possible due to relationship between the motor currents versus rate-of-turn of the skid steer UGV. This can be used analogously with the shear-stress vs. shear-displacement relationship.

By collecting experimental data (motor current) over varying terrains while effecting a variable frequency rate of turn it was possible to define curve characteristics for the differing terrains. The curves can be seen in Figure 3.4, it is of interest to note that both curves that are produced from 3rd order polynomials are represented on the figure along with raw data.

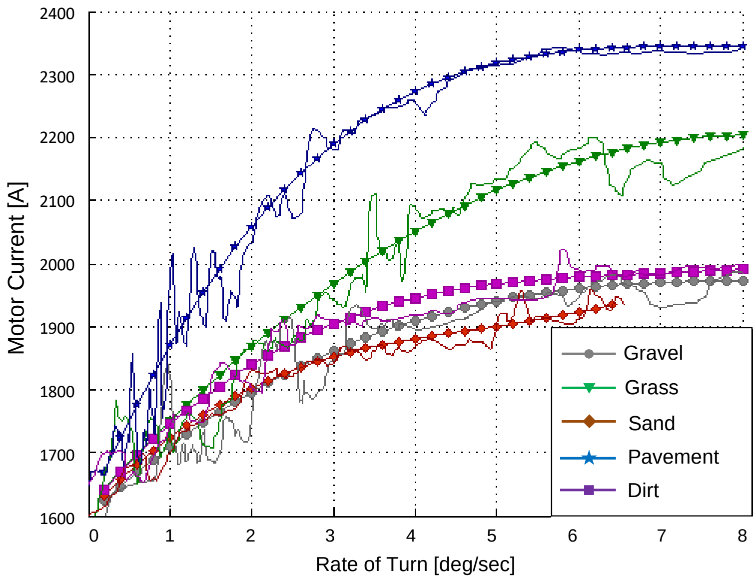


Figure 3.4: Curve characteristics for differing terrains (Note that the solid lines indicate polynomials from the data ranges) [53]

It can be seen that if the polynomials are used alone there will be some difficulty distinguishing between certain terrains (gravel and dirt from Figure 3.4). Ojeda concludes that it is possible to distinguish the two by examining the variance of the samples; there is sufficient difference due to increased noise on the gravel samples. This is interesting as it implies a method for detecting terrains that appear to behave the same from sensor data by avoiding gathering data from additional sensors. Further to this Ojeda introduces the issue of moisture on wheel/terrain interaction (see Figure 3.5) by showing the effects on motor current while effecting a turn on macadam. However, this effect complicates the issue of terrain detection and no method of addressing this is offered.

The above methods consider wheel-terrain interaction analysis which provides online indication/classification of terrain at the moment of terrain traversal. Vision based terrain classification/identification offers the opportunity for terrain identification prior to the UGV traversing a particular terrain type, thus allowing for potential hazards being detected avoiding unnecessary mission failure. It is of interest to note that these methods are considered resource heavy in both hardware and software contexts.

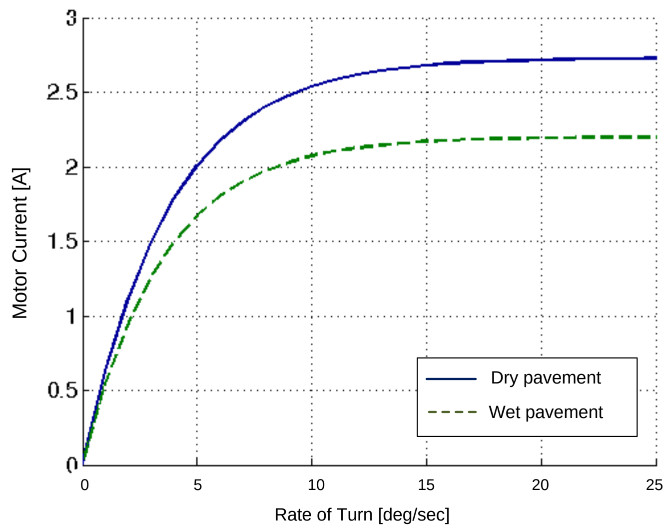


Figure 3.5: Rate of turn of the robot vs. average current on wet vs. dry pavement [53]

Early work in this area by Lacroix et al [58] does not attempt to categorise terrains but uses a vision-based system to segment the terrain into four categories, flat, uneven, obstacle and unknown. The system has both 2D (for mainly flat terrain) and 3D navigation (for uneven terrain) modes, data for which is collected either via Laser Range Finder of a Stereo Vision Algorithm. The work provided favourable results while navigating 2D environments.

It is important to note that research to date is for the primary reasons of proving the trafficability of the terrain and to ensure the safety of the vehicle, opposed to resource prediction.

During route traversal through rough unforgiving terrain when adopting vision based systems for terrain identification, the velocity of the UGV is generally hampered by the high computational cost as images are converted into full descriptions of the terrain topology. Kelly et al [59] address this issue and coins the phrase "perceptual throughput problem" as the speed of the vehicle while navigating rough terrain is limited by the throughput of the system. The approach to the problem has been to insert an architectural layer between strategic planning and actuator control (named tactical control). This layer, being faster than planning and more intelligent than the control layer improved the "perceptual throughput".

Another layer of complexity on terrain classification/identification not yet discussed is that of terrain cover that is made up of compressible vegetation. Vision based systems that are used for terrain classification and obstacle detection may detect objects such as tufts of grass of small bushes that may not present a traversal problem to a UGV to be an obstacle. Manduchi et al [60] addresses this issue with the use of two separate algorithms, one for obstacle detection and the other for terrain cover classification. Data for the obstacle algorithm is derived from a laser rangefinder. Terrain cover classification data is affected from two complementary systems, colour cameras for stereo and colour analysis and range data processing from the laser range finder. The complementary system addresses the issue of detecting compressible vegetation from other smooth surfaces that present physical obstacles.

Iagnemma [55] and Odedra [25] both discuss frameworks for using both the vision based system and wheel-terrain interaction analysis in a complementary manner. Iagnemma also includes off line prior data to produce a three stepped approach:

- Phase 1. What will happen before getting there? Previously gathered data, reconnaissance images, terrain maps etc.
- Phase 2. What is going to happen next? Data from visual passive sensors (Laser range finders etc.) to look ahead.
- Phase 3. What is happening right now? Real time data from terrain wheel interaction.

While the above research focuses on the use of on-board sensors with the use of pre-mission data to characterise/identify the terrain, it does not consider in detail the impact that weather conditions have on vehicle/terrain interaction and while considering the strength properties (that dictate the trafficability) of particular terrains initially depend on the type of soil (characterised by grain size/distribution), it is influenced (to varying degrees dependent on type) by moisture content and density [61]. As consumption of a UGV is primarily effected by slip and sinkage which in turn is affected by weather conditions (moisture content, etc.), it is not necessarily feasible to build an accurate estimation of rolling resistance based on terrain appearance from vision systems [22].

3.2.3 Prior Terrain Knowledge

The previous section discusses methods of live terrain sensing during mission execution and assumes lack of pre-mission data regarding terrain types. However, the availability of pre-mission information regarding terrain types has improved in recent years with the availability of systems to assess terrain types from aerial imagery [62] and the growth of geographical information systems [63].

The available technology should not be considered a replacement for online methods but at a minimum should complement them. Mission planners are likely going to require at least a rudimentary understanding of terrain types prior to mission starting at least to determine if a viable path exists, also when considering the prediction of resource allocation and the previously mentioned effects that terrain types can have on energy consumption prior knowledge is obviously invaluable.

There are situations where it is not possible to attain a full understanding of the environment from the information gathered by on-board sensors. One obvious limitation being the range of vision based systems (typically limited to 100m [64]), of the view being obscured by structures or natural topology. Further, when traversing at high speeds and relying on on-board sensors, negative obstacles (ravines, potholes etc.) can become difficult to avoid [62, 64] possibly resulting in mission failure.

The growth of Geographical Information Systems (GIS) makes it is possible to find a high-resolution terrain map for virtually any location in the world. The availability of these maps allows for the computation of energy-minimising paths for UGVs, with the variance of the friction coefficient in different areas of a proposed route, which impacts on energy consumption and would aid in offline energy prediction. Despite the obvious potential applications in both commercial and military areas, there has not been enough interest in the energy-minimising path problem and the potential utilisation of this pre-mission data has not been realised.

Hudjakov [64] presents an approach to terrain classification using an unmanned air vehicle (UAV) complete with passive optical sensors (infrared and RGB cameras). Image processing is carried out by a convolutional neural network. The system could be trained by both offline and online data. The result being a weighted map that allowed for the planning of the most energy efficient route. Although the results from this work show that the resulting maps cannot be relied upon for full navigation it does provided valuable data regarding terrains that may be outside the vision of on board sensors. This indicates that it is a useful aid for offline energy prediction.

Sofman et al [62] also utilises a neural network to effect terrain classification from aerial imagery. However, he utilises additional sensor information in the form of colour and signal reflectance to improve sensory perception allowing for significantly improved classification of a wider variety of map features.

From the above a pre-mission prediction can be made regarding consumption accounting for expected rolling resistance values. Unfortunately, it is unlikely that the prior assessment of predicted consumption will be perfectly accurate (at least for a portion of the mission) due to fluctuating resistances (due to weather effects) or not entirely accurate prior information.

3.3 Terrain Characterisation

In order to achieve accurate energy prediction, any identified terrain must be described in terms of the energy required for the UGV to traverse it, more usefully, over a range of likely climatic conditions that will affect energy requirements. Several approaches to terrain characterisation are possible.

Significant research has been focussed on economy for road vehicles and has led to numerous simulation packages to aid the designer in producing vehicles that are as efficient as possible. The same progress is not evident for off-road vehicle simulation packages. The rolling resistance for the road vehicles is relatively easily modelled and the road surface type impacts little on energy usage. The simulations that are primarily concerned with road vehicles' energy prediction tend to focus on driving styles, cruise control algorithms, drive train design etc. opposed to the wheel surface interaction (with the exception of research into tyre design).

The subject of terramechanics has the goal of establishing mathematical models for vehicle–terrain systems that will assist the vehicle designer/mission planner to evaluate, on a rational basis, a wide range of options and to select an appropriate vehicle configuration for a given mission and environment [26]. But when consideration is given to power resource management regarding simulation for predicting required mission resources for a UGV, the simulation would also need to consider the above mentioned factors along with other mission criteria, such as route plan, varying terrain types, the effects of weather on the terrains such as moisture content etc.

Early work into simulation of off-road wheel terrain interaction utilising algorithms was developed Rula et al [65] and resulted in the AMC-71 mobility model which addressed three principle categories of users:

- Vehicle design and development community.
- Vehicle procurement community.
- Vehicle user community.

This is of particular interest as it led to the AMC-74 model that recognises that terrain encountered on a mission is not necessarily homogeneous and the modelling problem is more complex due to this. The NATO Reference Mobility Model (NRMM) [66] furthers this work by producing a collection of algorithms and equations designed to simulate cross-country movement of vehicles. In order to produce a useful simulation NRMM simplifies the problem by separating terrain types of a particular mission route by defining terrains that are sufficiently uniform so that a segment of terrain has uniform characteristics throughout its extent. This allowed for maximum safe speed predications to be made for every segment. Although the model is primarily for permissible maximum speed predictions, it also has the ability to generate data concerning fuel consumption.

Wong's [26] work on Terramechanics discusses methods of simulation of vehicle-terrain interaction. One method is that of modelling the terrain as an assemblage of finite elements, this has only recently been possible with the recent advance of both computer technology and computing techniques. However, the finite element method is hampered due to the lack of development for determining the values of the parameters of the finite element model to properly represent terrain properties. It also assumes that the terrain is a continuum which would limit its use as it would not be suitable for simulating large, discontinuous terrain deformation that usually occurs in vehicle-terrain interaction.

The discrete element method is an alternative approach discussed by Wong which relies on the study of interaction between a vehicle and granular terrain (discrete element modelling), such as sand for example. This method, similar to the finite element method, is also hampered in its development due to the lack of reliable methods for determining the values of model parameters to realistically represent terrain properties in the field. Further to this considerable computation requirements would be required.

The NRMM relies on empirically based relationships based on measurements taken from actual vehicles run over a variety of terrains. During the period when NRMM was developed the vast majority of military vehicles weighed more than 700 KG.

Although still used mainly for the procurement phase of projects, the emergence of lightweight UGVs leads Ahlvin et al [67] to question the use of NRMM for smaller vehicles. His work concludes that although NRMM has potential for use as a design and evaluation tool for the suitability of small vehicles, its use is hampered by the lack of available mapped terrains of suitable fidelity.

For any modelling simulation method to be of any use with respect to energy management, a thorough understanding of energy usage for a particular UGV is required. Broderick et al [67] highlights that energy characterisations of both commercially available and military UGVs are currently lacking and as numbers of deployed UGVs increases so does the need for methods and standards to analyse UGV performance. Further to this he presents a methodology using a 'packbot' UGV as a case study. Rather than implementing a Terramechanics model, Broderick's methodology is based on empirical data recorded during live UGV operation. The proposed methodology characterises energy usage based on:

- Energy usage per distance travelled at a given speed.
- The most efficient speed for a given terrain.
- A terrain-independent electrical-to-mechanical energy curve.

Using this information a mission planner can optimise a mission route based on prior data regarding terrains and mission goals. Further to this, the methodology allows for the comparison of different UGVs for a given mission. Although it is not stated, it is assumed that the methodology would also allow for differing configurations of a particular UGV to be explored for a particular mission. Broderick's methodology for determining energy usage consists of the following three steps [67]:

1. Selecting a series of tests. A set of test routes and trajectories based on desired velocities and terrains for which energy is to be characterised.
2. Recording the necessary data during the tests.
    a. Electrical voltage and currents.
    b. Motor speeds.
    c. Distance travelled.
3. Processing the data to analyse energy usage after the tests. To produce:
    a. Energy usage per distance travelled at a given speed.
    b. The most efficient speed for a given terrain.
    c. A terrain-independent electrical-to-mechanical energy curve.

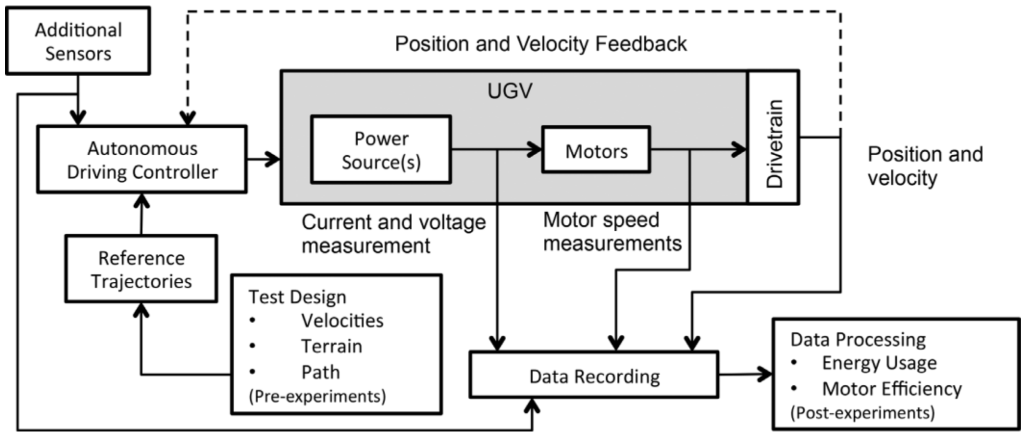


Figure 3.6: Flow of methodology used for UGV energy characterisation [67]

Figure 3.6 shows the methodology for data capture and analysis, it shows that there is included an autonomous driving controller, this is for controlling the velocity of the UGV as to the given test velocities, this can be replaced by a tele-operated system. For testing parameters Broderick suggests for both the independent variables (speed and terrain) a series of set points are required to be defined. Maximum and minimum speed values should be chosen as a minimum, intermediate speeds can also be used to expand the test data, the trade-off being resolution of data versus additional resources required for testing. Terrain selection should be based on the application of the particular UGV. Broderick points out that variation will always exist between terrain parameters and real world parameters but a set of basic terrains can be chosen to predict general performance. If the UGV is intended to be used on off-road terrain then the terrain set should include at least one deformable terrain.

Broderick uses “cost of transport” (defined as energy used per metre per kilogram) as one method of measurement, which is the common metric for biped robots, this is so that results allow for consideration to be given for alternative configurations where the UGV mass may be increased. This is calculated by dividing the average energy usage over a test run by the platform mass. Terrains selected for the packbot trials were hard grass, soft grass and asphalt, the results when considering the cost of transport revealed that, for asphalt the cost is significantly lower and is roughly constant over the test speeds, the grass test shows a decrease in cost as velocity increases.

Available simulation packages that address off-road vehicles appear to focus on the design of vehicles, opposed to an aid for mission planners. Sinha [68] recognises the problem of limited operating duration of robotics vehicles due to energy losses, and the need for systematic analysis of locomotion and energy dynamics, which would enable an efficient design of the vehicle. By focusing on skid-steer vehicles his research results in a simulation package (SimUGV) that aids designers in the development of more efficient UGVs by the optimisation of design variables to minimise energy losses. Sinha’s work uses simulated data for different surfaces (both off and on road) but does not consider the effects of prevailing weather conditions of the surfaces.

3.4 Energy Prediction Approaches

Once the mission terrains are identified, knowledge of UGV performance data, current energy storage level, mission route plan, terrain identity, terrain characteristic and weather data can be combined to generate future mission energy predictions.

Initial work by Sadrpour [32], considers the mission as a whole and addresses the issue of varying rolling resistances on differing terrains. Sadrpour's work proposes a method for mission energy prediction for a battery operated UGV undertaking a specific mission where some information is known a priory. The prediction is in the form of quantity of energy available on completion of a mission. The mission example used is that of a surveillance mission. The focus is on energy used for propulsion rather than energy required for sensors processing etc. (although this is not ignored). The contribution offered by Sadrpour's work is the comparison of two methods of mission propulsion energy prediction during the execution of a simulated typical UGV mission. The two methods are as follows:

1. A linear regression model when there is no prior knowledge of the mission. (By no prior knowledge, the author is referring to knowledge regarding terrain types and values for rolling resistances, there is prior knowledge regarding mission distance and expected future velocity).
2. A Bayesian regression model when the prior knowledge is obtainable. (The prior knowledge here includes mission length and terrain types).

Sadrpour expresses the UGV power consumption to be:

$$P(t) = F_x u(t) = \Big(W \sin\big(\theta(t)\big) + fW \cos\big(\theta(t)\big) + ma(t)\Big) u(t) + b + \varepsilon(t) \qquad (3)$$

here $\mathrm{F_x}$ is the total traction, W is vehicle weight, f the rolling resistance coefficient, m the mass, $a(t)$ acceleration, $u(t)$ is velocity, $\varepsilon(t)$ is the modelling error and b other electrical loads and where $W\sin\big(\theta(t)\big)$ is the effect of incline and $fW\cos\big(\theta(t)\big)$ the effect of rolling resistance (see Figure 3.7). The non-linear nature of this expression is removed due to the fact that the intended inclines of the perceived routes will not be greater than 15 degrees resulting in:

$$P(t) = F_x u(t) = \big(W\theta(t) + fW + ma(t)\big)u(t) + b + \varepsilon(t) \tag{4}$$

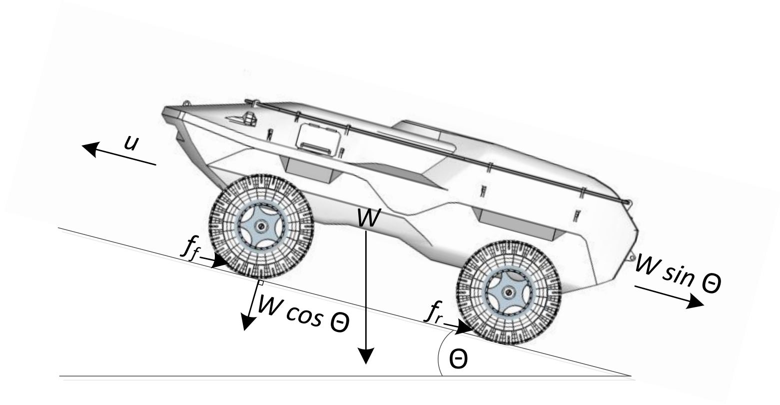


Figure 3.7: Forces acting on UGV

This allows a linear regression model to be used. The two methods are compared using a theoretical mission where a UGV has to traverse a route comprising differing terrains. The route is as shown in Figure 3.8.

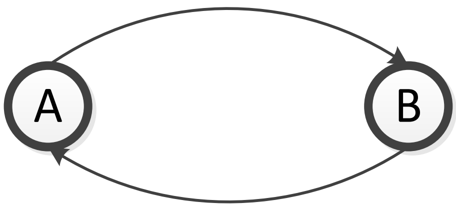


Figure 3.8: Two segmented mission, showing terrain types and inclines

The nature of the terrains including whether they can be considered off-road terrains is not described in detail, but the rolling resistance coefficient values stated are suitably different. The rolling resistance encountered on the terrain in segment 1 is higher than that of the second segment. For both methods of prediction, samples for power (presumably voltage and current of the propulsion motors) are taken at discrete time intervals and the predicted total power requirements are calculated along with 95% confidence levels. The same driving style (velocity) is used for both methods.

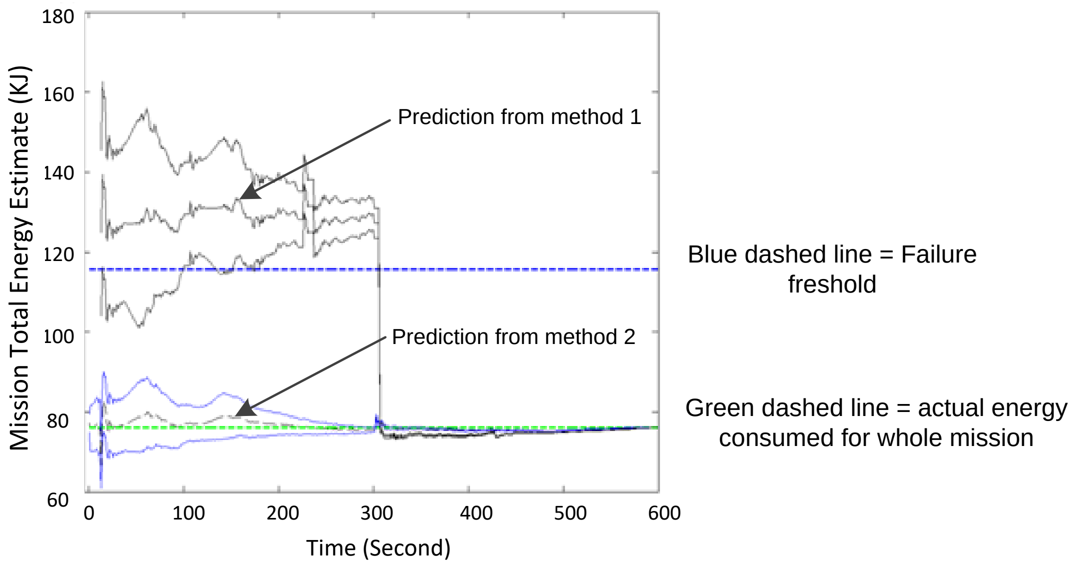


Figure 3.9: Comparison of linear regression model (method 1) and Bayesian regression model (method 2) results from simulation [32]

The results in Figure 3.9 show that the Bayesian regression model provided a more favourable prediction over that of the linear regression model. This is largely due to the linear regression model only considering online velocity and power measurements. It can be seen that prior to the UGV reaching the 300 second point, the linear regression model over predicts energy required to the point where mission failure is predicted, when this point is passed the prediction is far more acceptable. The point at 300 sec is where the terrain change takes place. As there are no more terrain changes for the remainder of the mission the remaining prediction remains reasonably accurate.

The Bayesian model outperforms the former (particularly in the initial stage of a mission) due to the fact that it exploits available prior knowledge of the yet un-traversed terrain in the form of the rolling resistance coefficient and also the distance from the start of the mission to the point of the terrain change.

The work concludes that the availability and use of prior knowledge improves mission energy prediction by reducing both false and miss detection of abrupt changes in energy consumption by the propulsion wheels.

The method proposed (Bayesian model) only adjusts the prediction for terrain types already traversed (based on live data values) on a predefined route. The energy prediction assumes that any new resistances for un-traversed terrains are as prior values and also that prior information about terrain types is entirely accurate. For example, assume that the UGV is travelling in segment 1 from Figure 3.8, the rolling resistance for this segment can be calculated, and a reasonable prediction can be made based on live sensor data opposed to relying on pre mission data that may be inaccurate, the prediction for segment 2 assumes resistance values based on pre-mission values.

The expression (3) used should only be considered to specific “favourable” driving surfaces, where the rolling resistance term describes the losses due to friction in the tyres when rolling on a hard uniform surface such as tarmac [29]. It is not described if the terrain for segment 1 is considered a hard uniform surface, it is described as very rough, but it should be noted that the above method is not ideally suited to off-road terrains.

It also considers the problem of prediction to be linear in nature, which is not necessarily the case when considering consumption of a UGV that has to contend with steep inclines and varying factors such as excessive wheel slip.

3.5 Conclusions

While it can be argued that an Energy Management System does not necessarily require a predictive element for future energy resource requirements it should be considered a critical component for the development of UGVs that are deployed into mission critical situations. Conventional approaches such as energy storage over provision and mission constraining safety margins will result in negative effects such as overall platform weight and physical size.

The shortfalls of conventional approaches are highlighted by their direct contradiction to the stated Network Enabled Capability (NEC) military strategy aspirations. Improved energy prediction methods enabled greater 'effective' capability to be delivered as existing resources can be deployed to maximum effect. Existing approaches such as over provisioning energy storage or excessive safety margins directly constrain the delivery of capability.

Existing methods have reached maturity, resulting in a technology gap where the requirement exists for the development of accurate and adaptive models which predict a platform's energy requirement throughout a mission.

Historically, the ability to effectively predict future resource requirements has been hampered due to the fact that energy consumption is influenced by varying rolling resistance values of differing terrain types and often, pre-mission information regarding terrain types has been lacking. The rapid increase of availability of terrain data now enables improved energy prediction as terrains that are likely to be traversed during a mission can be known a priory. In the absence of terrain data possibilities exist for terrain maps to be prepared using satellite information or data collected from Unmanned Air Vehicles (UAVs).

Recent energy prediction methods attempt to take advantage of the newly available pre-mission data and have shown significant improvement on overall mission energy resource prediction requirements compared to previous attempts. However, current methods of prediction focus on prepared surface terrains where rolling resistances are not significantly influenced by prevailing weather conditions such as moisture. Despite this shortcoming, they provide a useful basis for methods of relevant sensor data collection and interpretation for use with energy prediction.

There is significant potential to improve on current prediction efforts to allow for the more efficient use of stored energy and effecting the reduction on the dependency of larger stored energy sources while not compromising the capability of the platform. If consideration is given to the impact that weather conditions can have on rolling resistance values (and, hence energy consumption) a significant improvement on prediction would be to account for the effect of moisture on yet to be traversed terrain types of a UGV mission.

For this to be effective, a new method is required where influences of weather such as moisture content can be extrapolated from live sensor data, while not increasing the complexity of the system or requiring the addition of sensors which would reduce the effective capability of the platform by increasing the physical size and weight and result in an increase of energy expenditure.

4 Resource Management System Simulation

4.1 Introduction

The principle aim of this work is to improve the current state of the art energy resource prediction approaches and algorithms for military UGVs. As discussed in previous chapters, military UGVs are required to operate in a variety of environments, with varying climatic conditions and a range of terrains, all of which have significant effect on power resource usage. The research challenge is to develop an approach to identifying and characterising terrain and then to accurately predict and manage the limited available power resources, typically via some energy prediction algorithm approach.

To support this effort it is necessary to define a toolset and methodology for the development and analysis of novel mission energy prediction algorithms as described in the following contribution chapters. It was therefore necessary to design and construct a toolset that is capable of representing the problem and evaluating potential solutions.

Therefore, as a methodology and a supplementary research contribution this chapter presents the novel Resource Management System Simulation as a means to represent the scope of the UGV mission energy problem and to develop and evaluate novel solutions.

4.1.1 Simulation Approach

Developing new terrain identification / characterisation and energy prediction algorithms, and assessing their relative performance, may be achieved using various approaches each with varying cost, performance and flexibility. The accuracies of the various approaches in terms of fidelity with physical reality vary, as do the costs in terms of time and financial capital required to implement a given solution or to make subsequent changes to that solution.

At the low cost, low fidelity end of the spectrum, manual approaches such as simple thought experiments or static pre-mission calculations can be used. These represent the current state of the art in the military UGVs applications, the shortcomings of which are discussed comprehensively in previous sections.

Such manual approaches are limited as a basis for improvement. They are inflexible as any small change in the problem space typically requires laborious reconfiguration (using new parameter sets) or even complete re-authoring of equations (using new mathematical functions). Static equations must be, by definition, carried out by human calculation and so are limited in complexity, are time consuming and are error prone. The methods have little application beyond some basic pre-mission analysis and are ill equipped to address changing mission requirements.

A high degree of accuracy can be achieved via physical testing using some appropriately instrumented test-bed or prototype UGV. Unlike the other approaches discussed here which all aim to model the physical reality, empirical testing of this type generates minimal opportunity for error beyond flaws with instrumentation or result processing. The major drawbacks to such an approach are high cost (both monetary and time) and limited flexibility.

Depending on configuration, the physical creation of a test-bed UGV can be expensive and time consuming. The operation of the system is also costly as each experiment is likely to take considerable planning and execution time as well as physical access to an appropriate test site.

Perhaps the most prohibitive cost of the test-bed approach is the cost generated by change. The physically complex experiment takes considerable time to reconfigure. Extra complexity of a test UGV would be also required in order for the algorithm to be hosted. Consider that on every occasion a small change is made to a prediction algorithm multiple sets of tests must be re-run, over multiple terrains, routes and climatic conditions. Also consider that algorithm development is by nature a highly iterative process, typically involving numerous modification and test cycles. Clearly the use of a physical UGV for development would generate an unacceptable overhead and is therefore considered inappropriate.

Despite obvious limitations for iterative algorithm development, the use of a physical UGV test bed for collecting sets of reference data that describe the performance of a given UGV, traversing a given terrain with given moisture content, is considered to offer significant value for both reference and validation activities, and is therefore employed by this study as described in chapter 6. The appropriate use of such a data set strongly routes any experimental approach to the reality of at least one real-world situation.

Correctly implemented computer simulation approaches offer an acceptable level of accuracy with a high degree of flexibility and low cost [69]. A principal advantage of the simulation approach is speed and flexibility. Any modification of the algorithm, UGV or environment can be effected quickly at a laboratory opposed to in the field. In addition, multiple simulated tests can be conducted over a wide variety of conditions in a fraction of the time taken for real world tests.

In order to validate and compare presented algorithms in the following chapters, ideally an already available off-road simulation package that could accept the required parameters and stimulus used for the prediction algorithms would be used. However, as the problem is unique and the previous focus of research is concerned with other areas of off-road traversal such as finding the fastest route dependent on terrain traversabity, no such simulation package exists that allows for the comparison of energy prediction algorithms.

A large variety of suitable simulation platform software exists that would allow for the building of an off-road simulation with the required functions. AnyLogic [70] was selected primarily as it allowed for rapid development compared to other platforms as it directly supported the use of Geographical Information System (GIS) maps, allows for flexibility in programming techniques and provides functions for discreet event modelling.

This chapter describes the design approach, creation and implementation of the simulation package that was required to validate the work described in previous chapters. Also the method used to validate the simulation itself.

4.1.2 Related Work

While the previous section discusses the current state of research into the simulation of off-road vehicles it can be seen that existing simulation packages are focused on assistance for the design and procurement of UGVs, as opposed to assisting with mission planning and live energy resource monitoring. While the NATO Reference Mobility Model (NRMM) [66] goes some way to address this, its limitations have been realised [71]. It is also important to note the lack of modelling and simulation for small UGVs is highlighted by the U.S. Army Battle Command, Simulation, and Experimentation Directorate's Urban Operations Focus Area Collaborative Team (UO-FACT) [72].

It should be noted that NRMM has been successful in the use of empirical data for simulation [71]. Wong also highlights the usefulness of empirical data for simulation [26] "In view of the limitations of the techniques for modelling terrain behaviour described above, to study vehicle mobility in the field, practical techniques for measuring and characterising terrain properties are required".

As previously mentioned the power reserve limitation of UGVs is likely to impact on mission survivability. It is therefore surprising how little work there is in the field of simulation of power requirements for UGVs, although Broderick's [67] recent work not only highlights the lack of available empirical data, it goes some way to establishing a reference point for obtaining empirical data required for modelling and simulation.

4.1.3 Aims

The primary aim of the work presented in this chapter is to produce a method and tools for the development, assessment and validation of energy prediction algorithms for UGVs that traverse off-road terrains in various weather conditions, and to quantify any improvements a particular solution may offer. An additional aim is to produce a tool capable of predicting mission energy requirements for use by mission planners, that can be used for both prior mission and during live missions.

4.1.4 Goals

In order to achieve the stated aims, we set the goal of this work to be creating tools that allow the user to achieve the stated aims by creating a simulation tool-set that provides functions for the creation, development, simulation and analysis of mission energy prediction algorithms.

This naturally leads to the underlying goal of producing an accurate simulation model of a UGV, with particular focus on the accurate modelling of drive-train / terrain interaction with regards to power consumption over a planned route with various terrain types and climatic conditions. In addition, the simulated UGV model must be able to host the energy prediction algorithms that are the focus of this research.

Another critical goal of the simulation is the accurate modelling of the UGV environment, with particular focus on the various terrain types and weather conditions. A further goal is therefore to produce a process for describing the environment topology and the prevailing weather conditions.

In the context of these goals, the system must provide a user interface that allows the user to quickly make changes to simulation parameters and behaviours. The system should also provide the user facilities to selectively display real-time simulation results or to store results for later analysis.

Finally the simulation should be validated against some known and accepted reference in order to ensure that its results are legitimate.

4.1.5 Scope

The aim of this contribution is to provide a simulation toolset that is capable of modelling energy consumption of a UGV. The focus of the tools are the factors having the most significant effects, rolling resistance and subsequent power consumption of an off road UGV, such as drive-train performance, mission route, terrain interaction behaviour and climatic conditions. Other factors that may impact consumption such as acceleration rates, inclines, lateral slip and turning losses are not taken into consideration in this work. However, the simulation package is designed using a modular design paradigm enabling the future expansion of the scope to include other factors that affect UGV power consumption.

4.1.6 Design Method

A design method suitable for building the simulation is required, prior to this being chosen a high level user requirement was formed as a starting point to design:

> "A Simulation that hosts algorithms for the use of energy prediction of UGV traversing a typical off-road mission with varying weather conditions for the purpose of comparing the efficiency of the algorithms. The simulation is to use prior collected data relating to UGV's behaviour over varying terrain types. A process must be provided to validate the realism of the simulation compared to live experiments".

This indicates that there will be significant user interaction required, how much, at the early design stages is debateable, also, as defined in the scope, the simulation is required to be flexible so to allow for future expansion. An example being the inclusion of inclines in the terrain map. For these reasons a technique known as "Evolutionary Prototyping" was selected as the approach for the design methodology. The desired result of this approach is very robust prototype that allows for the constant refinement and improvement, and for the prototype to form the core part of the desired system.

Evolutionary Prototyping still requires the design to be based on initial user requirements, however it allows for a subset of the requirements to be fully realised at the early stages of the design cycle, while others are satisfied in subsequent design iterations. A particular appeal of this approach that is relevant to this work is the fact that in the first stages of the design, effort can be focused on the part of the system that is well understood. In this case, a test bed for the comparison of prediction algorithms. On completion of this task, it is anticipated that a more comprehensive understanding of the requirements for mission planning will be gained, resulting in further development of the simulation software.

4.2 Resource Management System Simulation Design

4.2.1 Concept of Operation

As a first step of development, a natural language description of the required system is presented. The following describes a system that would achieve the aims and goals of an acceptable solution as presented above:

The simulation system should represent an unmanned ground vehicle model in a two dimensional off-road environment. Where UGVs are to be described by mass and drive-train characteristics or by mobility models that describe a relationship between a particular UGV's interaction with a particular terrain. The UGV is to have a user defined energy storage capability. The mobility models are to further represent the influences of prevailing weather conditions on the interaction of the UGV with a particular terrain. The models should allow for the implementation of both hypothetical and empirical data sets. User defined mission plans are to be graphical descriptions of particular routes over user defined terrain maps detailing waypoints and desired target velocities between waypoints.

Prediction algorithms are to be loaded into the simulation to prove their efficiency and accuracy over a variety of terrain types and weather conditions. On simulation execution all components are employed to give graphical results depicting both energy required for a given mission and the performance of a particular energy prediction algorithm.

4.2.2 User Requirements

The concept of operation is refined and elaborated to form a set of user requirements, defined as a specification of the user's expectation of the system. It is important to note that the set of initial user requirements are not exhaustive, but rather serve as a starting point for the design process. The selected evolutionary prototyping design process and modular design approach allows the system to be extended and adapted to meet emerging requirements.

1. The system must allow for the importing of terrain map data.

2. The system must allow for the input of terrain/UGV interaction data based on user selection.
3. An HMI must provide a facility to allow the user to plot a route over a selected terrain map.
4. A facility has to be provided that allows the user to define reference velocities along a given route.
5. The Simulation HMI must provide an interface for the mapping of terrain segmentation.
6. The simulation must execute experiments that add “unknown” conditions to weather conditions.
7. The simulation must be able to accurately mimic live sensor data.
8. Results and comparisons from the simulation must be represented graphically.
9. The system must be expandable in order to satisfy emergent user requirements.
10. The simulation is to allow for the description and development of prediction algorithms.
11. A facility needs to be provided whereby a UGV model can be modelled based on user input.

4.2.3 High-Level Simulation System Design.

From the above Concept of Operation it is clear that the core function of the simulation package described here is a tool to provide a platform for the development and assessment of energy prediction algorithms, in order for this to be effected the simulation is to provide the following functions.

1. UGV mission Energy Requirement. Given a UGV with unlimited resources and stated energy/terrain information, calculate energy requirements for a given route plotted over a given terrain map, with user defined weather conditions.
2. Live energy Prediction. Given a UGV with limited energy resources and stated energy/terrain information, calculate live mission energy prediction

based on random weather effects for a given route plotted over a given terrain map.

A further function of the simulation is the ability to provide live mission information for a mission planner and allowance for the experimental design of differing mission routes that may improve mission survivability when mission resources are deemed to be insufficient to complete current mission goals.

In order to give a particular algorithm a context and to be executed within the simulation and by initial analysis of the concept of operation it is apparent that there are three distinct sets of user defined data descriptions required, being configuration parameters, prediction algorithms and models in order to produce graphical results as shown in Figure 4.1.

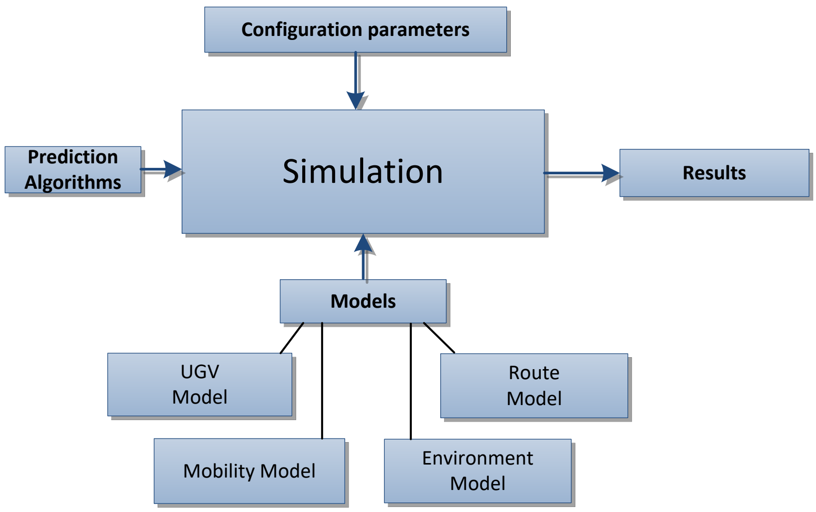


Figure 4.1: High level simulation design

The following sections describe each part of the simulation architecture.

4.2.4 UGV Model

The operation of the UGV is the focus of this work. The following section describes the created simulation functions for modelling the physical reality of a UGV using limited power resources to move through its environment whilst implementing a given prediction algorithm as the subject of the experiment.

4.2.5 UGV and Mobility Models

The preceding background sections discuss the wheel / terrain interaction as a complex relationship. As such the models required to achieve a useful level of fidelity are equally complex.

As previously discussed, as the UGV moves through a given environment it converts electrical energy into mechanical energy to affect propulsion. The conversion is not perfect as the system experiences losses, primarily due to wheel slip and resistance.

Resistance to motion is described earlier in 3.4, where for flat prepared surfaces resistance comprises of wind resistance (which is minimal due to the slow speeds of off road UGVs) and rolling resistance coefficient which is largely caused by the deformation of the tyre in the case of wheeled vehicles. Where consideration is given to off road vehicles resistance to motion is complicated by the fact that not only does the tyre deform, but also the terrain may deform during slippage of the wheel, this deformation has two components vertical (sinkage), and horizontal (reconfiguration of surface due to wheel slippage). The complexities of energy consumption of off-road traversal are increased by the fact that not all off-road surfaces are readily deformable.

Section 3.4 highlighted the difference of calculating rolling resistance between prepared road surfaces and off-road terrain and concluded that the usual model (3) is unsuitable for energy prediction for off-road vehicles. Where it would be possible to use typical on-board sensors (for incline, velocity, current and voltage) to sample data at a given frequency and conclude a value for rolling resistance, consideration needs to be given to the fact that an increase of slip increases the consumption of a UGVs propulsion requirement, and that slip also varies with velocity (dependent on terrain type). Also slip will vary dependent on the terrain type and more importantly the moisture content of the terrain.

Expanding on the NRMM where empirically based relationship measurements are taken from actual vehicles run over a variety of terrains [71], if current vs. velocity samples are taken along with slip vs. velocity, samples for a range of terrains in differing weather conditions then based on empirical data it should be possible to successfully simulate energy requirements for a given mission.

The approach used by this simulation tool is to allow the user to directly describe the behaviour of the subject UGV in terms of current usage and slip for a range of velocities. This allows the user to provide hypothetical data or estimated data sets describing UGV-terrain interaction, or provides the opportunity to improve accuracy through the use of real-world data collected from experimental UGV platforms (as described in Chapter 5) or even on-going UGV operations. This approach minimises the complexity of modelling wheel terrain interaction whilst providing high fidelity with real world behaviour.

The facility exists within the simulation tool to allow for the input of data sets (in the form of comma separated value files) by the user to describe any number of UGV/terrain interaction relationships, it is also possible to describe realistic noise which is based on results from sampled empirical data. Chapter 5 shows results from data collection and analytical methods to validate the data. The deviation values (which are on the whole from standard normal distributions) allow for the use of a probability density function for normal distribution to replicate real world sampled noise.

The user view of the model can be seen in Figure 4.2. A mobility model is required for every terrain type included in a simulated mission.

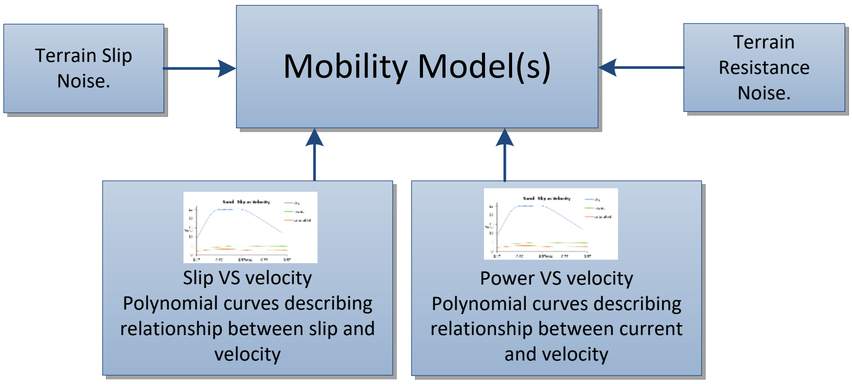


Figure 4.2. Mobility model

Where the mobility model describes the interaction of a particular UGV with a terrain type the user view of the UGV can be simplified (see Figure 4.3). As the mobility model describes the relationship of the UGV/terrain interaction, the UGV model is only concerned with energy capacity and set velocities. Any number of traversal velocities may be selected by the user.

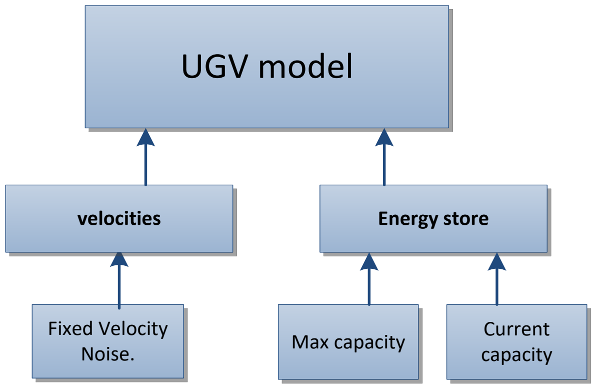


Figure 4.3: UGV model

4.2.6 On-Board Sensors

In order to provide input data for the energy prediction algorithms the simulation system models the operation of a basic set of typical UGV on-board sensors.

A configurable model of an on-board speed (velocity), wheel slip ratio and motor current consumption sensors are provided. The sensor models are configurable with accuracy and noise parameters in order to enable the modelling of real world inaccuracies.

The velocity sensor provides data describing the instantaneous angular velocity of the non-driven wheel of the UGV. The behaviour of a slip sensor that monitors the angular velocity of the driven wheels and compares it to that of the non-driven wheels is also provided. This sensor provides a result describing the proportional difference between driven and non-driven wheel speed for a given instant in time.

The motor current sensor model provides data describing the instantaneous electrical current being drawn by the propulsion system drive motors. The data is based on the current terrain and UGV velocity using the user defined terrain interaction data described above.

During simulation runtime, the hosted prediction algorithms can read the sensors at a configurable 'sample rate' defined in samples per second of simulated time.

4.2.7 Energy Prediction Algorithms

A critical function of the simulation system is the hosting of the energy prediction algorithms. The simulation system enables the user to 'plug in' prediction algorithms prior to simulation commencement. The algorithms can read live sensor data at simulated mission runtime as well as accessing stored prior mission data (described below) in order to make predictions about the energy likely to be used (see Figure 4.4). The comparative performance of the algorithms under varying conditions provides evidence of relative improvement compared to the state of the art approaches.

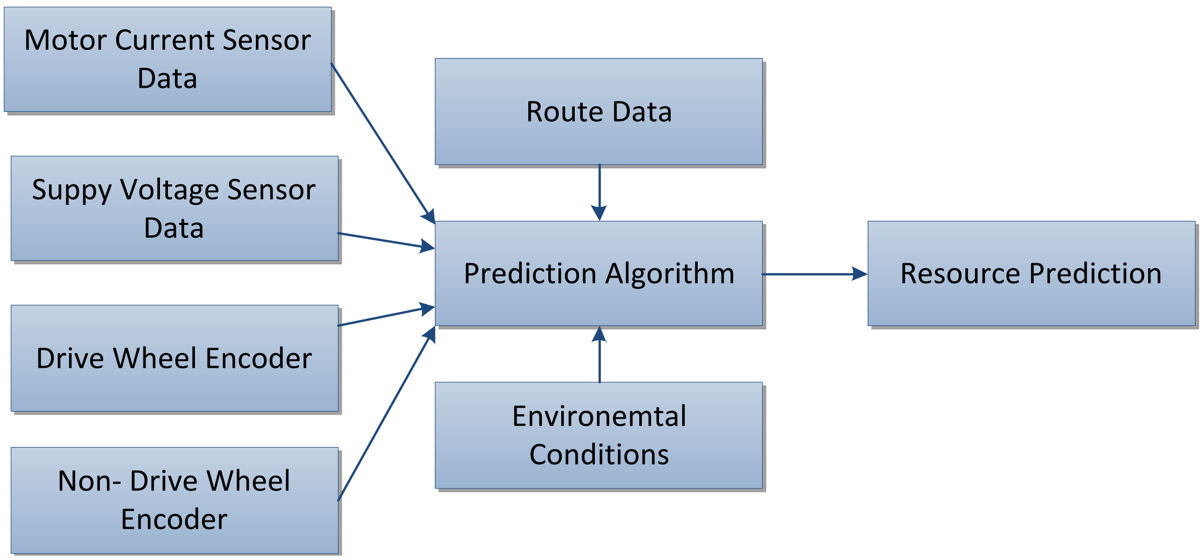


Figure 4.4: Algorithm model

4.2.8 Environment Models

The simulation provides facilities for a user to define an environment topology for a simulation in order to describe differing terrain types (see Figure 4.5). In order to provide flexibility in both mission planning and the testing of algorithms the system allows for the user selection and import of landscape images opposed to having a singular landscape fixed purely for the validation of a single algorithm, by varying the terrain map further possibilities are possible regarding comparing algorithms. The purpose of the image is to serve as a basis for a landscape that can be broken down in to terrain type segments and ensure that experiments are carried out on realistic terrains.

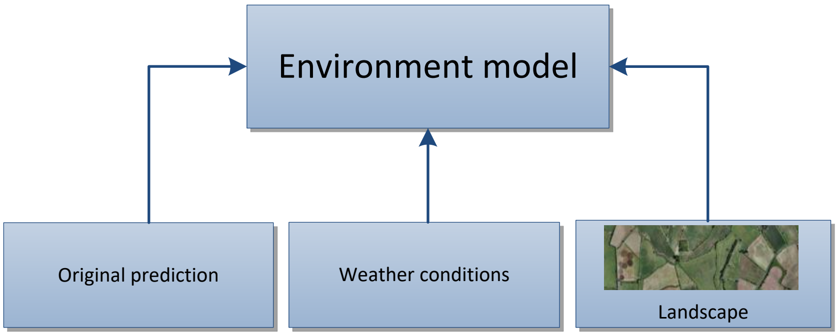


Figure 4.5: Environment model

A modelling problem for off-road vehicles exists that has been highlighted by AMC-74, where sections of a particular mission route are not necessarily homogenous. The NATO Reference Mobility Model methodology addresses this issue by separating terrain types of a particular mission by defining sections of a route which are sufficiently uniform. Allowance was made so that the user can segment the landscape without limitation so that like terrain types are grouped and allocated to a common terrain type (see Figure 4.6).

Figure 4.6. Example of imported landscape and partially segmented landscape

The segments that are considered to be uniform are left to the user to decide which ensures maximum flexibility the types are stored in a vector (X).

$$\overrightarrow{TerrainTypes} = \{X_i \mid i = (1:n)\} \tag{5}$$

4.2.9 Route Modelling

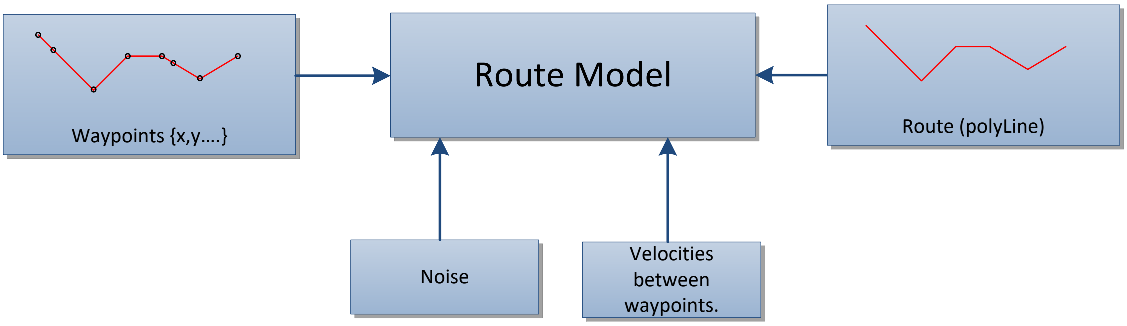


Figure 4.7: Route model

In addition to the environmental model, the user must be able to perform route planning based upon the imported terrain maps. An HMI is provided to allow the user to plot a route and desired UGV velocities over a selected terrain map.

The simulation allows for a route to be plotted anywhere within the terrain map (see Figure 4.8). The user also has the option to scale the length of the route to a realistic length. Waypoints can be added at any position along the route. The waypoints allow the user to segment the route to specify differing velocities (and levels of noise) for segments.

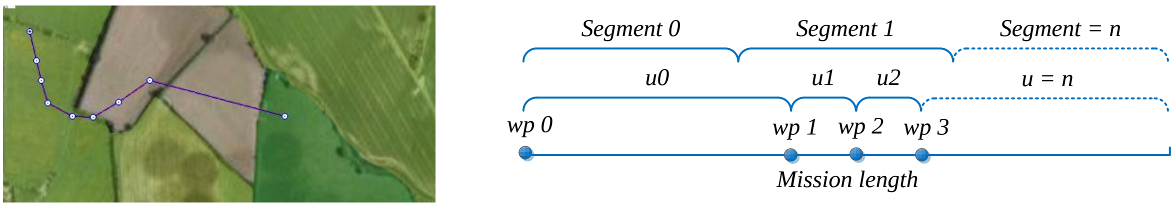


Figure 4.8: Simulation route plot

4.2.10 Result Collection

The system provides facilities for collection and storage of a range of live simulation data. The output of live sensor data, the vehicle performance and critically the data describing the real-time prediction of the algorithm under test can all be viewed in real-time or recorded for later analysis. User selected results are stored to disk using the common ‘Comma Separated Value’ (CSV) format.

Graphical real time outputs for sensor data are in the form of graphs for power slip and velocity (see Figure 4.13, Figure 4.14 and Figure 4.15). Graphs for power resource prediction algorithms allow for the comparison of two algorithms, see Figure 4.9.

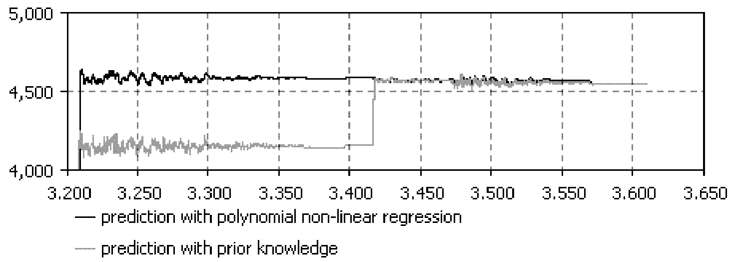


Figure 4.9: Comparison of power prediction algorithms

4.2.11 Simulation User Interaction

The models/algorithms discussed in the preceding sections are accessed by the user utilising either the simulation HMI or CSV files (see Figure 4.10). The HMI also provides a graphical output of the simulated mission and the algorithm results. The model input methodology is as follows:

- Environment Model. This model is described by the user both graphically by the way of a landscape map (which can be segmented by user) and by the use of a “csv” file describing the weather conditions and original prediction.
- UGV Model. This model is defined by a “csv” file that describes the UGV attributes such as maximum battery capacity, traversal velocities and the level of noise of velocities (from empirical data).
- Mobility Model. This model is defined by a “csv” file that describes the UGV/terrain interaction relationships using polynomial curves (from empirical data). The user can also specify noise signals to the curves which are derived from empirical data.

- Route Model. This model is described both graphically and by the use of a “csv” file. The user has the facility to draw a polyline over landscape map and add waypoints to the polyline. Desired velocities between waypoints are added via the “csv” file.
- Algorithms. Algorithms are inputted to the simulation via java source code files.

Output from the HMI is as follows:

- Pre-mission Prediction Data. This displays a prediction of how much energy is required for the mission.
- Live Mission Data. Displays live mission data such as fuel (energy) used and remaining fuel.
- Live Slip, Current and Velocity. Displays graphically live simulated values.
- Energy Prediction Result. The results from the prediction algorithms are displayed graphically and stored as a “csv” file.
- Graphical Representation of Mobility Model. This is a static representation of the UGV/terrain interaction relationships.

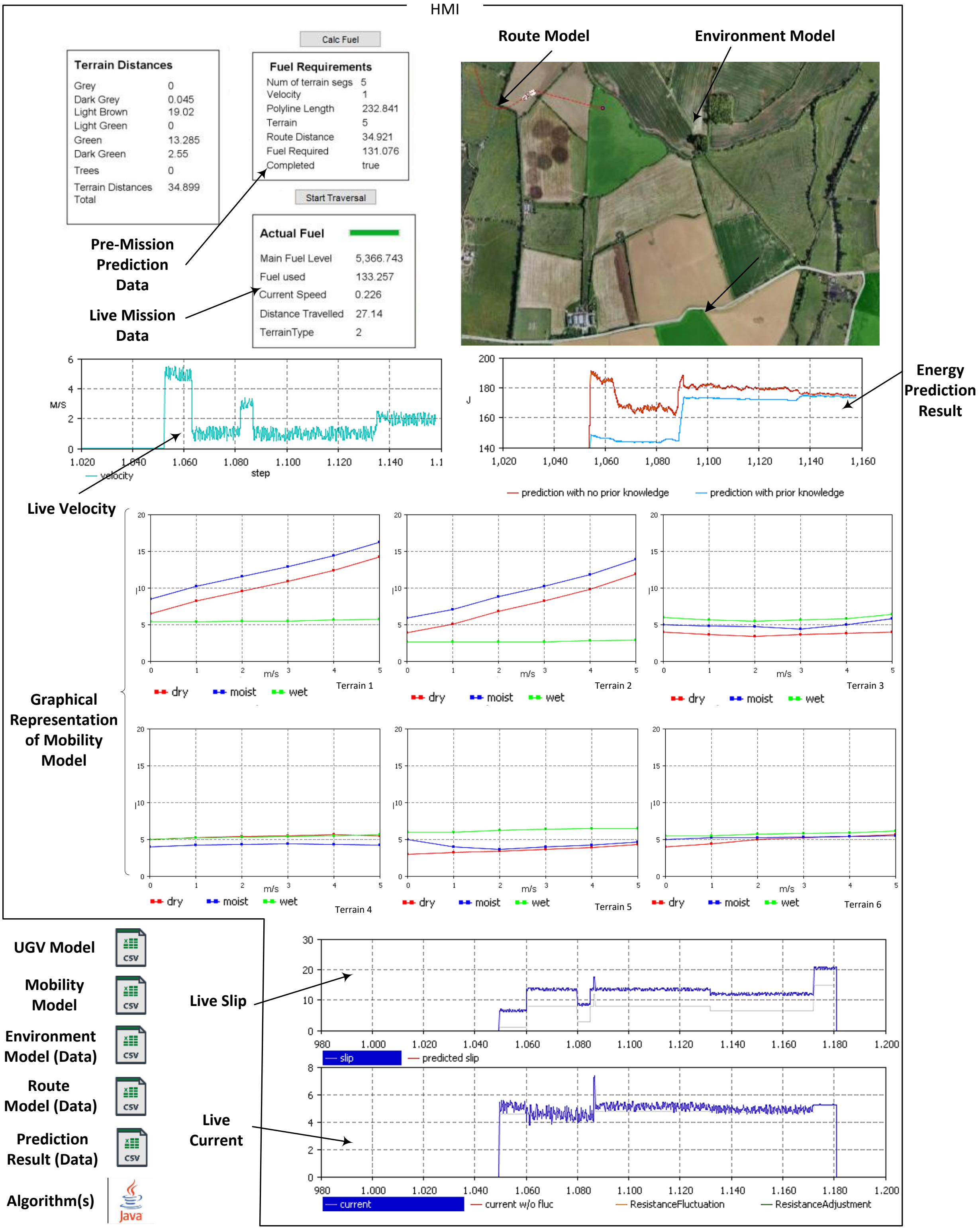


Figure 4.10: Simulation User Interface

4.3 Simulation Tool Validation

It is crucial that the simulation provides adequately realistic modelling of the problem. Correct simulation implementation that represents all significant elements (in terms of effect on results) of the physical reality with appropriate levels of fidelity, and a thorough approach to validation is essential in order to achieve meaningful results.

The performance of the simulated UGV in terms of energy use and prediction algorithm performance whilst traversing multiple terrains under a range of test terrains must be shown as equivalent to some known reference. In this case the availability of a physical UGV test vehicle (see Chapter 5) provides an ideal opportunity to assess the correlation between simulated and physical UGV behaviour.

4.3.1 Validation Method

An experiment that conducted equivalent simulated and real world missions creating the opportunity for direct result comparison was created. The mission is composed of two terrain segments traversed at the fixed velocities and for distances shown in Figure 4.11 and Table 2.

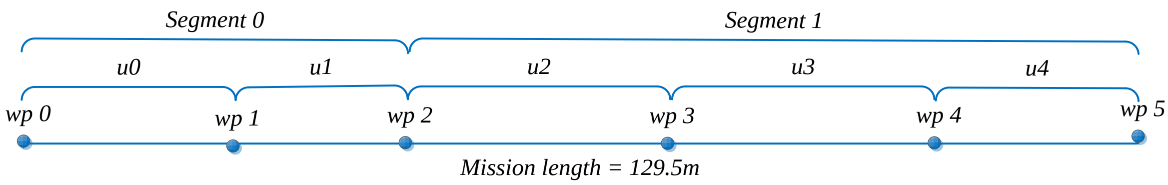


Figure 4.11: Mission detail for validation experiment

Segment 0 = Grass, condition = Saturated				*Segment 1* = Sand, condition = Saturated			
Velocity (m/s)		Distance (m)		Velocity (m/s)		Distance (m)	
u0	0.33	*WP 0 – WP 1*	22	*u2*	0.33	*WP 2 – WP 3*	35
u1	0.66	*WP 1 – WP 2*	20	*u3*	0.5	*WP 3 – WP 4*	33.5
				u4	1	*WP 4 – WP 5*	19

Table 2: Mission parameters for validation experiment

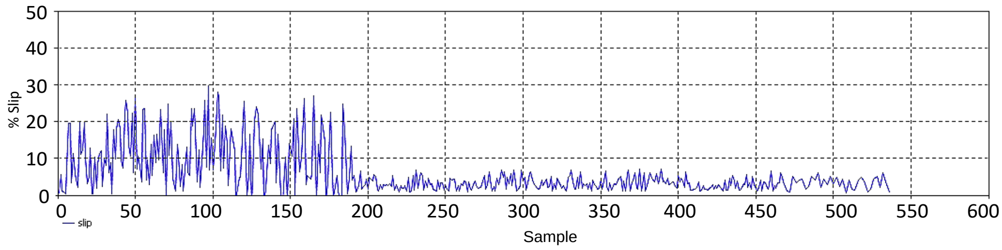
The UGV described in detail in Chapter 5 was used to collect real world data regarding power, slip and velocity over the described mission, sample rates were taken at 440 m/s intervals. The method for sampling and recording data is described extensively in section 5.2 where the UGV is used here for validation.

Figure 4.12: Mission route

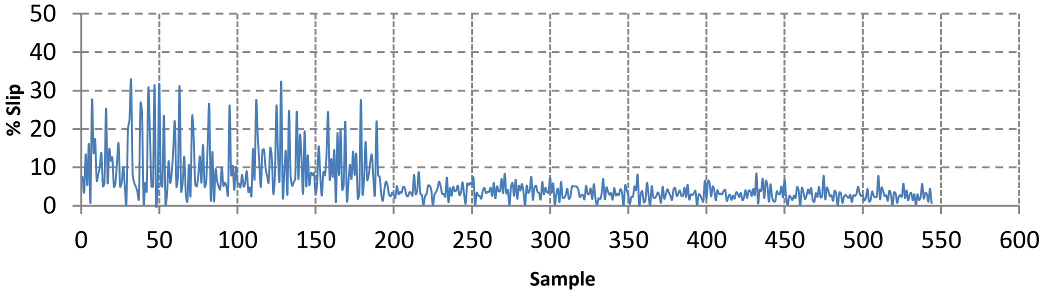
The simulation was configured using the parameters shown in Table 2. A route was plotted as described in Figure 4.11 and can be seen in Figure 4.12. The simulation was loaded with mobility models that were described in Chapter 5.

4.3.2 Validation Results

This section presents the results from the equivalent simulated and real world missions. It provides a comparison of real life actual results of a given UGV mission and the simulation based results.



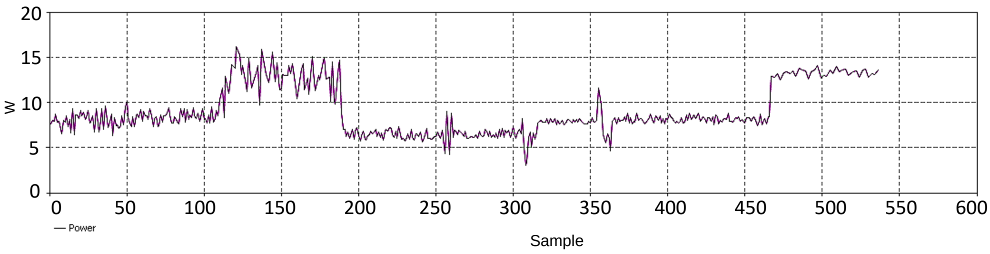
a) Simulated slip results



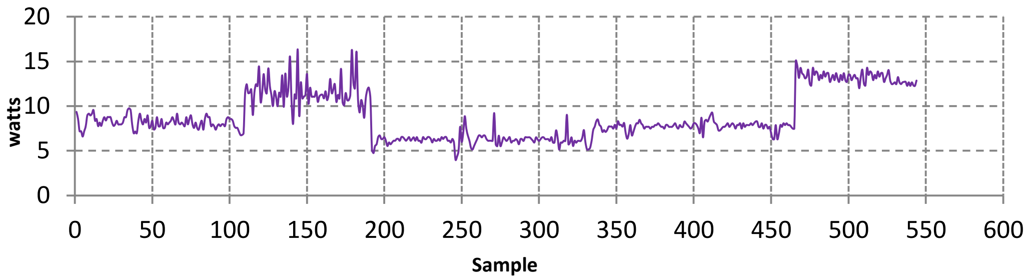
b) Real world slip results

Figure 4.13: Validation results for slip

The simulated results for slip show a slightly different pattern in deviation around the mean for samples 0 to 180 compared with the real world results (Figure 4.13). The remaining samples show a high correlation between the simulated and real world samples.

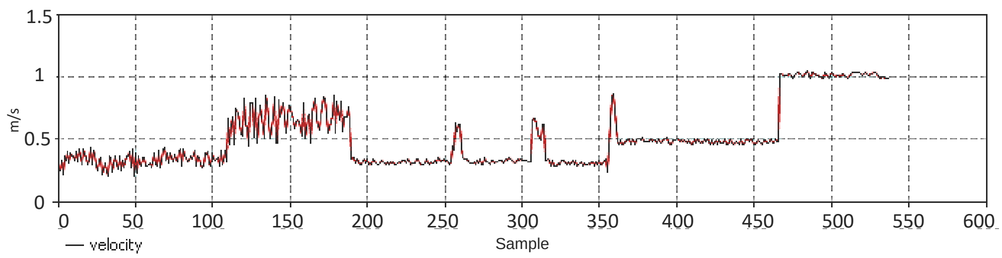


a) Simulated power consumption

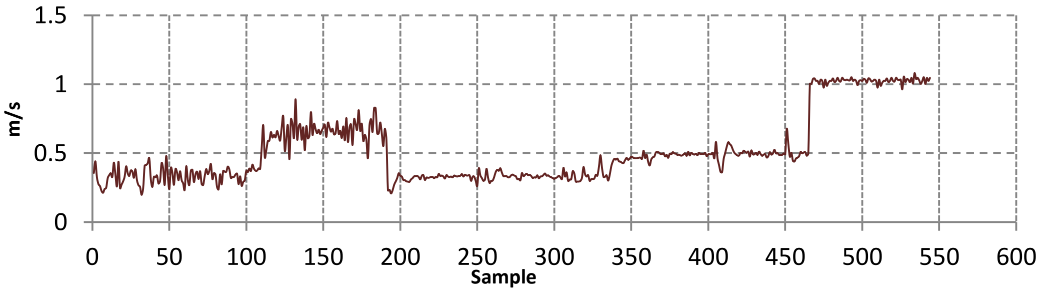


b) Real world power consumption

Figure 4.14: Validation results for power



a) Simulated velocity results



b) Real world velocity results

Figure 4.15: Validation results for velocity

The results for simulated power consumption show a close correlation with the observed reality. There is a difference in the observed noise characteristic of the results observed for the second terrain segment, between 110 and 180 samples.

The velocity results show high correlation between simulated and real world results. The most significant differences are observable in the simulated results at 260 and 310 samples with the simulated occurrence of short term deviations of approximately 0.2 m/s for duration of ~5 samples.

Velocity			
Segment	Actual Vel	Simulated Vel	%Error
U0	0.334751441	0.338	0.97044
U1	0.656297	0.658	0.25949
U2	0.326361	0.335	2.64707
U3	0.479805	0.493	2.75008
U4	1.026045	1.039	1.26262

Table 3: % Error for velocity comparison

Power			
Segment	Actual P	Simulated P	%Error
U0	8.144363097	8.235	1.112879
U1	11.57686605	11.811	2.022429
U2	6.228109	6.342	1.828661
U3	7.660849	7.81	1.946925
U4	13.19745	13.414	1.640847

Table 4: % Error for power comparison

Slip			
Segment	Actual Slip	Simulated Slip	%Error
U0	10.0603876	10.947	8.812905
U1	10.7691349	11.931	10.78884
U2	3.78840234	3.989	5.295046
U3	3.07732369	3.245	5.448771
U4	2.72705782	2.873	5.351635

Table 5: % Error for slip comparison

4.3.3 Validation Discussion and Conclusion

On inspection of the graphs shown in Figure 4.13 and Figure 4.15, it can be seen that there is a close correlation between the simulated results and the actual recorded data for power and velocity. However, on inspection for slip it can be seen that (for steps between 0 and 180) although the range of the data is similar for both graphs there is a difference that can be seen regarding the distribution around the mean value.

The real world results shown in Figure 4.13 (a) show an asymmetrical pattern around the mean with the majority of samples above the mean, this is opposed to Figure 4.13 (b) which shows a more symmetrical distribution. This is due to the actual recorded data having a slightly skewed distribution, where the method for introducing noise for the simulation assumes that a normal distribution is always present.

This is also reflected in the % error for slip as shown in Table 5 where the worst case error is 10.79%, when compared to that of velocity (Table 3) which is 2.75% and power (Table 4) which is 2.02%.

Figure 4.14 shows a good general correlation between simulated and real world results. The most significant difference is the observed noise characteristic throughout the second terrain segment. This is explained by the normal differences that exist between different areas of a common terrain type at any given time.

Figure 4.15 shows a generally high correlation except for a difference in the occurrence of short term velocity disturbances from the target velocity. The simulated system models the occasional occurrence of small obstacles in the terrains, such as small stones, that affect velocity for a short period. The real world terrain used in this experiment exhibited fewer and less severe disturbances.

The primary purpose of the simulation was for comparing power prediction algorithms as described in section 6.7. The result from this simulation comparison shows an improvement of 9% which indicates that, overall the simulation has demonstrated an acceptable level of fidelity with the physical reality of a UGV travelling in a range of terrain and environmental conditions. Specifically the behaviour of the UGV in terms of energy use provides the required level of accuracy.

The observed differences in the Figure 4.13 to Figure 4.15 were short term in nature. As shown in the tables above, the effect on the overall mission power consumption, slip and velocity values are negligible.

4.4 Conclusions

The aim of the methodology and toolset is to produce a simulation platform that enables the development, assessment and validation of energy prediction approaches for UGVs that traverse off-road terrains. The presented Resource Management Systems Simulation (RMSS) achieves this aim by providing the user a method to create accurate simulations of a UGV traversing a described environment under various weather conditions whilst operating a variety of mission energy prediction algorithms.

The system allows the modelling of complex interactions between a UGV drive-train and the terrain it is traversing from the perspective of the power management system. The user can develop and evaluate a mission energy prediction algorithm using any combination of terrain type, moisture content, UGV performance, mission plan or available on board sensor data.

The user interface provides real-time feedback regarding numerous parameters from the simulated ongoing mission such as live sensor data for speed, wheel slip or power consumption, or the current energy prediction output from the hosted algorithm, as well as result storage for later analysis.

The tool is validated by comparison between the performance of the created simulation tools and physical reality. The simulation tools produced results that are highly correlated to the empirical result set which provides a high degree of confidence in the performance of the simulated tool.

The exception to this is in the instance where noise is applied to data sets where empirical data produces distributions other than a standard normal distribution. This was the case for empirical data relating to slip. While the simulation hosted algorithms that focused on power for prediction this may not always be the case. In order to address this error, the simulation should allow for addition of noise using distributions other than standard normal.

5 UGV / Terrain Interaction - Empirical Data Collection

This chapter presents a set of experiments and resulting data sets that describe the UGV / terrain interaction in terms of current consumption and slip for a test-bed UGV over a range of terrains and climatic conditions. The results sets are analysed in order to assess the feasibility of detecting terrain conditions using information from typical on-board UGV sensors. The results are reused in Chapters 4 and 6 to provide reference information for the presented IPM algorithms and for validating the Resource Management Simulation System.

While the previous section discusses the current state of research into the simulation of off-road vehicles it can be seen that current available simulation approaches are focused on assistance for the design and procurement of UGVs opposed to assisting with mission planning and live monitoring of resources. While the NATO Reference Mobility Model (NRMM) goes some way to address this, its limitations have been realised [71], largely due its lack of both definition when considering smaller UGVs, and of mapped terrain of suitable fidelity.

It is also important to note the lack of modelling and simulation for small UGVs is highlighted by the U.S. Army Battle Command, Simulation, and Experimentation Directorate's Urban Operations Focus Area Collaborative Team (UO-FACT) [72]. This results in the lack of empirical data currently available for small UGVs.

In addition, consider that NRMM has been successful in the utilisation of empirical data for the use in simulation [71]. Wong also highlights the usefulness of empirical data for simulation [26] "In view of the limitations of the techniques for modelling terrain behaviour described above, to study vehicle mobility in the field, practical techniques for measuring and characterizing terrain properties are required".

Where the above consider mission specific variables that are constant for any UGV, the required prior knowledge for a particular UGV interacting with the terrain surface presents an interesting problem due to the complexities of vehicle/terrain interaction. The previous section highlighted issues of modelling and simulation based on analytical methods alone, however, NRMM has successfully employed empirical data for the study of off-road traversal for the primary reason of vehicle design and procurement with a focus on calculating the fastest velocity permissible over terrains.

Chapter 2 highlighted the difference of calculating rolling resistance between prepared road surfaces and off-road terrain and concluded that the usual model (3) is unsuitable for energy prediction for off-road vehicles. Where it would be possible to utilise typical on-board sensors (for incline, velocity, current and voltage) to sample data at a given frequency and conclude a value for rolling resistance, consideration needs to be given to the fact that an increase of slip increases the consumption of a UGVs propulsion requirement, and that slip also varies with velocity (dependent on terrain type). Further to this, slip will vary dependent on the terrain type and moisture content of that terrain type.

Expanding on the NRMM where empirically based relationship measurements are taken from actual vehicles run over a variety of terrains [71], if current vs. velocity samples are taken along with slip vs. velocity, samples for a range of terrains in differing weather conditions, then based on empirical data it should be possible to successfully simulate energy requirements for a given mission.

Based on the NRMM, a valid method of UGV mission simulation is to segment a particular region of terrain into a mosaic of terrain units within each of which the terrain characteristics are considered sufficiently uniform and homogenous throughout their extent, so that a set of terrain attributes could then be allocated to particular terrain segments. This common methodology is also adopted by the simulation presented in the simulation tool chapter.

With the recent growth geographical information systems (GIS), it is possible to find a terrain map for most locations in the world [63] that could be used for a UGV simulation. However the corresponding sets of empirical data that describe the nature of the terrain in terms of relative trafficability and response to weather are not currently available for UGVs.

While advances have been made for the collection of empirical data that relates to UGVs on non-deformable surfaces, the same cannot be said about terrains that are considered off-road. The problem is further exasperated by the lack of an explicit list of terrain types, and it would appear that researchers have their own classification methods [50]. For systems that focus on energy requirements for prepared surfaces, the empirical data sets used for energy prediction only need to describe energy consumption over a range of velocities. For electric drives, this would require voltage/current measurements for a given set of vehicle speeds (assuming only small inclines). Methods for empirical data collection exist for some off-road surfaces that focus on energy consumption (Broderick [67]) but they exclude any consideration for other factors that greatly impact on consumption such as wheel slip.

This chapter details a methodology and experiments for the collection of empirical data that relates to both the power consumption of a particular UGV and its ground/wheel interaction in relation to slip. The focus of the experiments in the following chapters is the interaction of UGVs on off road terrains that are deformable, so data collection is primarily carried out on such terrains.

5.1 Aims

The primary aim of this chapter is to produce a collection of data sets that can be used both in an energy/resource simulation as described in the previous section and use by mission energy prediction algorithms during a live UGV mission. The section details the methodology, system design and experiment execution for the collection, synthesis and analysis of such data sets.

Although the primary purpose of the experiments is for data collection for empirical data there also exists a requirement to validate the assumption that there is enough variance in the effects of weather conditions on terrains that moisture content conditions can be detected using standard on-board sensors. The section concludes with a discussion on the feasibility of using the empirical data for such detection methods.

5.2 Methodology

The methods used for collecting the empirical data (to be used by the simulation) are based on methods outlined by Broderick [67] which are focused on characterising energy usage of UGVs. The methodology described here improves upon Broderick's techniques by allowing for the inclusion of varying weather conditions on the collected data. Further to this, the data collected is not limited to energy consumption, but wheel slip is also considered.

As previously discussed, energy usage of an "off-road" UGV is mainly due to slip and sinkage, which in turn is due to, most significantly the moisture content of a terrain. Therefore the intended outcome from the empirical data collection will be data sets describing *current vs. velocity* for three moisture content conditions (dry, moist and saturated). As it is likely that moisture content cannot be distinguished on all terrain types, *slip vs. velocity* results for the three terrain moisture conditions are also collected.

A commercially available "off the shelf" four wheeled skid-steer UGV was selected as a test bed (see Figure 6.1) as it provided a cost effective platform that allowed for rapid development whilst providing the complete result coverage required. In order for instantaneous power consumption to be recorded the UGV was fitted with current sensors for monitoring motor currents and a voltage sensor for battery terminal voltage.

Monitoring wheel slip is not the focus of this work and is considered a complex problem where research is still ongoing. It is considered especially difficult on off-road vehicles that comprise of all-wheel drive vehicles that do not include redundant encoders [73] and considerable complexity is introduced when slip during changes of vehicle direction is considered. As the UGV comprises of an "all-wheel drive" system it was augmented with a redundant non-drive wheel and encoder and gearbox shaft encoders in order to monitor wheel slip.

Figure 5.1: UGV test bed for collecting empirical data

The overall architecture of the test UGV is shown in Figure 5.2, the location of the sensors used for empirical data collection are highlighted in yellow.

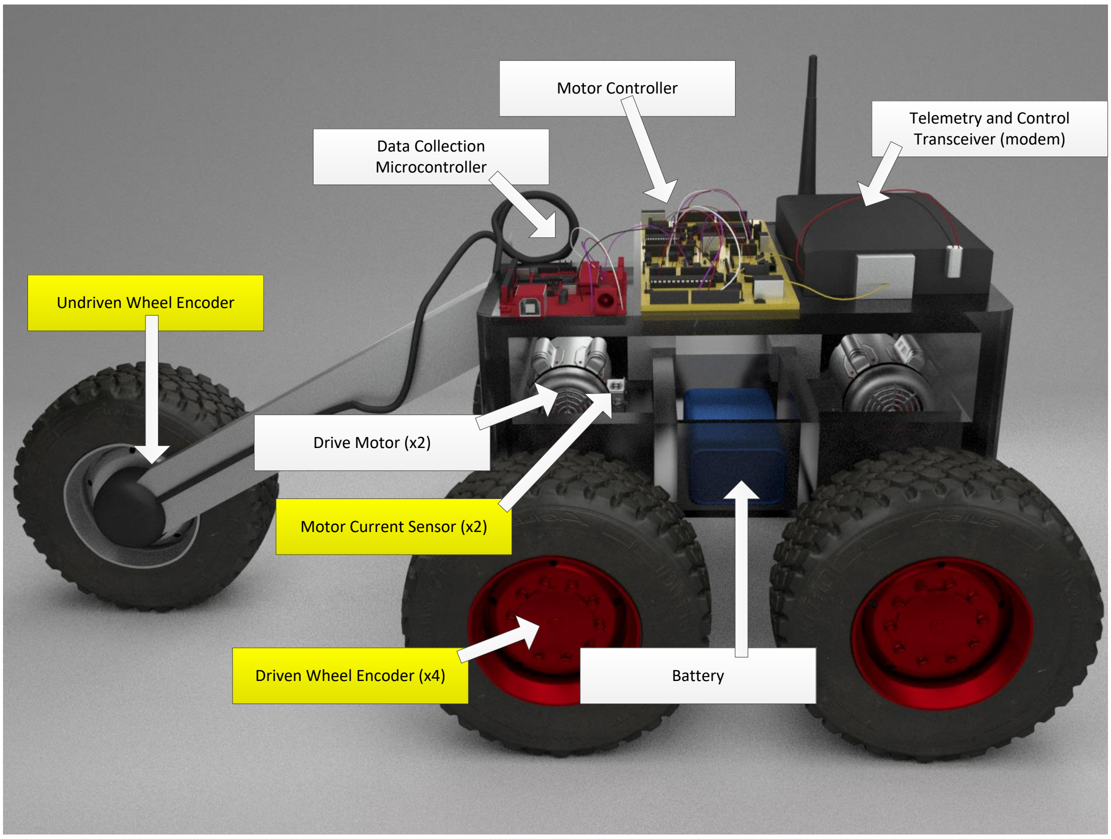


Figure 5.2: Test UGV Architecture.

To limit complexity, the sample data was collected on straight line runs and encoder readings could be verified for accuracy by comparing encoder readings with measured length of test runs. The redundant wheel/encoder (in co-operation with the UGVs processor) proved an effective method for measuring velocity and slip, providing samples were collected during tests where only straight runs were used.

For both the independent variables, terrain and velocity, a set of desired test points are defined. For velocity, a set of values are required between the maximum and minimum velocity of the UGV. However, depending on the terrain type, some wheel slip is expected, so the maximum velocity should be below the maximum velocity of the UGV to allow for the anticipated slip. The quality of data collected from the test results improves with the number of test points but time constraints must be traded off with quantity of data. Six sample test velocities were chosen (as suggested suitable by Broderick [67]) and can be seen in Table 10. The maximum test velocity of 1m/s was selected so that it was suitably less than the maximum velocity of the UGV (of 2 m/s) to allow for maintaining the test velocity and allowing for 20% slip.

TEST POINT	VELOCITY (M/S)
1	0.163
2	0.33
3	0.5
4	0.66
5	0.832
6	1

Table 6: Velocity test points

Terrain selection for the empirical data collection should ideally be based on the likely terrain required by the UGV mission application. The methodology for terrain selection should include at least one firm terrain and one deformable terrain [67]. As it is expected that performance would vary little regarding firm terrain types (prepared road surfaces) only one firm terrain type was selected (concrete). Three deformable terrain types were selected, grass, loose dirt and sand, which are estimated to provide significant coverage for typical UGV missions, and as such serves as a good starting point for data collection.

It is important to note that other factors than moisture content affect the amount of wheel slip (acceleration, incline, lateral slip, turning etc.), but moisture content alone is focused on in this work as a proof of concept. In order to neutralise the effect of these other factors all tests are conducted at fixed velocities and on straight line, flat track of 50m length.

It was necessary for the velocity of the UGV to be autonomously controlled as it would be an impossible task for the operator to increase the angular velocity of the wheels to compensate for the slip and maintain the desired velocity, especially when consideration is given to the fact that the UGV may be up to 50m away and he/she would also be tasked with the direction of the UGV.

The previously described experiments effected by Broderick [67] were carried out using "fully autonomous" control, that is, both the speed and direction were controlled by the system opposed to the requirement of a human-in-the-loop. As suggested by Broderick, semi-autonomous control (mixed initiative) is suitable where the speed is regulated automatically and the direction of the UGV is selected by the operator.

5.2.1 Slip and Sinkage

As the factors that have the largest effect on energy consumption are slip and sinkage (which, in turn is affected by moisture content) consideration was given to the factors that contribute to these effects. Off road terrains largely consist of two types of soils, granular (sand and gravel) and cohesive (silts, clays, top soil). Where slip and sinkage occur a shear effect is experienced where the terrain itself is moved. Soils have a property referred to as shear strength which, when reduced, increases the probability of wheel slip.

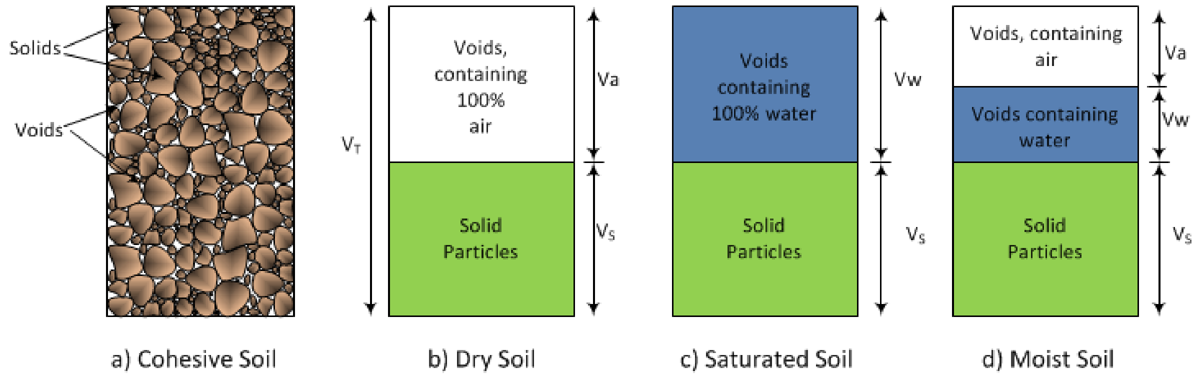


Figure 5.3: Water/air contents of soil [74]

Granular soils, sand for example have very little shear strength, however when moisture is present a cohesive effect is experienced which increases its shear strength. Cohesive soils on the other hand have shear strength when dry which may be reduced when moisture is present. Cohesive soil consists of a mass of solids separated by voids (see a), Figure 5.3), these voids can be occupied by either air or water or a mixture of both, where (from Figure 5.3) Total Volume (V) = volume of voids containing water (V_w)+volume of voids containing air (V_a) + volume of solid particles (V_S) [74] .

The terrain conditions (moisture content) for the experiments were defined as "dry" being no moisture content at all, "moist" being the terrain is noticeably wet but no surface water is visible and "saturated" being surface water is visible.

Test sites for empirical data collection were selected based on availability. Sand proved an ideal medium for data collection as reasonably flat areas that contained all three moisture content types were available locally on the coast line (during dry weather conditions). The site chosen was Wittering bay as large flat areas are available with very little slope, with grain size (fine to medium) being similar for the breadth of the test area.

Access was also available on a local farm for a considerable area of loose soil. This area was made up of fresh "bulk top soil", the weather conditions were simulated with the utilisation of a water supply and sprinkler system. This terrain was prepared before sampling by fine raking as to grade the soil and remove any large stones and to ensure a flat as possible surface.

The farm also provided a large area of flat, tightly mown grass that was used for the third “deformable” terrain type. This area required no preparation, and moisture content was simulated as in the above example. For the non-deformable terrain a strip of concrete was available located close to the Vetronics Research Centre (Brighton University).

5.3 System Requirements

In order to design and develop a test system that satisfies the stated aims, a set of system requirements is presented. The requirements are also used to verify the system operation and to validate the test results. Error parameters are defined along with methods of calibration and proof that sensors provide a resolution within stated error parameters.

To summarise the intended output from the experiments the following defines the experiment output.

1. A table of results that depict mean power consumption (W) for a set of fixed velocities for a range of terrains.
2. A table of results that depict mean wheel slip for a set of fixed velocities for a range of terrains where.
3. To produce the above, calculations are required that rely on sensor data to produce:
    1. UGV velocity
    2. UGV Instantaneous Power
    3. UGV Instantaneous Slip

Table 7 summarises all required recorded variables and the calculated values along with acceptable errors.

Measurement	Source	Variable	Units	Max
Left wheel Position	UGV	*pulse*	Bit/ms	N/A
Right Wheel Position	UGV	*pulse*	Bit/ms	N/A
Redundant wheel Position	UGV	*pulse*	Bit/ms	N/A
Terminal Voltage	UGV	V	V	1%
Motor Currents	UGV	$I_{RIGHT,LEFT}$	A	1%
Time elapsed	UGV	T	s	N/A
Velocity (Calculated)	Laptop	v	m/s	1%
Power (Calculated)	Laptop	$P_{RIGHT,LEFT}$	W	N/A
Slip (Calculated)	Laptop	$\%S$	%	2%

Table 7. Acceptable error magnitudes

For velocity, distance travelled and time elapsed is required. Distance travelled is recorded via the redundant wheel encoder, calibration was effected by traversing the UGV over flat smooth tarmac over a known fixed distance of 10m where the total number of state changes from the encoder was recorded and the distance per state change calculated. Time elapsed is available from the UGV processor. On completion, three traversal distances were selected (5m, 15m and 20m) for the UGV to ascertain the accuracy of the recorded distance travelled when compared to the measured distances, calibration results are as follows:

- Encoder resolution = 0.97mm
- 5m test run measured result = 5.026m
- 15m test run measured result = 14.876m
- 20m test run measured result = 19.823m

Instantaneous power is to be calculated using battery the terminal voltage meter and both drive wheel ammeters. Resolution and calibration error were proved by comparing recorded results from the sensors with a calibrated (< 1% error) laboratory digital multi meter. With the UGV drive wheels rotating at two different angular velocities recorded voltage and current were compared to that of observed readings from the multi meter as follows:

- Multimeter Ammeter resolution = 10mA
- Multimeter Voltmeter resolution = 10mV

- UGV ammeter resolution = 10mA
- UGV Voltmeter resolution = 10mV
- Angular velocity comparison at 25% of full range
  - Measured Terminal Voltage = 8.18V , UGV recorded voltage = 8.26V
  - Error = 0.97%
  - Measured Left Drive current = 510mA, UGV recorded Left current =520mA
  - Error = 1.92%
  - Measured Right Drive current = 520mA, UGV recorded Right current =530mA
  - Error = 1.88%

- Angular velocity comparison = 75% of full range
  - Measured Terminal Voltage = 8.08V , UGV recorded voltage = 8.15V
  - Error = 0.98%
  - Measured Left Drive current = 720mA, UGV recorded Left current =730mA
  - Error = 1.36%
  - Measured Right Drive current = 730mA, UGV recorded Right current =730mA
  - Error = 0%

For slip, the angular velocity of the drive wheels are compared to that of the redundant non-drive wheel. Calibration for the drive wheels was effected by traversing the UGV over flat smooth tarmac over a known fixed distance of 10m where the total number of state changes from the left and right encoders was recorded and the distance per state change calculated. On completion, three traversal distances were selected (5m, 15m and 20m). To ascertain the accuracy of measured slip, comparisons between the calculated distances travelled of the drive wheel encoders are compared to that of the measured distance.

- Left/Right Encoder resolution = 0.331mm
- 5m test run measured result = 4.821m
- 15m test run measured result = 14.878m
- 20m test run measured result = 20.120m

Table 8 summarises the tests to be conducted and parameters for collecting sample data.

Terrain	Condition	Sample Velocities (m/s)
Short Grass	Dry	0.163, 0.33, 0.5, 0.66, 0.832, 1
Short Grass	Moist	0.163, 0.33, 0.5, 0.66, 0.832, 1
Short Grass	Saturated	0.163, 0.33, 0.5, 0.66, 0.832, 1
Sand	Dry	0.163, 0.33, 0.5, 0.66, 0.832, 1
Sand	Moist	0.163, 0.33, 0.5, 0.66, 0.832, 1
Sand	Saturated	0.163, 0.33, 0.5, 0.66, 0.832, 1
Top Soil	Dry	0.34, 0.46, 0.58, 0.69, 0.82
Top Soil	Moist	0.34, 0.46, 0.58, 0.69, 0.82
Top Soil	Saturated	0.34, 0.46, 0.58, 0.69, 0.82
Tar macadam	Dry	0.163, 0.33, 0.5, 0.66, 0.832, 1

Table 8: Empirical data collection test conditions

5.4 System Design

In order to satisfy the experiment and to implement the methodology described in section 5.2 and satisfy the requirements described in 5.3, the system design shown in Figure 5.4 was implemented.

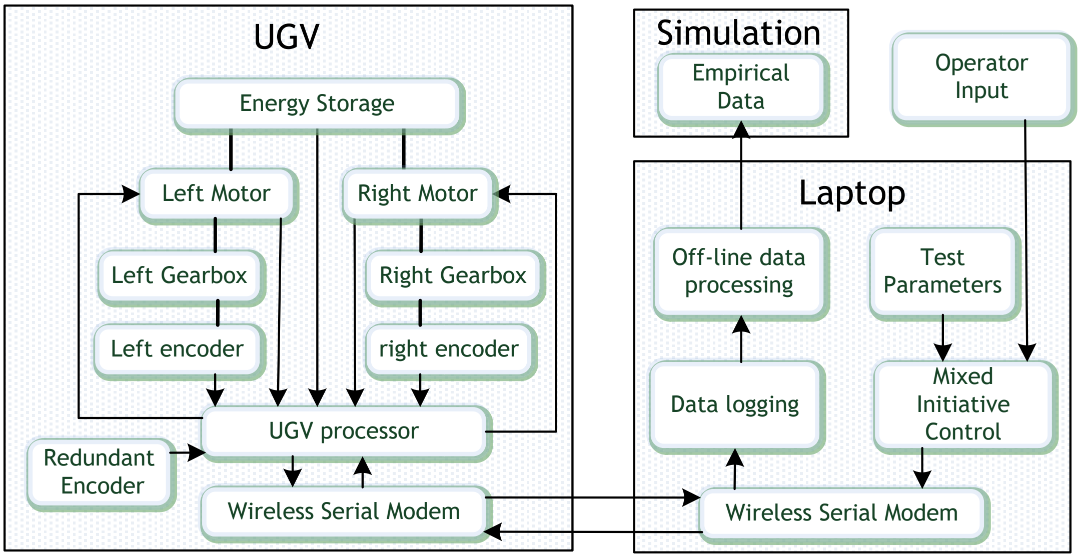


Figure 5.4: High level system design

The UGV platform performs the data sampling and passes the result to the controller laptop for storage. In order to satisfy the system requirements the UGV platform sensor suite comprised of the following:

- Left Wheel Encoder: Incremental, 1200 pulses per rotation.
- Right Wheel Encoder: Incremental, 1200 pulses per rotation.
- Rear wheel Encoder: Incremental, 400 pulses per rotation.
- Battery Terminal Voltmeter.
- Left motor Ammeter.
- Right motor Ammeter.

Samples are taken every 225 milliseconds. Sampled data is transferred to the control laptop for storage via a pair of wireless serial modems. The controller laptop provides the following functionality.

- Human User Interface for UGV control.
- Mixed Initiative control for UGV.
- Interface for operator input.
- Storage medium for sampled data.

To assist in the control of the UGV test bed for the operator and to ensure that all tests were carried out with like test conditions it was necessary to provide functionality that limits the amount of user input for the system. A standard joy pad controller comprising of a direction pad and 6 function buttons was implemented for the experiments. However, during data collection the user input is limited to steering only, which may be required should slip be experienced on a singular drive wheel. Assistance is given for straightening the vehicle after any corrections are effected. Although sampling is to be carried out on straight runs, where slip is experienced on one drive wheel only the UGV may require straightening. The following functionality was provided from the joy pad controller:

- Function Buttons:
  1. Start/stop recording.
  2. Autonomous speed control, off/on.
  3. Straighten UGV.
  4. Stop UGV.
- Direction pad.
  1. Steer Left/Right.
  2. Speed, increase/decrease (only available if autonomous speed control is off).

5.4.1 Speed Control Design

For autonomous speed control the equation shown in (6) was selected where k is the sample number, *u*(*k*) is the controller output value, *y*(*k*) is measured velocity, *e*(*k*) is the error term (desired velocity–*y*(*k*)), KP (proportional) = 130, KI (integral) 20 and KD (derivative) =1. The equation was selected as rapid changes and large differences between the desired velocity and the angular velocity of the drive wheels may be expected when traversing terrains where large slip ratios are expected.

$$u(k) = u(k-1) + K_p(-y(k) - e(k-1)) + K_I 0.25e(k) + (K_D / 0.25)(-y(k) - 2e(k-1) + e(k-2)) \quad (6)$$

5.4.2 Data Collection and Storage

It is of importance to note that other factors affect the amount of wheel slip (acceleration, incline, lateral slip, turning etc.) but as moisture content alone is focused on for this research as a proof of concept, all samples were taken at fixed velocities (as described in) and on straight line, flat test runs. Data was sampled and stored in the form of:

$$\overrightarrow{X} = \{X_i \mid i = (1:n)\} \tag{7}$$

Where X is the instantaneous values of time (*T*), motor currents (*LI, RI*), left, right and rear encoder values (*LE, RE, REE*) and battery terminal voltage (*BV*). Angular velocity for the left, right and rear (redundant) wheels (*LV, RV, REV*) is then calculated as follows:

$$\overrightarrow{LV} = \left\{ LV_i = \frac{(LE_i - LE_{i-1})*CalL}{(T_i - T_{i-1})} \mid i = (2:n) \right\} \tag{8}$$

$$\overrightarrow{RV} = \left\{ RV_i = \frac{(RE_i - RE_{i-1})*CalR}{(T_i - T_{i-1})} \mid i = (2:n) \right\} \tag{9}$$

$$\overrightarrow{REV} = \left\{ REV_i = \frac{(REE_i - REE_{i-1})*CalRE}{(T_i - T_{i-1})} \mid i = (2:n) \right\} \tag{10}$$

CalRE, *CalL* and *CalR* are calibration coefficients that were obtained from test runs over ideal surfaces and for known lengths. The slip ratio for both the left and right drives (*LS, RS*) is calculated as follows:

$$\overrightarrow{LS} = \left\{ LS_i = \frac{(LV_i - REV_i)*100}{LV_i} \mid i = (2:n) \right\} \tag{11}$$

$$\overrightarrow{RS} = \left\{ RS_i = \frac{(RV_i - REV_i)*100}{RV_i} \mid i = (2:n) \right\} \tag{12}$$

5.5 Data Analysis Methods

The principle aim of this chapter is to investigate the viability of employing predictive statistical methods to empirical data sets collected from on-board UGV sensors in order to successfully predict the moisture content of terrains. This requires that there is information within the empirical data (power usage and wheel slip over a set of velocities) that describes the actual level of moisture in the terrain.

As discussed, terrain reference data sets are derived from the UGV sensors as it traverses a set of known terrain types, with a range of known moisture contents, at a set of predefined velocities. The resulting data sets describe the relationship between power use, wheel slip and velocity for a set of terrains and a set of moisture contents.

It is intended that during a live mission these data sets will be used by the prediction algorithms (along with knowledge of current terrain type and live sensor data) to determine the moisture content of the terrain.

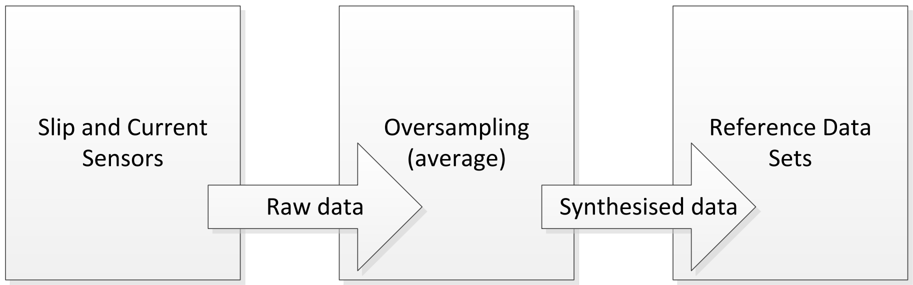


Figure 5.5: Data Collection and Oversampling.

In order to address short term variances in the data (many small disturbances such as bumps, stones, slippery patches cause 'noise' that is irrelevant to overall moisture prediction), an oversampling approach is employed whereby each value within each data set is a mean average value of a configurable number of individual samples taken from the sensor (Figure 5.5). The result is a reference data set that does not include unrepresentative information. A first step in determining the feasibility of describing the data based on averages, is to gain an understanding of how representative the recorded mean average is of the underlying set of result samples.

An analysis is carried out in order to understand the statistical distribution of the raw data about the mean values recorded in the reference data sets. Tests for type of probability distribution and subsequently calculation for standard deviation are conducted, as well as analysis of outlying results. A discussion of the results and their relationship to the average mean values employed in the relationship graphs is presented.

The best method for examining data sets for a normal distribution is a much debated topic in the field of statistics, a full discussion on which is beyond the scope of the work presented here. But research was carried out into which tried and tested method is best suited to the sample data sets collected and one single method is not relied upon.

A common method for making an assessment on a probability distribution is the utilisation of histograms which allows for a graphical representation of the distribution of numerical data which is continuous, and offers the opportunity for a visual interpretation of the probability distribution.

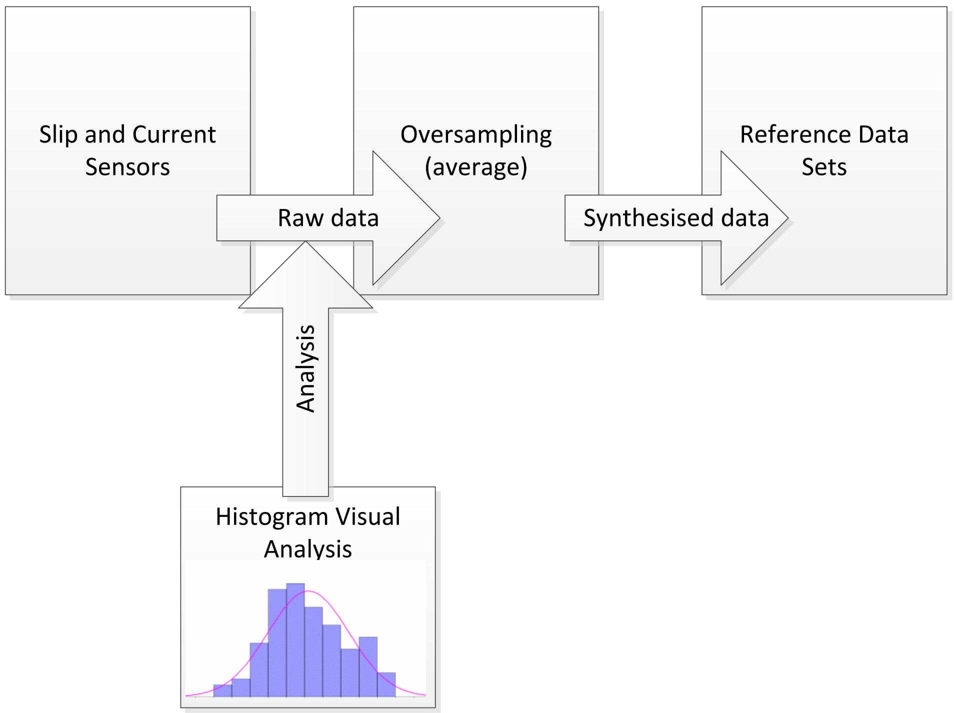


Figure 5.6: Histogram Analysis of Raw Sensor Data.

As a first step in examining our raw data sets for normality, visual analysis of histograms is employed (Figure 5.6). To create a meaningful histogram the optimum interval size (bin size) has to be calculated. There are several methods of providing this and the most suitable one for a particular application needs to be selected.

The "Sturges's Rule" was selected to calculate the interval size as it performs well for data sets that contain more than 30 and less than about 200 items and where the data set is roughly a normal distribution. A histogram was produced for every test value for every terrain type for every weather condition.

Using this rule many of the resultant histograms had several attributes of a normal distribution where many items are clustered about the mean and the variance was generally small.

The histogram method is considered to be "descriptive graphical" and is based on the empirical data only, an improvement on this is a method that considers the empirical data and a theoretical distribution.

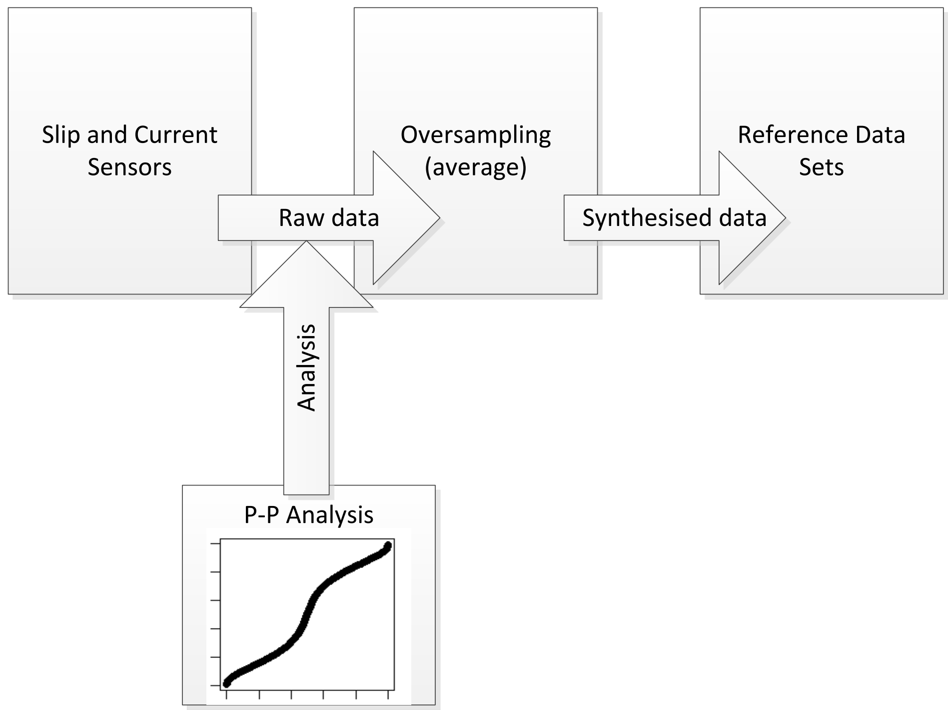
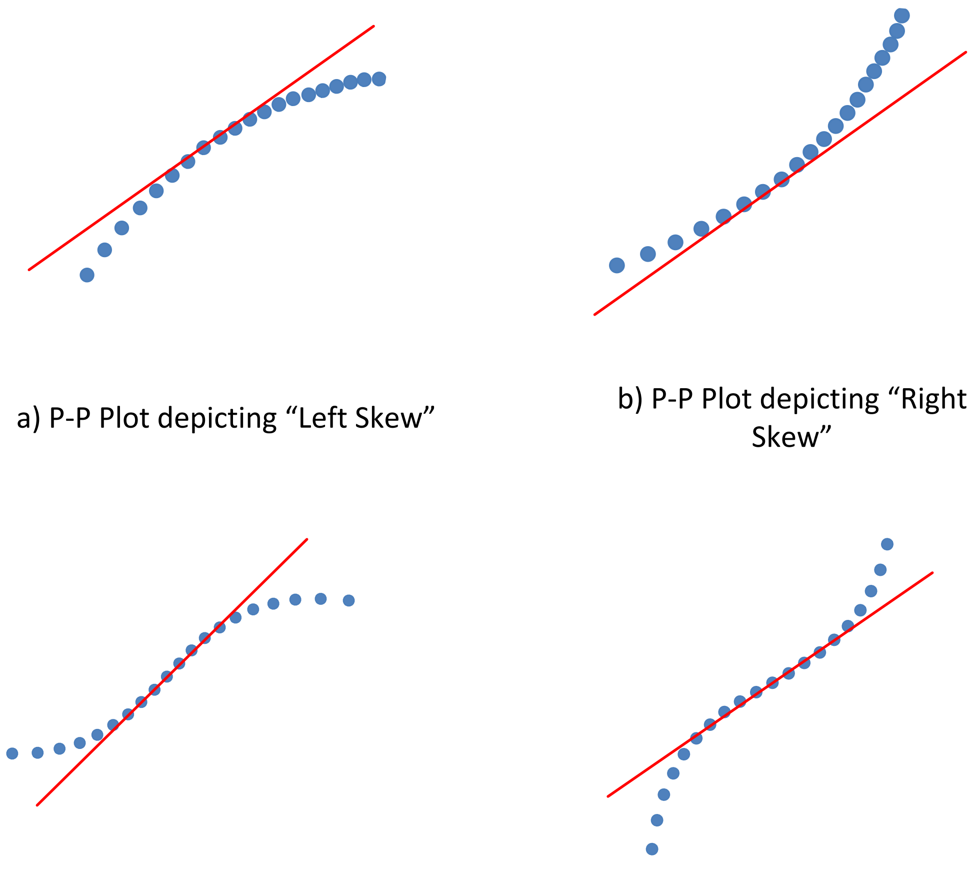


Figure 5.7. P-P Plot Analysis for Normality of Raw Data.

The method selected was a probability-probability plot (p-p plot), which, although is a graphical method it is theory driven (Figure 5.7). The p-p plot we used compared the Cumulative Distribution Function (CDF) of the data against the CDF of the Normal Distribution Function. We compared the data against the Normal Distribution Function because the histograms appeared to follow the Normal Distribution Function for many of our data sets.

If the p-p plot plots a relatively straight line then the data conforms to a normal distribution. If it depicts one of the charts shown in Figure 5.8, it is approximately normal with the stated differences.



a) P-P Plot depicting “Left Skew”

b) P-P Plot depicting “Right Skew”

c) P-P Plot depicting “Short Tails”

d) P-P Plot depicting “Long Tails”

Figure 5.8: Probability-Probability plot analysis [75]

For each set of raw sensor data points assumed into the reference data set, a histogram and P-P plot were produced and inspected. If the data was found to be reasonably normally distributed, mean average and standard deviation values were calculated and used as a statistical description of the sensor data and are entered in to the reference data sets for future use in the prediction algorithm.

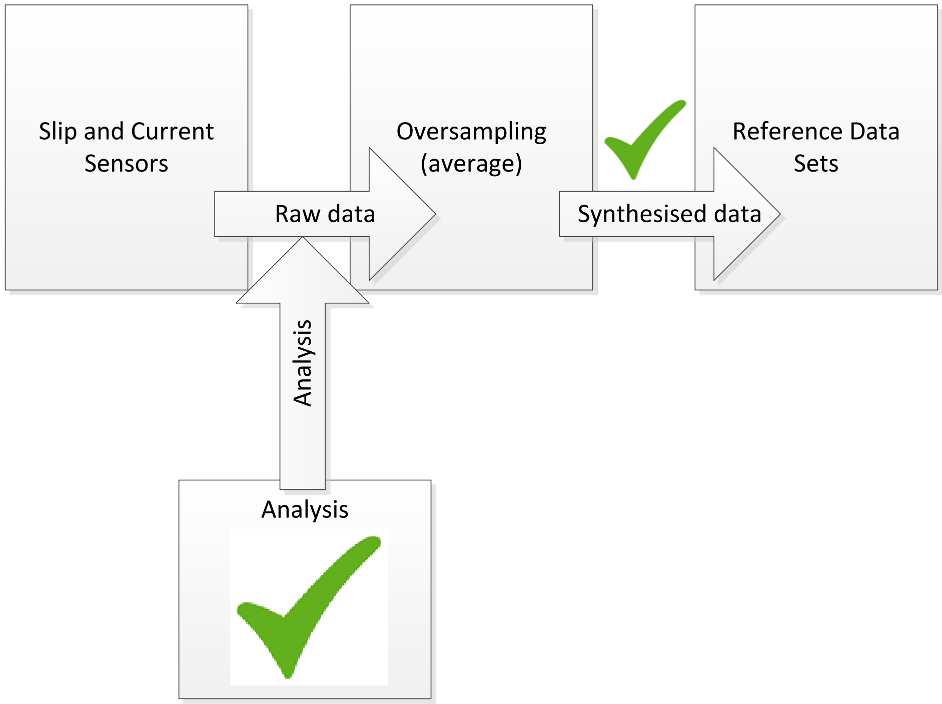


Figure 5.9. Overall Empirical Data Analysis for Rererence Data Set Synthesis

A secondary aim of this chapter is to characterise the behaviour of the UGV with regards to the collection of the data described here. As samples are to be taken at fixed velocities, the reliability and performance of the autonomous speed controller is of interest as the performance of the speed controller will have a direct effect on the current and slip values attained. It is therefore important to capture the performance of the controller as it relates to the collected data sets and then to properly simulate that behaviour in future experiments.

So that the controller parameters can be assessed for reliability for different terrains a method for comparing the sensitivity of the controller for the different terrains is required. Box plots have been selected as it offers a method of visually comparing the degrees of variance from the experiments. Further to this it also allows for the detection of outliers that may be useful for further data analysis.

The plots used are of the box whisker type (see Figure 5.10) where a line within the box depicts the median value and the box boundaries indicate the 25th (lower) and 75th (upper) percentiles, whiskers that are above and below the box indicate the 10th and 90th percentiles. Any sample that it outside these are shown as outliers. When making comparisons the length of the box (and size of whiskers) indicates a larger variance in comparison.

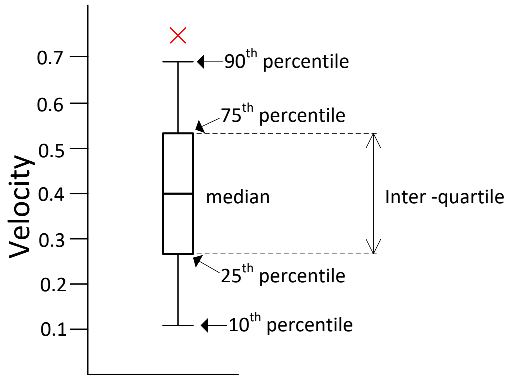


Figure 5.10: Whisker-Box plot example

5.6 UGV / Terrain Interaction Results and Observations

5.6.1 Sand

The curves in Figure 5.11 depict the relationships of “slip versus velocity” for the three weather conditions for traversal over sand. The curves are plotted from the average mean values of the set of values representing the results at each given velocity. For example, traversing sand at 0.17 m/s yields an average slip value of 9.41, as shown in Table 9.

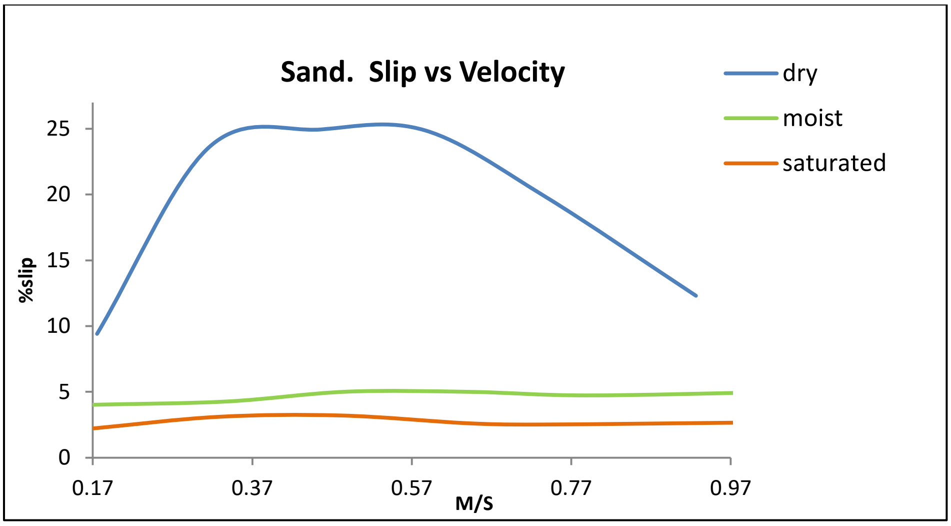


Figure 5.11: Graph depicting comparison of Slip vs Velocity for UGV traversing sand for the three weather conditions

Through inspection of the graph in isolation it would appear that the first observation of interest is the dramatic difference in slip when comparing the "dry" curve with either "moist" or "saturated". The large difference was expected and is explained by the fact that sand is granular by nature and has little shear strength when dry resulting in significant wheel slip. In contrast, the dramatic effect of velocity on slip on dry sand was not as expected. Slip for both moist and saturated remained fairly constant for all of the sample velocities.

		TERRAIN 1: SAND					
EXPERIMENT	VEL (M/S)	DRY		MOIST		SATURATED	
		SLIP (%)	DEVIATION(σ)	SLIP (%)	DEVIATION (σ)	SLIP (%)	DEVIATION (σ)
1	0.16	10.04264	15.56615	4.01641	4.26724	2.2435	2.98766
2	0.33	23.57438	30.88447	4.26749	4.3011	3.10461	3.31976
3	0.5	24.94497	28.24291	5.01676	3.50044	3.20481	2.13946
4	0.66	24.86856	25.47912	4.99929	2.91178	2.61651	2.37707
5	0.83	19.84937	15.37081	4.6333	2.68259	2.51774	1.16108
6	1	12.24118	7.13614	4.89505	1.82922	2.68995	1.49050

Table 9: Mean slip and related deviation results for sand traversal

Figure 5.12 depicts the comparison of "power use versus velocity" curves for the three weather conditions for traversal over sand. Once again the individual points defining the curves are the mean values of a set of results taken at that given velocity. The average and deviation values are as shown in Table 10.

Clearly, the most noticeable difference of Power consumption was during "dry" sand traversal when compared to "moist" and "saturated". The increase in consumption was due to (as observed) vertical terrain deformation (due to the UGV slightly sinking on the surface, and having to ascend out of the dip it has created) and horizontal deformation (caused by the wheels slipping resulting in reconfiguration of the terrain surface).

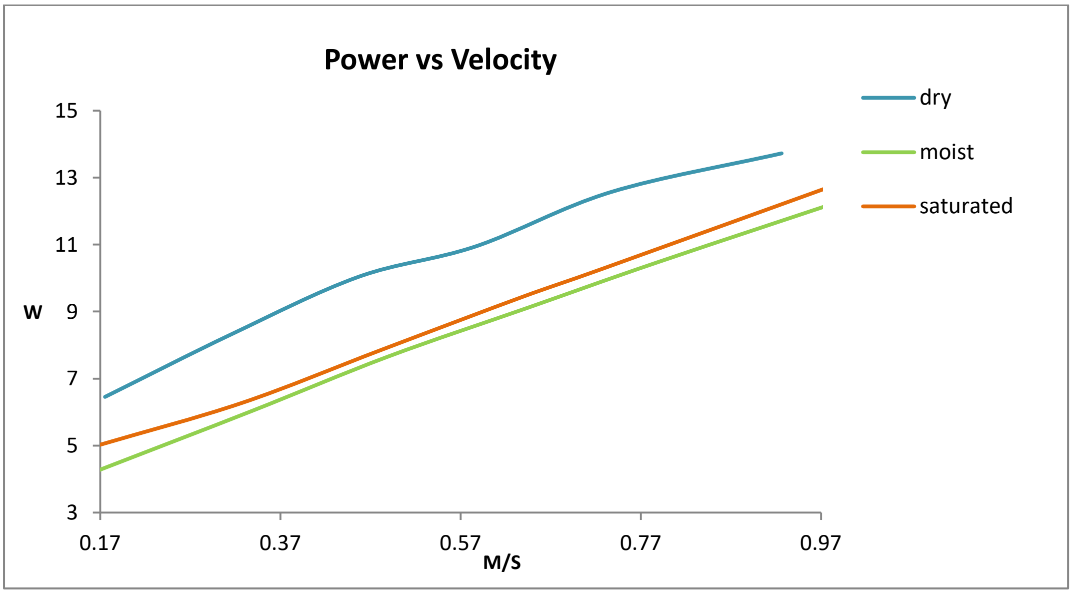


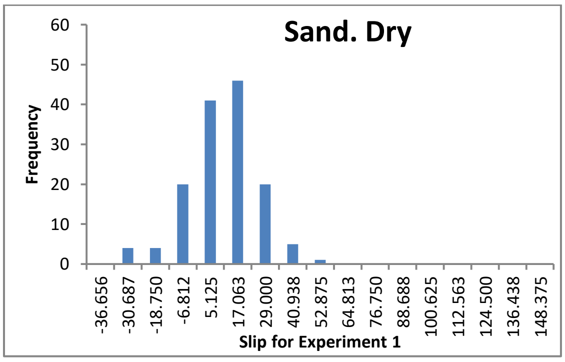
Figure 5.12: Graph depicting comparison of Power vs Velocity for UGV traversing sand for the three weather conditions

An unexpected observation is the shape of the "power versus velocity" curve when compared to that of "slip versus velocity" for dry weather conditions. Although they both have a larger difference when compared to that of the weather conditions, the Power curve shows a linear response to an increase in velocity, opposed to slip which increases towards the mid velocity sample, and then decreases with velocity.

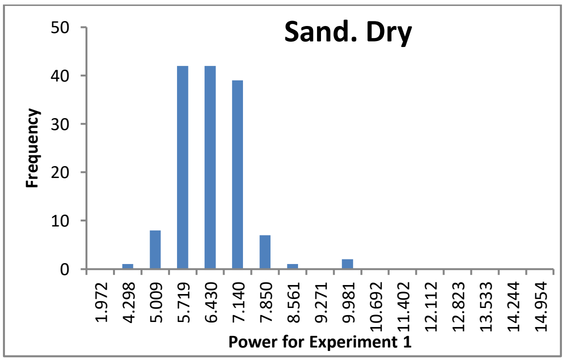
Experiment	Vel (m/s)	Terrain 1: Sand					
		Dry		Moist		Saturated	
		Power (W)	Deviation(σ)	Power (W)	Deviation(σ)	Power (W)	Deviation(σ)
1	0.16	6.45276	0.83649	4.24689	0.45723	4.93303	0.45398
2	0.33	8.32035	2.09966	6.02469	0.40803	6.23286	0.90367
3	0.5	10.03216	2.56627	7.65238	0.88274	7.80368	1.4324
4	0.66	10.94731	3.35688	9.11656	1.56979	9.44545	1.76066
5	0.83	12.56868	3.81507	10.36774	1.95182	10.28488	0.91014
6	1	13.66227	2.48483	12.7091	0.85626	13.01879	1.52474

Table 10: Mean Power and related deviation results for sand traversal

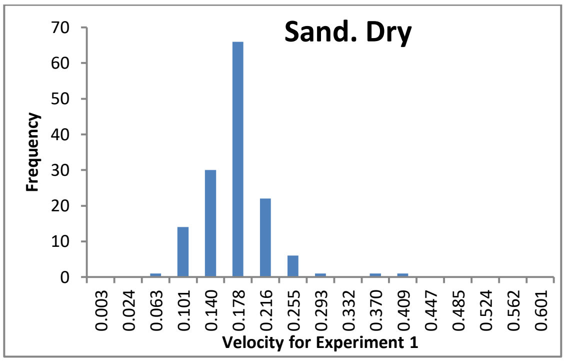
Analysis of the raw data is performed in order to assess the relationship between the mean values from Figure 5.11 and Figure 5.12 to the raw data. Analysis of all data is performed and the full results are presented in Appendix A. Here we conduct an analysis for the results on sand terrain for illustration of the full methods used.



a) Slip: mean = 10.04, standard deviation = 15.6



b) Power mean = 6.45, standard deviation = 0.84

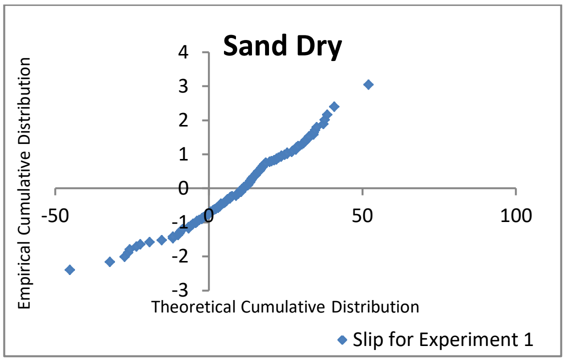


c) Velocity mean = 0.18, standard deviation = 0.05

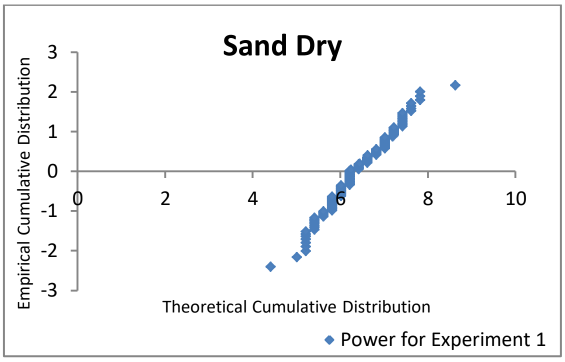
Figure 5.13: Histograms showing results from experiment 1 on dry sand

The distributions of raw results for wheel slip, power use and velocity on dry sand at a target velocity of 0.16 M/S (experiment 1) are shown in Figure 5.13. The appearance presented in the histograms would suggest a shape representative of a normal distribution.

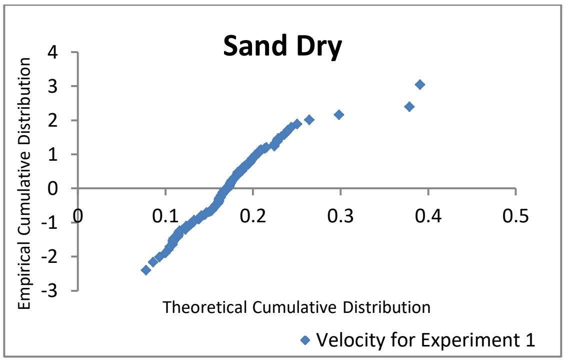
On initial inspection of the P-P plots (which depicts a comparison of the empirical data to that of a standard normal distribution) for experiment 1, it can be noted by the relatively straight line plotted that for all three measured variables (slip, velocity and power). These describe distributions which were that of a standard normal distribution (with very few outliers), this can be seen in Figure 5.14.



a) Slip: mean = 10.04, standard deviation = 15.6



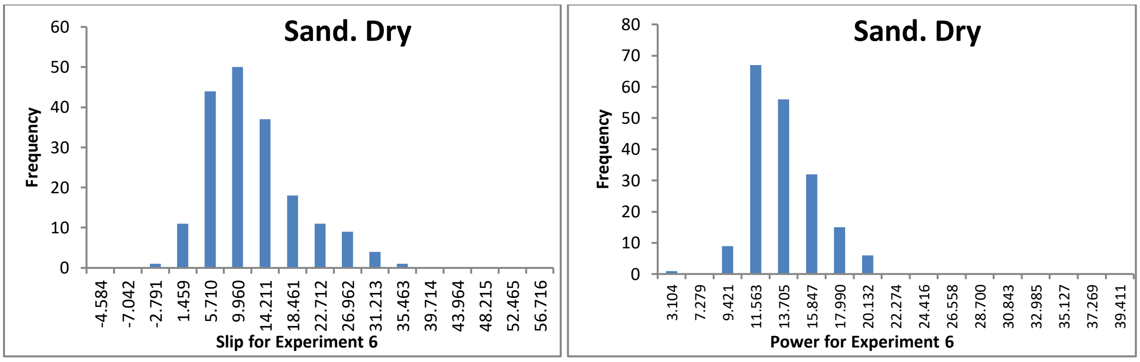
b) Power: mean = 6.45, standard deviation = 0.84



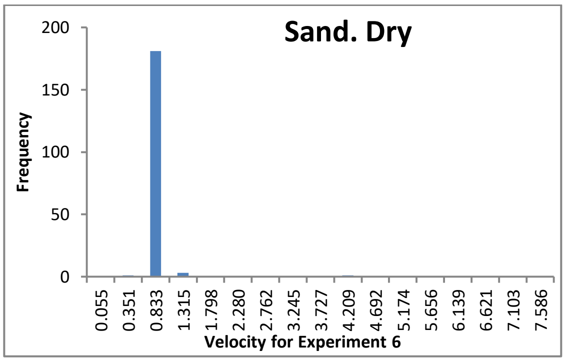
c) Velocity: mean = 0.173, standard deviation = 0.054

Figure 5.14: P-P Plots showing distribution for experiment 1 on dry sand

The analysis is repeated for the results of traversing dry sand at a target velocity of 1 M/S (experiment 6). Once again, from the histograms shown in Figure 5.15, the distributions for wheel slip, power use and velocity appears approximately normal.



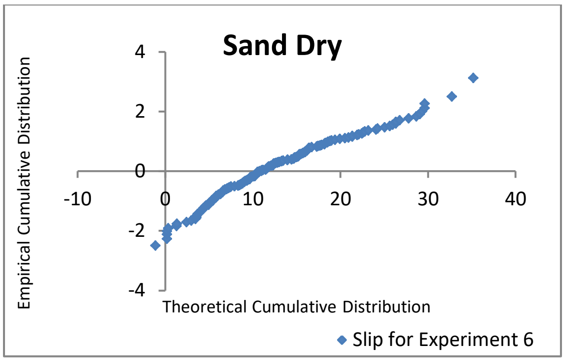
a) Slip: mean = 12.24, standard deviation = 7.14 **b) Power: mean = 13.66, standard deviation = 2.48**



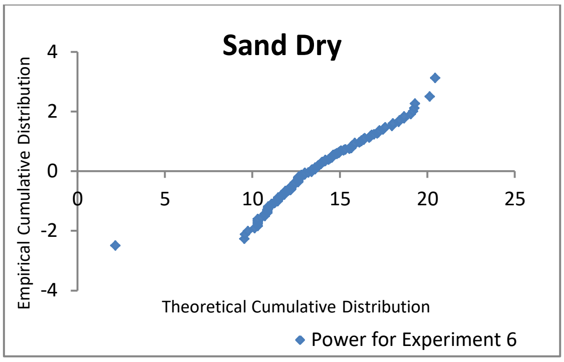
c) Velocity: mean = 0.93, standard deviation = 0.272

Figure 5.15: Histograms showing results from experiment 6 on dry sand

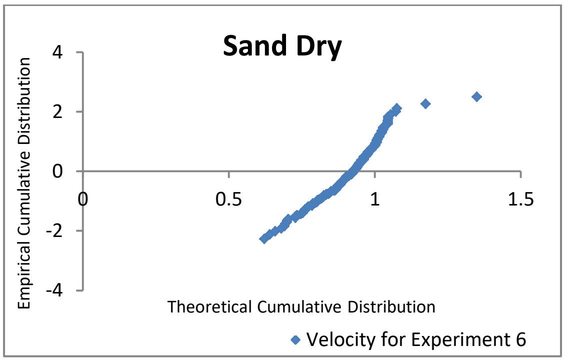
This is supported by the p-p plot analysis shown in Figure 5.16. Where standard normal distribution is shown by the relatively straight plots produced.



a) Slip: mean = 12.24, Standard deviation = 7.14



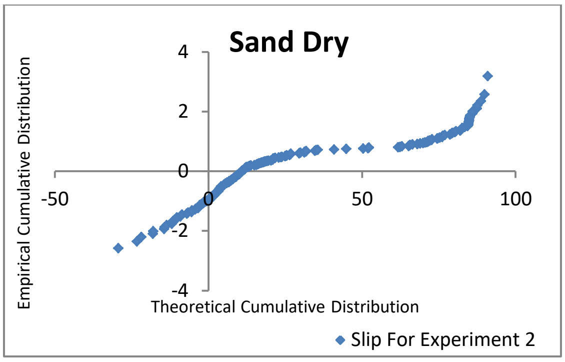
b) Power: mean = 13.66, standard deviation = 2.48

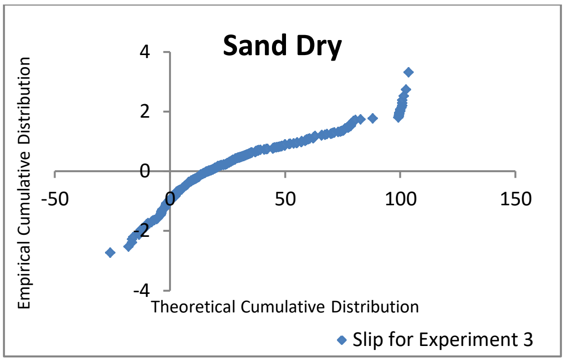


c) Velocity: mean = 0.93, standard deviation = 0.27

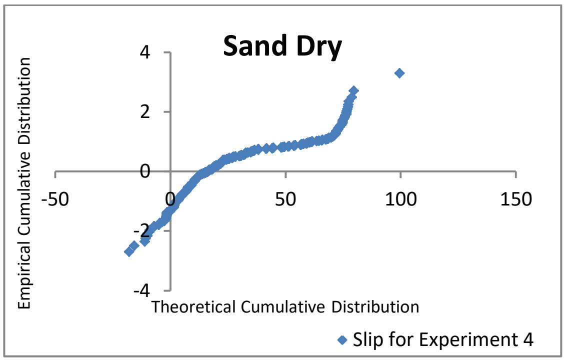
Figure 5.16: P-P Plots showing distribution for experiment 6 on dry sand

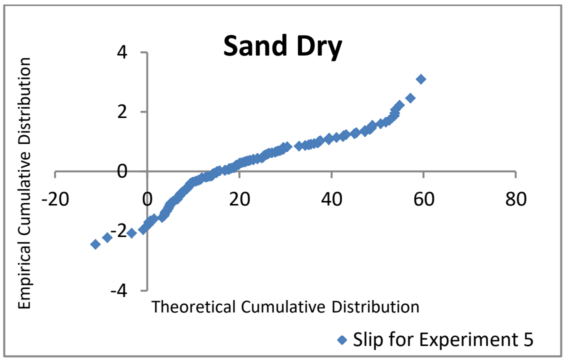
Slip response to the mid-test velocities (experiments 2 - 5) indicates a positive kurtosis highlighting that more variance was present, compared to that of a standard normal distribution and that variance was consistent for these velocities. From Figure 5.17 it can be seen that the mid velocities produced the largest slip ratio. During these experiments it was observed that during slippage, excessive vertical deformation was experienced (when compared to that of experiment 1 and 6) causing a crevice to be made on the terrain surface, in order to maintain the target velocity the speed controller then rapidly increases the wheel angular velocity and excessive slip is experienced while the UGV climbs out of the crevice, at which point the UGV velocity increases until the speed controller compensates, this process is then repeated.





a) Experiment 2: Mean = 23.57, Deviation = 30.88 **b) Experiment 3: Mean = 24.94 Deviation = 28.24**

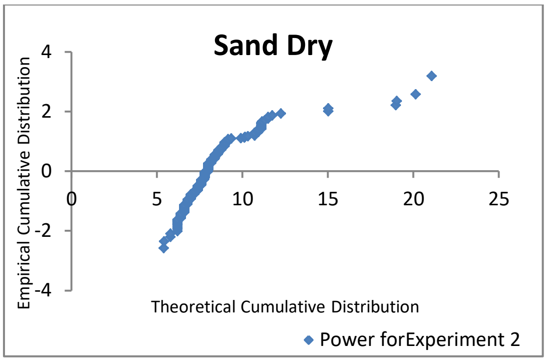


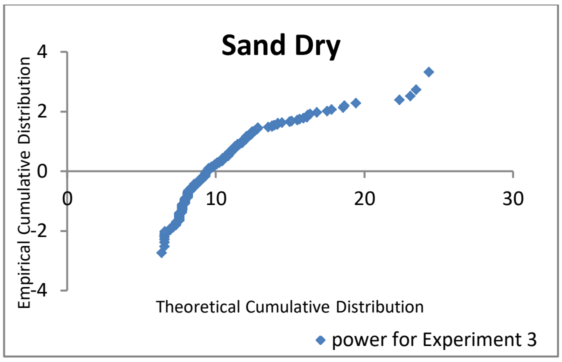


c) Experiment 4: Mean = 24.87, Deviation 25.48 **d) Experiment 5: Mean = 19.85, Deviation 15.37**

Figure 5.17: Distribution of slip samples for mid-range velocities (Experiments 2 -5)

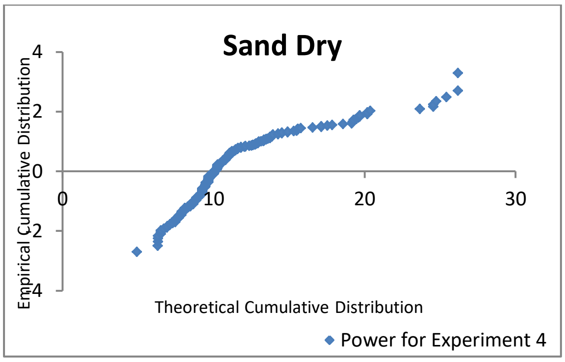
The increased slip and vertical deformation also had a consistent effect on the distributions for power for the mid-range experiments. The p-p plots depicted in Figure 5.18 show a right skew of the distribution, this is due to the power increase that was experienced every time the UGV was required to climb out of the crevice (slip was also experienced during these periods) caused by the surface shear.

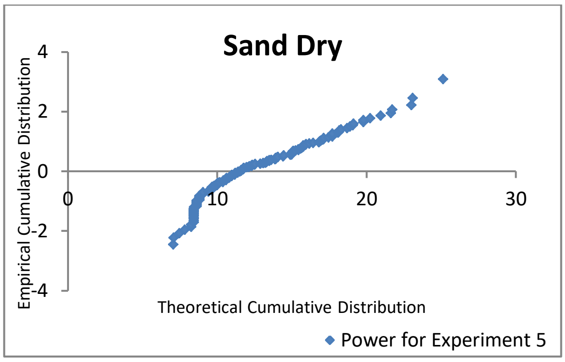




a) Experiment 2: Mean = 8.32, Deviation = 2.09

b) Experiment 3: Mean = 10.03, Deviation = 2.56





c) Experiment 4: Mean = 10.95, Deviation 3.35

d) Experiment 5: Mean = 12.57, Deviation 3.81

Figure 5.18: Distribution of power samples for mid-range velocities (Experiments 2 -5)

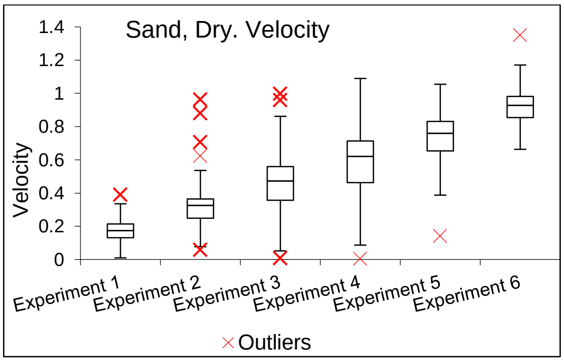


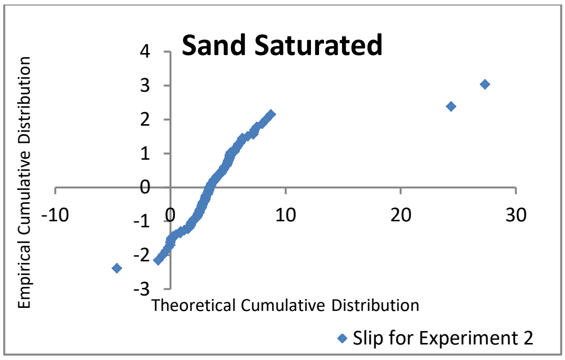
Figure 5.19: Box plot comparing target velocities for dry sand

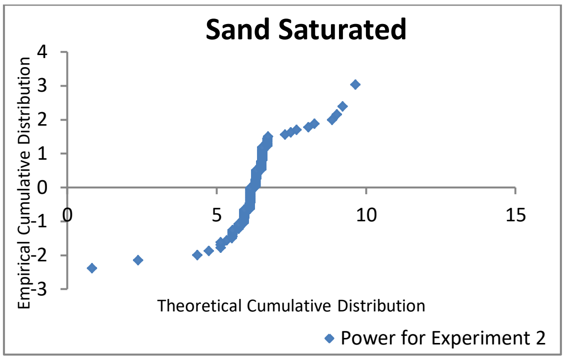
The excessive slip experienced during the mid-velocity experiments impacted on the variance on the target velocities for the experiments. By examining the box plot shown in Figure 5.19 it can be seen that the inter-quartile range is larger for the mid velocities when compared to that of experiments 1 and 6.

It was observed that during the condition of excessive slip the speed controller had a delay before increasing the angular velocity to compensate for the excessive slip. A slight overshoot was also experienced, followed by a delay prior to the speed controller reducing the angular velocity. This observed effect would account for the increase of variance recorded.

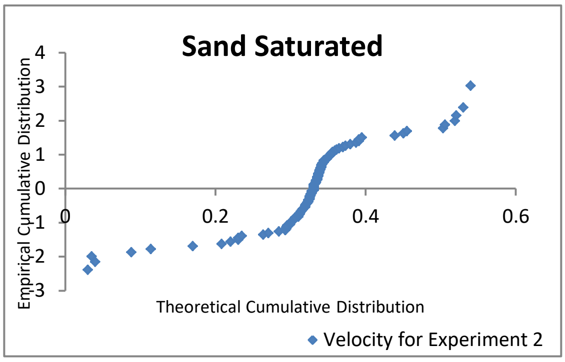
When considering the UGV behaviour for traversal over sand during moist and saturated weather conditions it can be observed from both Figure 5.11 and Figure 5.12 that for both slip and power the response was similar. However an increase in power can be seen when traversing saturated sand opposed to that of moist, it was observed that a slight sinkage was experienced (that was not present on moist sand), this resulted in approximately a 5mm build-up of lateral water on the terrain surface. An increase in consumption is expected during this condition as work is required to displace the water layer which adds significant resistance in the form of drag on the wheel surface [29].

From both Figure 5.20 and Figure 5.21 that both depict p-p plots (which are typical for all results on both the moist and saturated experiments) it can be seen that the UGV performance (for slip, velocity and power) resulted in either a standard normal distribution or one with less variance.





a) Slip: mean = 3.10, Standard deviation = 3.32 **b) Power: mean = 6.23, standard deviation = 0.90**

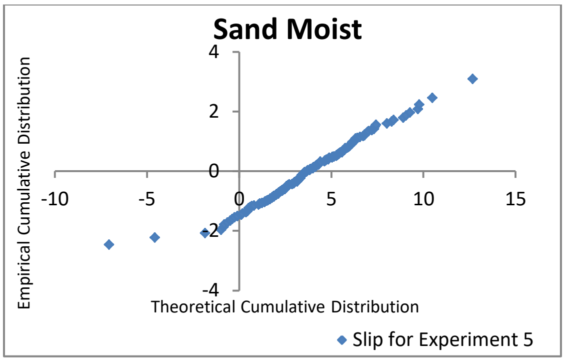


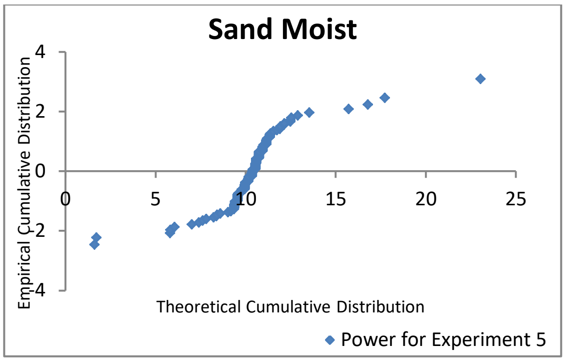
c) Velocity: mean = 0.33, standard deviation = 0.081

Figure 5.20: P-P Plots showing distribution for experiment 2 on saturated sand

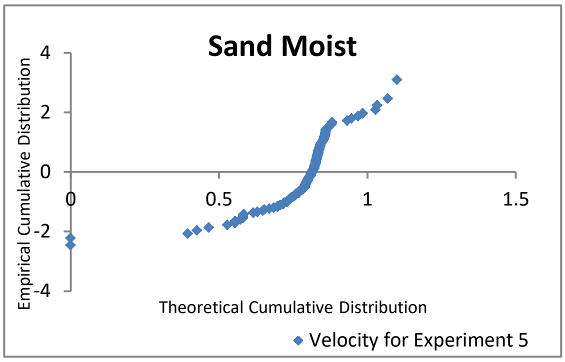
The recorded reduction in variance on slip is due to the presence of moisture which has a cohesive effect on the sand particles due to negative pore pressure of the grains of the sand resulting in the surface behaving in the similar manner of a cohesive soil type with greater shear strength compared to that of dry sand. It was observed that less vertical deformation of the terrain was experienced during these conditions, this meant that although slip was present, the UGV was not constantly climbing out of crevices. This also resulted in less mean values of slip compared to that of dry sand.

A further observation regarding slip on both moist and saturated sand is the result that slip does not alter with an increase in velocity, this is opposed to that of dry sand.





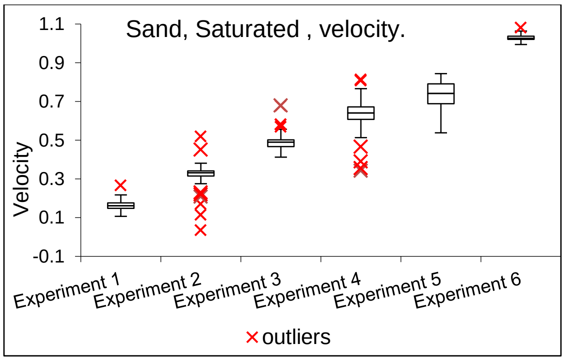
a) Slip: mean = 4.63, Standard deviation = 2.68 **b) Power mean = 10.37, standard deviation = 1.95**



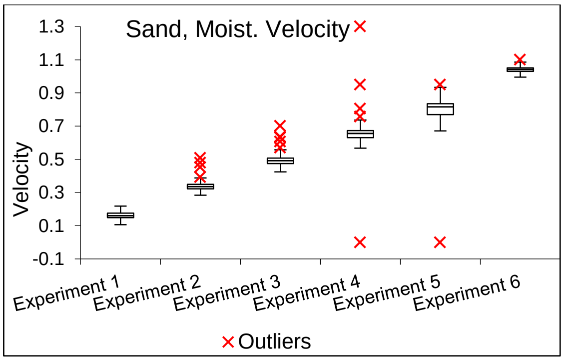
c) Velocity: mean = 0.79, standard deviation = 0.16

Figure 5.21: P-P Plots showing distribution for experiment 5 on moist sand

The reduced variance in slip also resulted in the speed controller not being required to make large rapid changes in angular wheel velocity, this resulted in the target velocities having less variance for all experiments and indicates that the parameters used for tuning the controller were adequate for these conditions. This can be seen when comparing the size inter-quartile ranges shown in a) and b) of Figure 5.22, which represents velocities for saturated and moist conditions respectively, with those depicted in Figure 5.19 that represent velocities for dry. It can be seen that for the dry, the quartiles are noticeably larger. Also, in all cases the upper and lower whiskers are larger for that of the dry experiments.



a) Velocity Comparisons for Saturated Sand



b) Velocity Comparisons for Moist Sand

Figure 5.22: Box plot comparing target velocities for saturated and moist sand

5.6.2 Top Soil

Figure 5.23 depicts the comparison of "slip versus velocity" curves for the three weather conditions for traversal over top soil, the curves are derived from mean values as shown in Table 11. It can be seen that slip for the moist and saturated conditions were similar for all velocities with the exception of the lower test velocity. Slip for the dry condition was comparatively less. This was due to the top soil being cohesive in nature and therefore having a certain amount of shear strength when dry (fully drained), which reduces the likelihood for wheel slip. During un-drained conditions (moist and saturated) shear strength is reduced raising the likelihood of wheel slip.

Apart from the samples that were taken at the lower velocity, the slip response varied little as velocity increased for all three weather conditions. The lack of increase of slip with velocity is also apparent on larger vehicles on similar terrain types and has been observed by Taghavifar [76] who makes the observation that rolling resistance (which is impacted by soil deformation) varies little with velocity (but on drained/dry soil only).

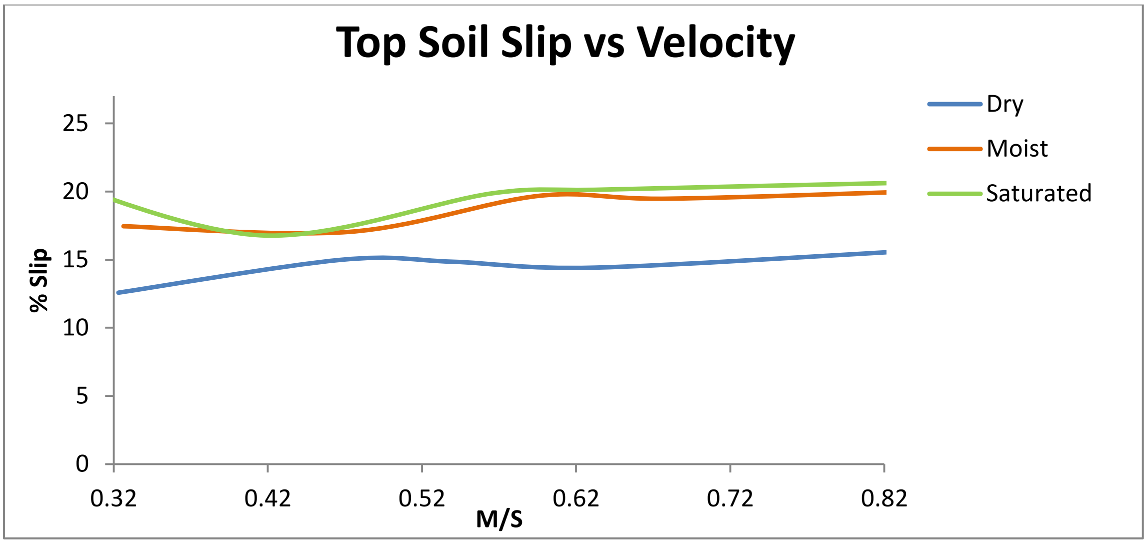


Figure 5.23: Graph depicting comparison of Slip vs Velocity for UGV traversing top soil for the three weather conditions

		TERRAIN 2: TOP SOIL					
EXPERIMENT	VEL (M/S)	DRY		MOIST		SATURATED	
		SLIP (%)	DEVIATION(σ)	SLIP (%)	DEVIATION(σ)	SLIP (%)	DEVIATION(σ)
1	0.34	12.57747	14.36945	17.45619	16.89838	21.03528	21.81159
2	0.46	14.98947	11.15225	17.04102	16.16255	16.77833	10.93657
3	0.58	14.8124	5.72810	19.69437	13.537	19.88019	14.38701
4	0.69	14.41729	7.89505	19.4774	11.2908	20.14693	14.02427
5	0.82	15.72096	7.85366	20.12156	15.191	20.64302	8.19452

Table 11: Mean power and related deviation results for top soil traversal

Figure 5.24 depicts the comparison of “power vs velocity” curves for the three weather conditions for traversal over top soil, the curves are derived from mean values as shown in Table 12. The increase in consumption for the moist and saturated conditions compared to that of the dry condition were, in part due to the reduced cohesiveness of the soil that increased wheel slip, the increased slip also caused slight horizontal deformation which resulted in the UGV being required to climb out of the created crevice .

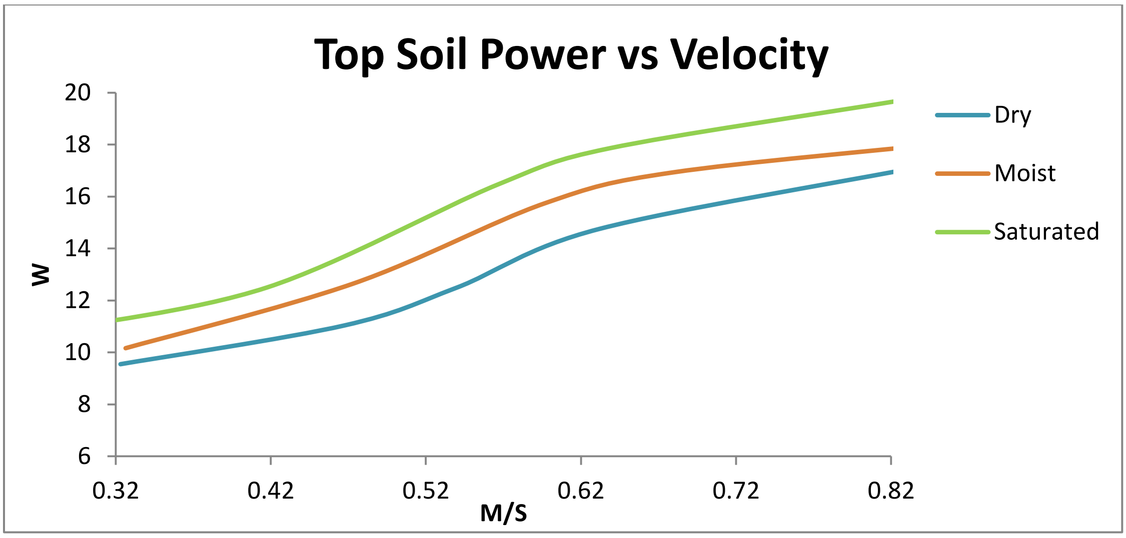


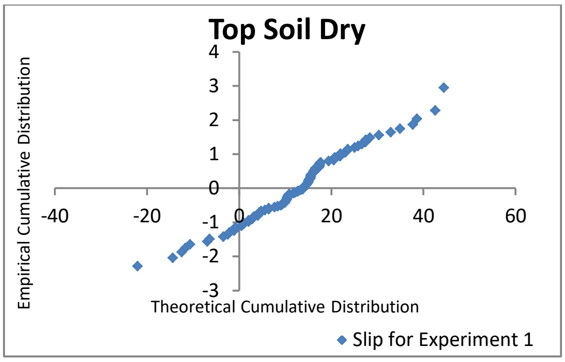
Figure 5.24: Graph depicting comparison of Power vs Velocity for UGV traversing top soil for the three weather conditions

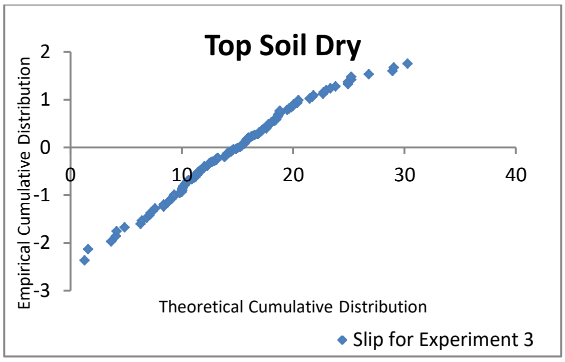
Although recorded slip was similar for both moist and wet conditions, an increase in Power draw is apparent between these conditions. This was likely due to a build-up of lateral water on the terrain surface. An increase in consumption is expected during this condition as work is required to displace the water layer which adds significant resistance in the form of drag on the wheel surface [29].

		TERRAIN 2: TOP SOIL					
EXPERIMENT	VEL (M/S)	DRY		MOIST		SATURATED	
		POWER (W)	DEVIATION(σ)	POWER (W)	DEVIATION(σ)	POWER (W)	DEVIATION(σ)
1	0.34	9.53906	1.990659	10.16375	2.42287	10.83404	2.52975
2	0.46	11.44455	2.67891	12.63966	3.23514	12.49964	1.95359
3	0.58	13.16848	1.69059	15.73789	4.80695	16.45868	4.75420
4	0.69	14.7567	3.02272	16.93408	4.58304	17.85816	4.85948
5	0.82	17.27115	2.513598	18.16021	4.15722023	19.74071	2.97411

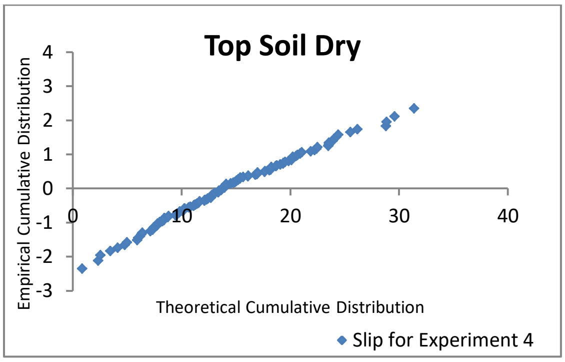
Table 12: Mean power and related deviation results for top soil traversal

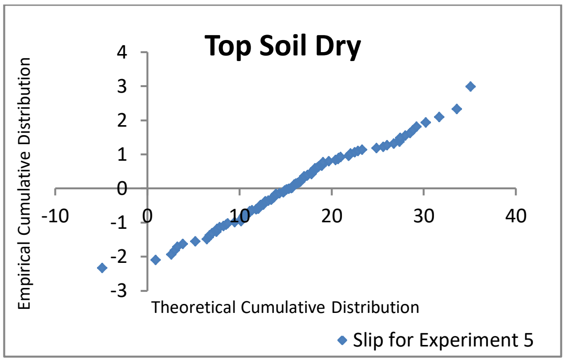
On initial inspection of the P-P plots for slip examples, which are shown in Figure 5.25, during the dry condition for all velocities it is observed that the samples taken are that of a standard normal distribution.





a) Experiment 1: Mean = 12.58, Deviation = 14.37 **b) Experiment 3: Mean = 14.81, Deviation = 5.73**

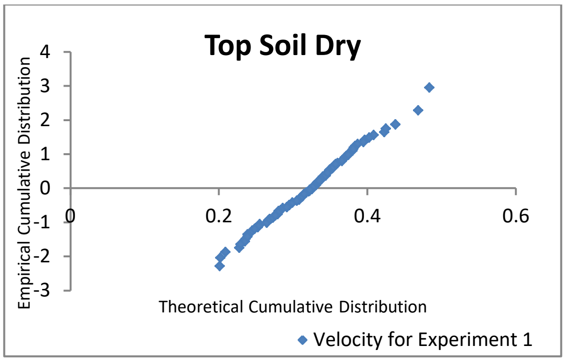




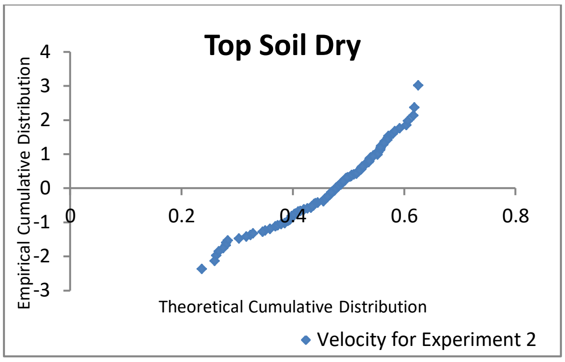
c) Experiment 4: Mean = 14.42, Deviation 7.90 **d) Experiment 5: Mean = 15.72, Deviation 7.85**

Figure 5.25: Distribution of slip samples for 4 velocities

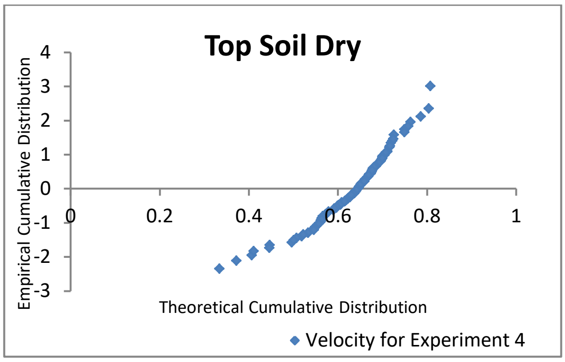
Although slip was experienced during this condition, the slip was fairly constant resulting in the speed controller required to only make small adjustments to the drive wheels angular velocity. This can also be seen in the velocity p-p plots shown in Figure 5.26, which indicate a standard normal distribution.



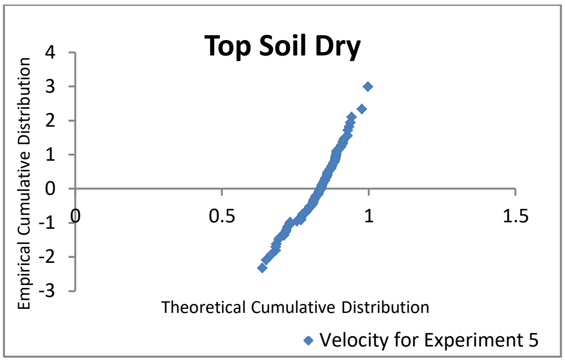
a) Experiment 1: Mean = 0.32, Deviation = 0.05



b) Experiment 2: Mean = 0.46, Deviation = 0.08



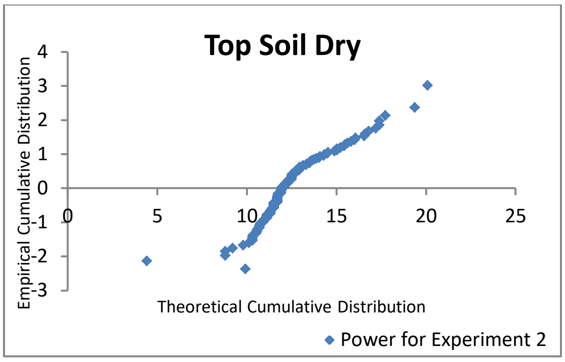
a) Experiment 4: Mean = 0.64, Deviation = 0.08

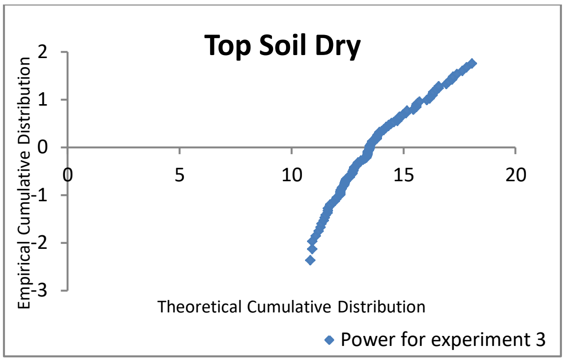


b) Experiment 5: Mean = 0.82, Deviation = 0.07

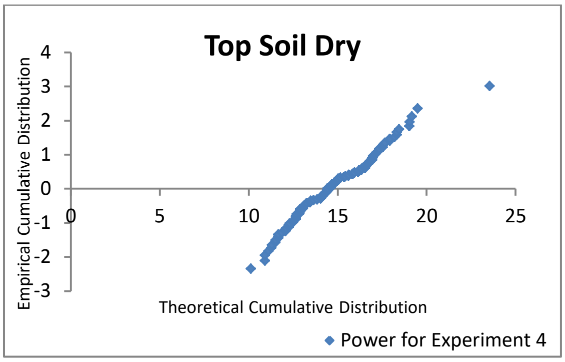
Figure 5.26: Distribution of velocity samples for 4 velocities

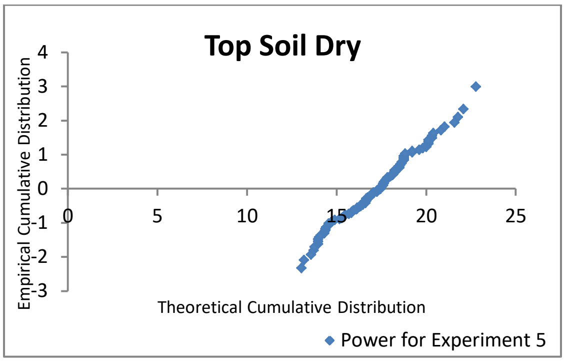
Results for power (see Figure 5.27) were also fairly consistent being either a normal distribution of a slight right skew, which would be expected due to a momentary rapid increase in power when angular velocity is increased in the drive wheels to compensate for a decrease in UGV velocity.





a) Experiment 2: Mean = 12.50, Deviation = 2.68 **b) Experiment 3: Mean = 13.17, Deviation 1.69**

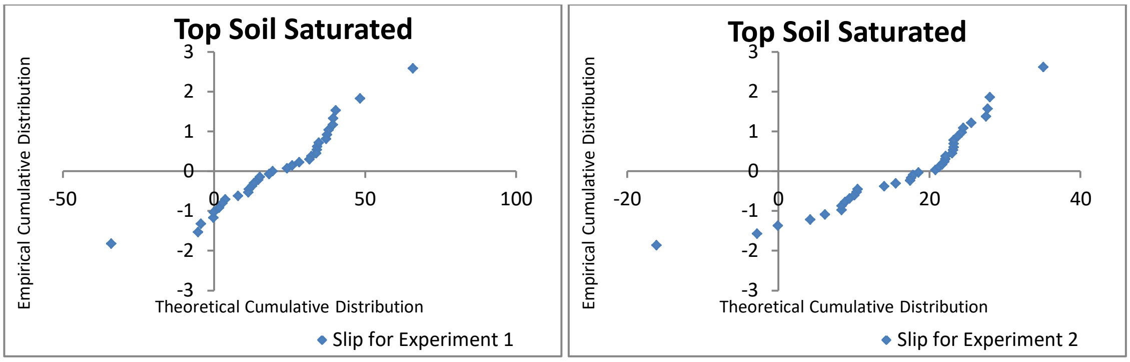




c) Experiment 4: Mean = 14.76, Deviation 3.02 **d) Experiment 5: Mean = 17.27, Deviation 2.51**

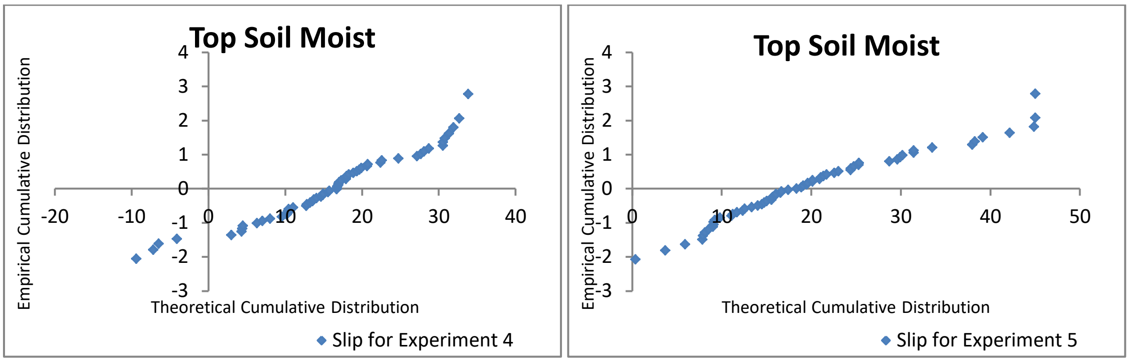
Figure 5.27: Distribution of power samples for 4 Velocities (indicating standard normal distribution)

In comparison, for moist and saturated conditions the P-P plots indicate that slip results were not consistently a standard normal distribution (as can be seen figures Figure 5.28 and Figure 5.29), indicating a larger variance to that of the dry experiments. This is likely due to the soil type being cohesive in nature, and its shear strength decreasing with moisture content, which results an increase in slip.



a) Experiment 1: Mean = 21.03, Deviation = 21.81 **b) Experiment 2: Mean = 16.77, Deviation =10.94**

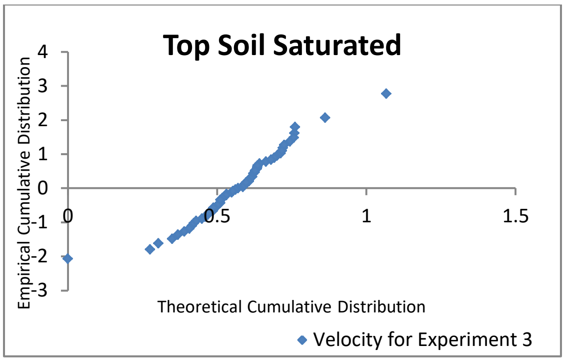
Figure 5.28: Distribution of Slip Samples for 2 Velocities on Saturated Soil

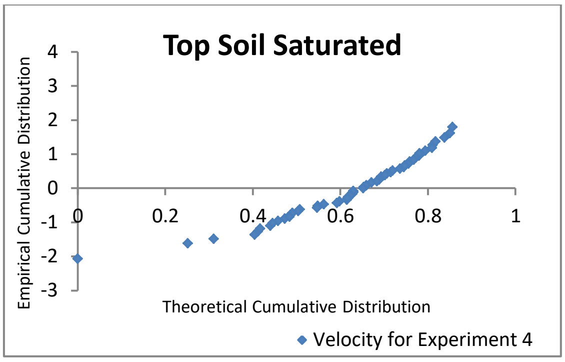


a) Experiment 4: Mean = 19.47, Deviation 11.29 **b) Experiment 5: Mean = 20.12, Deviation 15.19**

Figure 5.29: Distribution of slip samples for 2 velocities on moist soil

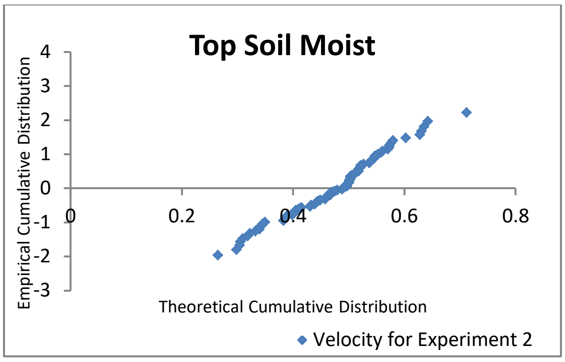
Although an increase of slip was encountered during both moist and saturated conditions compared to that of dry, which was of a larger variance, the velocity p–p plots shown in Appendix B and examples of which are shown in Figure 5.30 and Figure 5.31 indicate that the speed controller responded adequately and performed similar to that of the dry conditions as the majority of results show that of a standard normal distribution.

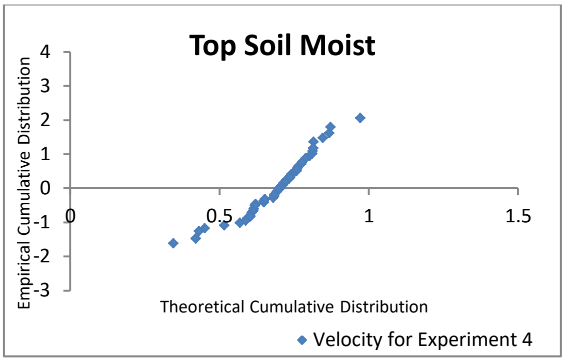




a) Experiment 3: Mean = 0.56, Deviation = 0.12 **b) Experiment 4: Mean = 0.64, Deviation =0.17**

Figure 5.30: Distribution of velocity samples for 2 experiments on saturated soil

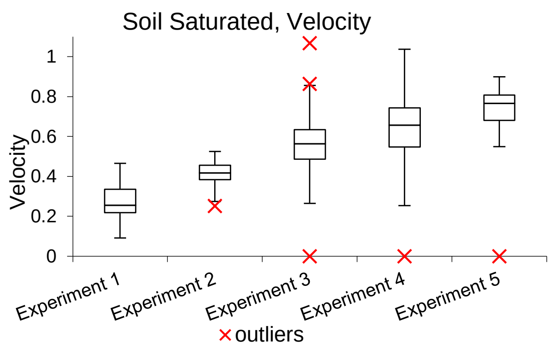




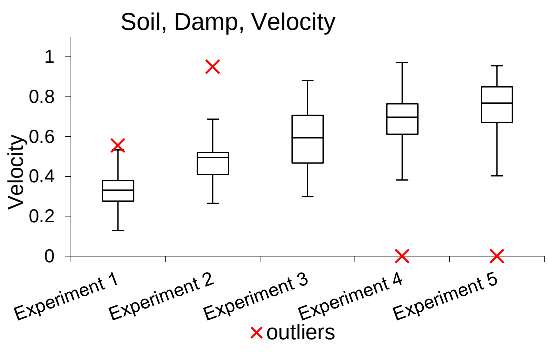
a) Experiment 2: Mean =0.47, Deviation = 0.08 **b) Experiment 4: Mean = 0.67, Deviation = 0.14**

Figure 5.31: Distribution of velocity samples for 2 experiments on moist soil

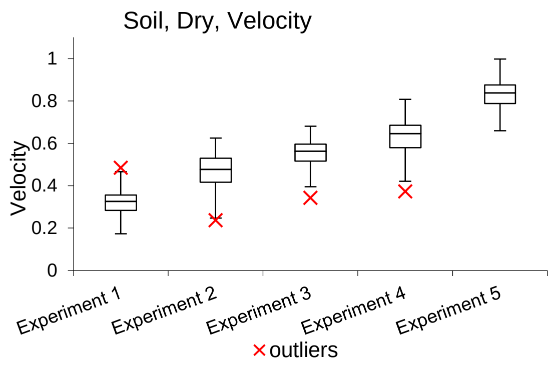
The fluctuation of slip is also apparent when considering the power response for both conditions. As the majority of the results producing a right skew with the remaining being a normal distribution (as can be seen in appendix A). The differing behaviour of slip when comparing dry to moist and saturated conditions and its resultant effect on velocity can also be seen in the box plots presented in Figure 5.32, which shows slightly larger inter-quartiles for almost all velocity samples from the moist and saturated conditions compared to that of the dry condition. Although a difference is present it is not as pronounced as that of the results from sand, further highlighting that the speed controller performed suitably for this terrain type.



a) Velocity Comparisons for Saturated Soil



b) Velocity Comparisons for Moist Soil



c) Velocity Comparisons for Dry Soil

Figure 5.32: Box Plots showing comparisons of results for velocity on all experiments on soil

5.6.3 Grass

Figure 5.33 depicts the comparison of "slip versus velocity" curves for the three weather conditions for traversal over grass, the curves are derived from mean values as shown in Table 13. When comparing the behaviour of the UGV regarding slip compared to that of the other two terrain types it can be noted that an increase of slip with velocity is present, however this does appear to level off towards the upper velocity experiments (for dry and saturated). It could be seen that for all weather conditions sinkage and surface sheer was not present for this terrain type. So, increased slip with moisture present is not due to (in part) terrain reconfiguration (as with other terrain types) but due to the surface becoming slippery with moisture.

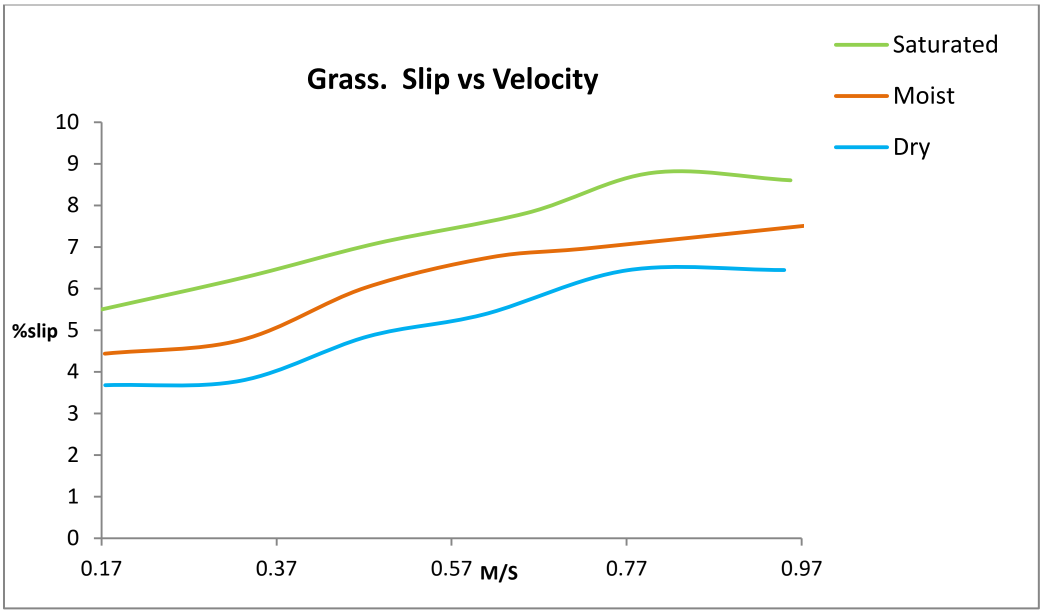


Figure 5.33: Graph depicting comparison of Slip vs Velocity for UGV traversing grass for the three weather conditions

EXPERIMENT	VEL (M/S)	TERRAIN 1: GRASS					
		DRY		MOIST		SATURATED	
		SLIP (%)	DEVIATION(σ)	SLIP (%)	DEVIATION(σ)	SLIP (%)	DEVIATION(σ)
1	0.16	3.67943	17.74512	4.43717	17.30929	5.56714	12.3958
2	0.33	3.78652	19.71796	4.76389	14.14061	6.27916	13.00428
3	0.5	4.84853	13.47525	6.01897	13.81087	7.092	13.50953
4	0.66	5.3816	15.46321	6.75405	9.8527	7.82147	13.36716
5	0.83	6.44262	10.12618	6.97855	10.93434	8.78619	8.93421
6	1	6.44831	7.835591	7.521	7.32017	8.60489	5.27974

Table 13: Mean slip and related deviation results for grass traversal

Figure 5.34 depicts the comparison of "power versus velocity" curves for the three weather conditions for traversal over grass, the curves are derived from mean values as shown in Table 14. In general, an increase in Power consumption is experienced with an increase in moisture content, the power increase being a result of more slip being experienced. It is also important to note that surface water (in the case of the saturated condition) also resulted in an increase of power. However, the difference in consumption decreases with velocity with little difference being apparent at the highest velocity.

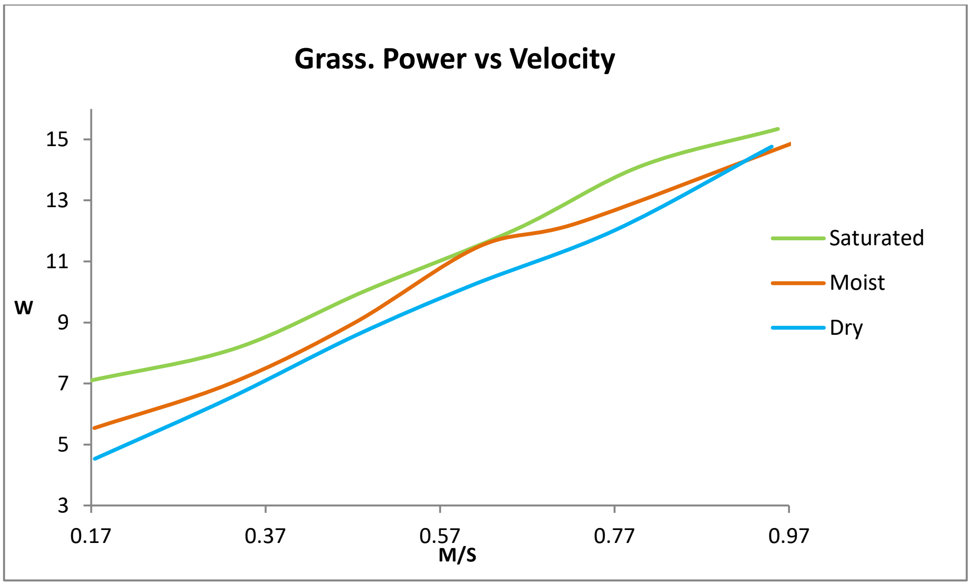
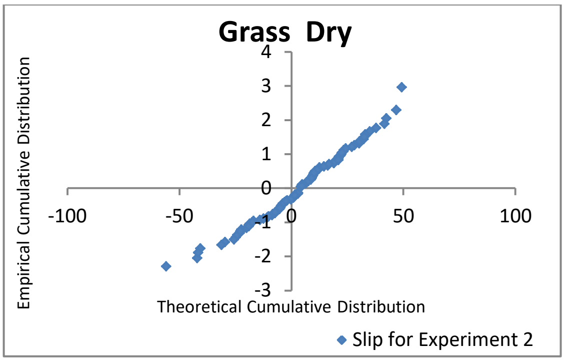


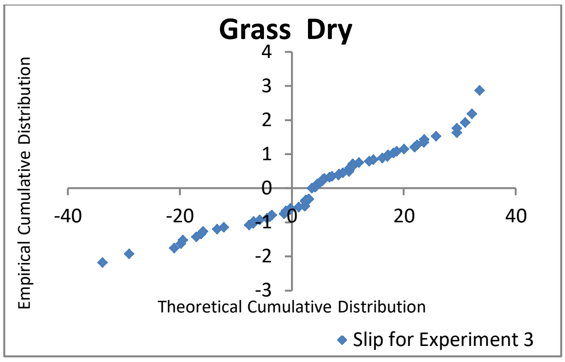
Figure 5.34: Graph depicting comparison of Power vs Velocity for UGV traversing grass for the three weather conditions

EXPERIMENT	VEL (M/S)	TERRAIN 3: GRASS DRY		MOIST		SATURATED	
		POWER (W)	DEVIATION(σ)	POWER (W)	DEVIATION(σ)	POWER (W)	DEVIATION(σ)
1	0.16	4.53135	0.615351	5.53938	0.6838	7.29854	0.62739
2	0.33	6.52197	0.79112	6.99718	0.6852	8.14436	0.69179
3	0.5	8.58376	2.14973	8.9723	1.42268	10.04574	0.84289
4	0.66	10.22574	2.19842	11.49059	4.39663	12.04312	2.21119
5	0.83	12.03069	4.07972	12.2783	3.27679	14.12125	3.52426
6	1	14.76247	3.2018	14.92047	3.02997	15.34183	2.53988

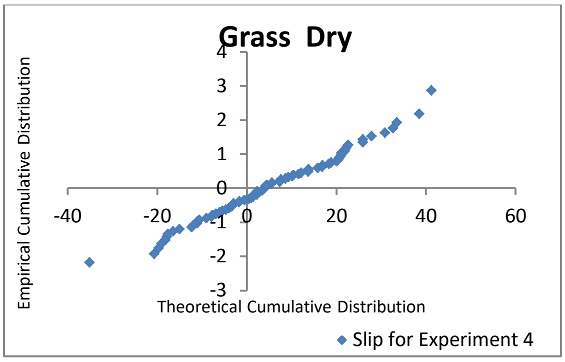
Table 14: Mean power and related deviation results for grass traversal

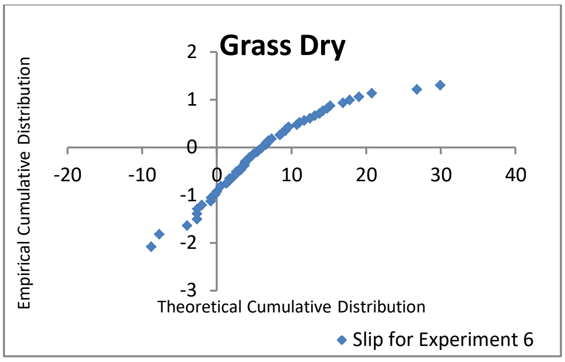
On initial inspection of the P-P plots for slip during the dry condition (see Figure 5.35) for all velocities it is observed that the samples taken are that of a normal distribution (with the exception of the lowest velocity which showed a slight right skew). Although slip was experienced during this condition, the slip was fairly constant for each experiment resulting in the speed controller required to only make small adjustments to the drive wheels angular velocity.





a) Experiment 2: Mean = 3.78, Deviation = 19.72 **b) Experiment 3: Mean = 4.84, Deviation = 13.47**

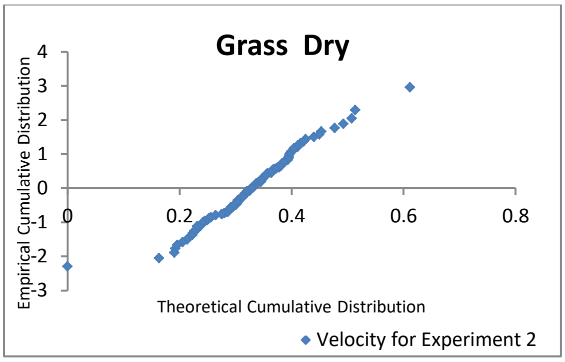




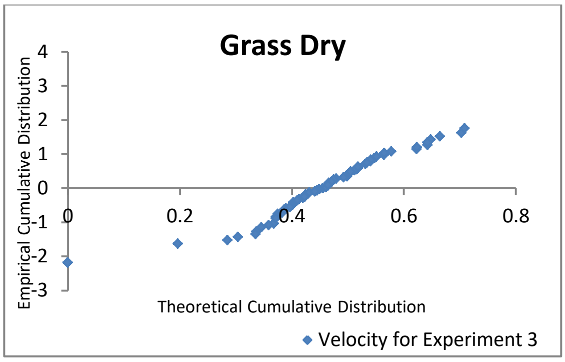
c) Experiment 4: Mean = 5.38, Deviation 15.46 **d) Experiment 6: Mean = 6.44, Deviation 7.83**

Figure 5.35: Distribution of slip samples for 4 velocities

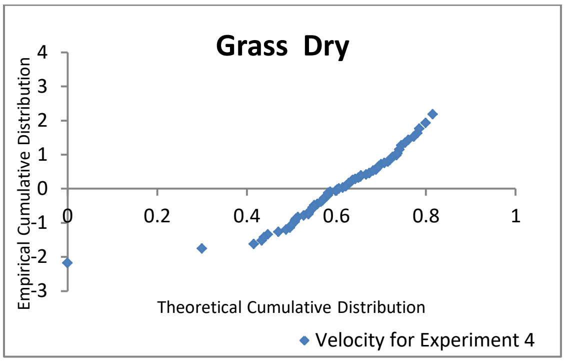
The efficiency for the speed controller for this condition can also be seen when examining all P-P plots for velocity which, examples are shown in Figure 5.36. These plots are all either a standard normal distribution or one showing a negative Kurtosis, indicating samples have minimal deviation around the mean compared to that of a standard normal distribution.



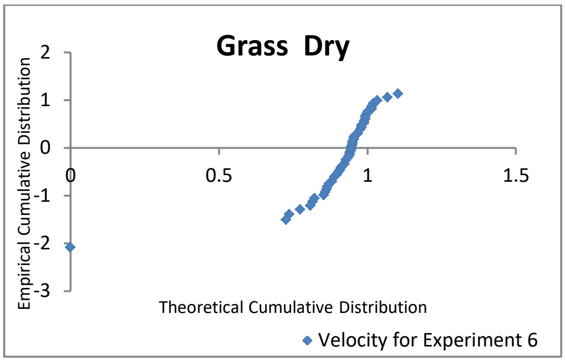
a) Experiment 2: Mean = 0.33, Deviation = 0.08



b) Experiment 3: Mean = 4.84, Deviation = 13.47



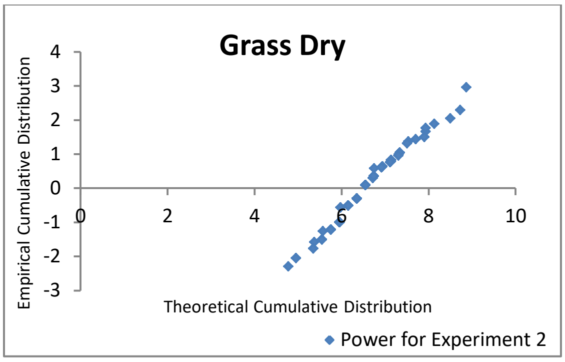
c) Experiment 4: Mean = 0.61, Deviation 0.10



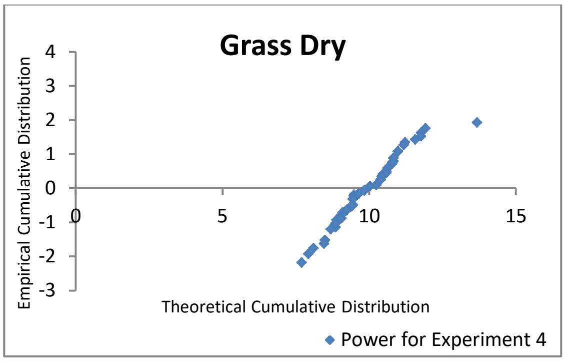
d) Experiment 6: Mean = 0.93, Deviation 0.08

Figure 5.36: Distribution of velocity samples for 4 velocities

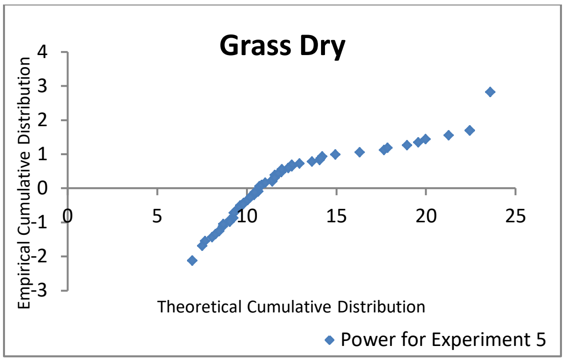
Distribution for Power samples are all either that of a standard normal distribution, or ones indicating a slight skew which would be expected with the slip results being that of a standard normal distribution, examples of which can be seen in Figure 5.37.



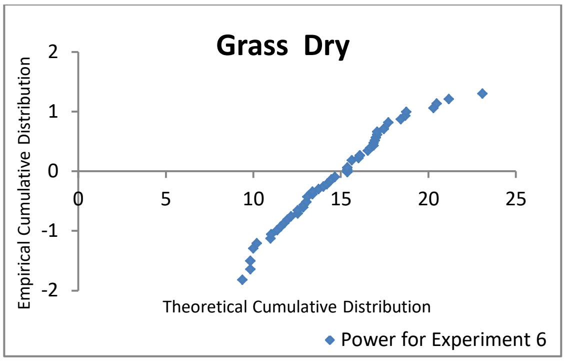
a) Experiment 2: Mean = 6.52, Deviation = 0.79



b) Experiment 3: Mean = 10.22, Deviation = 2.19



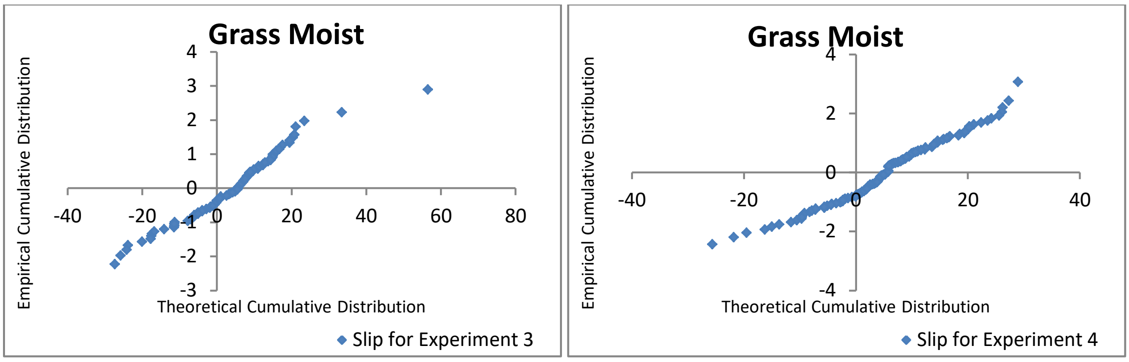
c) Experiment 5: Mean = 12.03, Deviation 4.07



d) Experiment 6: Mean = 14.76, Deviation 3.20

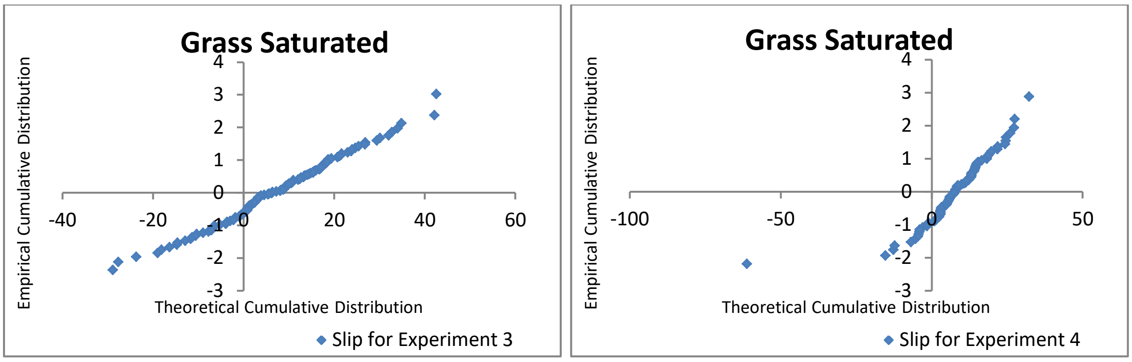
Figure 5.37: Distribution of power samples for 4 velocities

When considering slip distributions for both moist and saturated conditions it can be observed that the UGV behaviour was similar to that of the dry condition where either a standard normal distribution or with a slight skew were seen. Examples for the moist condition can be seen in Figure 5.38 and for saturated, Figure 5.39. Further results are shown in Appendix A.



a) Experiment 2: Mean = 6.01, Deviation = 13.81 **b) Experiment 3: Mean = 6.97, Deviation = 10.93**

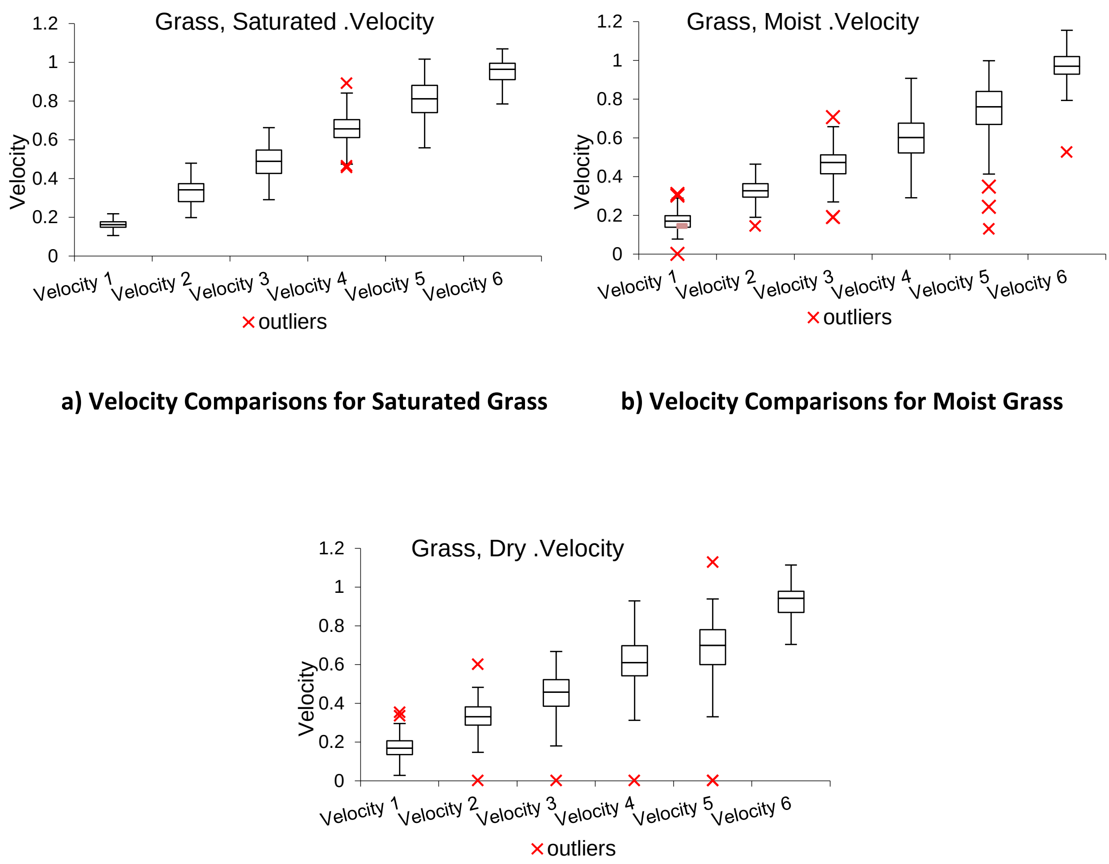
Figure 5.38: Distribution of slip for 2 experiments on moist grass



c) Experiment 2: Mean = 7.09, Deviation = 13.51 **d) Experiment 3: Mean = 7.82, Deviation = 13.36**

Figure 5.39: Distribution of slip for 2 experiments on saturated grass

The results for Power and velocity are also consistently similar to that of the dry condition being of a standard normal distribution (see appendix A). The similarities of performance for all three conditions is further highlighted by comparing the velocity box plots depicted in Figure 5.40, where the inter-quartiles are similar for experiments of different conditions. The similarities are due to the fact that no deformation was present for all weather conditions.



a) Velocity Comparisons for Saturated Grass

b) Velocity Comparisons for Moist Grass

c) Velocity Comparisons for Dry Grass

Figure 5.40: Box Plots showing comparisons of results for saturated, moist and dry grass

5.7 Conclusions

The purpose of this chapter is the synthesis of data sets that describe UGV performance over differing terrain types and of varying moisture contents, and to validate the assumption that enough information is present in the data collected from sensors that differing moisture content can be reliably detected using standard sensors so that its potential for use in power prediction algorithms is realised.

To effect the data collection the required test platform configuration was designed and components selected with thought given to typical UGV configurations regarding sensor selection and drive configuration to keep the experiments typical to that of a UGV mission. The exception to this was the use of a redundant wheel and encoder to measure longitudinal wheel slip. The calibration method and results showed that this method of detection offers reasonable accuracy as long as the UGV is kept on a reasonably straight line. Other sensor data was shown to provide accuracy to within 1 %.

It was shown that the process of data collection was readily effected by the on-board processor which was typical to that of which is installed on a small low end UGV indicating that the method employed here for data collection would readily be implemented on UGVs without the requirement of additional hardware.

For consistent data collection it was required that consideration be given to ensure the speed controller holds the speed of the UGV relatively constant. On the deformable surfaces it was found that there was a difference in the effect of the speed controller when comparing granular terrain types to that of cohesive types.

Slip, on dry granular terrain (sand) varied with velocity, also variance of slip readings were greater for the mid-range velocities. There was also a slight increase in variance of velocity readings for the mid velocity examples. It was observed that the speed controller exhibited delay in compensating for the excessive slip during these conditions and also tended to overshoot slightly. However, the controller performance improved on damp and saturated granular terrain.

When comparing the speed controller with dry granular terrain types and cohesive terrains the same comparison can be made. Although the collected data for the mid-range velocities is acceptable, it could be improved upon by having the speed controller tuned independently for not only varying terrain types but also possibly for differing moisture conditions.

The independent tuning would improve the accuracy of the data collected by holding the velocity constant for sample collection. Further to this, inefficiency in power consumption would also be a result of non-optimum tuning, while this would not impact directly on empirical data collection, consideration should also be given to velocity control of UGVs carrying out live missions where speed control is implemented. Therefore further empirical data collection trials could serve to improve speed control tuning parameters for a variety of terrain types and conditions to improve UGV propulsion efficiency and live speed control.

As discussed in 3.2.2, the Coulomb-Mohr soil failure criterion soil failure to support the applied torque:

$$\tau_{max} = c + \sigma_{max} tan\phi \qquad (2)$$

The value of internal friction angle varies considerably across terrain types. For example, in sand or gravel the friction angle can be as high as 50 degrees [77], whereas in clay based soils the friction angle can be as low as 17 [78]. In terms of evaluating torque that the terrain will support, the value of Applied Stress (σ_{max}), and therefore vehicle weight applied to the soil is more significant for when friction angle is high.

In contrast, the cohesion value of soil (c) is unaffected by vehicle weight. Loose sand or gravel typically has 0 cohesion [78], whereas Clay based soil can have a cohesion value of up to 105 [79]. Figure 5.41 shows the results of maximum torque (τ_{max}) with vehicle weight range 1 kg to 4000kg with the same 0.1m^2 contact area, for both sandy gravel and compacted clay soils. The clay trace shows the maximum applicable torque before inducing slip is significantly less dependent upon vehicle weights across the range of vehicle weights.

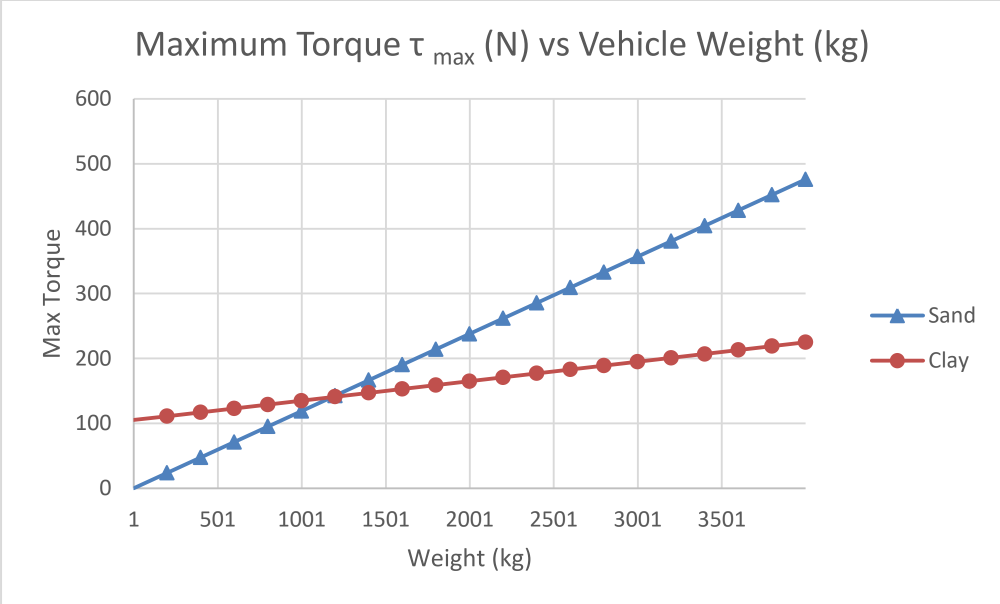


Figure 5.41 Coulomb-Mohr soil failure criterion: Maximum Torque vs. Weight for Clay and Sand

This terramechanic model suggests that a low weight vehicle such as the test UGV (3.6kg) would generate significantly more slip in sand compared to a clay based soil. This agrees with the collected empirical data 14.9% max slip value for top toil compared to 25% max slip for dry sand.

The two data sets (current vs velocity and slip vs velocity) produced for each terrain type indicate that an exploitable difference in data series is present for the data to be used for the terrains used for the experiments. However the charts also highlight the fact that more than one type of data series is required. The graphs for grass highlight this. It can be seen in the power reference chart that at the mid higher velocities it is not possible to distinguish between the moisture content conditions, where the slip chart indicates that a suitable difference is present. This is in opposition to soil, where the power chart presents the data series that could be used to predict moisture content.

Dry sand conditions yielded an increased variance (when compared to that of both moist and wet), offering another possibility for a third data set to be used without the requirement of additional sensors. During live prediction it would be possible to also use the empirical data relating to the variance of the samples.

Results for velocity vs slip on cohesive soils provided a result similar to previous research for larger vehicles that shows slip to not vary with velocity and also to be relatively constant for a given velocity. Although this indicates that the reference charts can be used for moisture content detection of terrains, it has to be noted that slip can be non-linear on granular materials, dependent on the moisture content. While examining the chart shown in Figure 5.11 it can be seen that from the mid velocity to the highest velocity, slip decreases for the dry condition. Although tests were carried out at up to 90% of the highest obtainable UGV speed, it may be the case that slip continues to decrease with a further increase in velocity on this terrain condition to an extent where it has a lower slip ratio compared to that of the other moisture conditions.

The result above indicates the varying behaviour not only of the effects of moisture on UGV/terrain interaction but also the differing effects of moisture on cohesive and granular terrain types, which adds complexity to moisture prediction. Although it would appear that this situation may not present an issue to the UGV used for data collection, it may not be the case for one with differing mass of velocity requirements. This highlights the requirement of data collection at the complete velocity range of the UGV under test.

The three off-road terrain types selected for data collection were considered typical for UGV missions. As discussed previously, the two components of terrain deformation are horizontal, where the surface is sheared and vertical, where the UGV sinks into the terrain. Most research on off-road traversal focuses on the complexities of deformable terrains.

While conducting experiments on grass, although differences were shown regarding slip and power consumption it was not due to surface deformation. Terrains that contain grass have traditionally been considered multi-layered, that is, the surface grass is sheared leaving a differing surface that may be considered deformable.

Although deformation would be apparent for a larger vehicle and a multi-layered effect would be experienced, this is not the case for the smaller vehicle, such as many modern UGVs.

The grass surface behaved more like a (poorly) prepared road surface where slip increased with moisture but with no terrain deformation. Previously, where terrains have been categorised by their geographical type (sand, loam, grass etc.) with regards to vehicle traversal the focus was primarily on the terrains ability to support the vehicle opposed to UGV power prediction. Where UGVs are considerably lighter to manned vehicles consideration needs to be given to categorisation that includes terrains that are non- deformable when being traversed by the lighter UGV. This also highlights the requirement of modelling off-road surfaces on other factors than their sheer and compaction strength.

6 Polynomial Non-linear Regression Mission Energy Prediction Algorithm

6.1.1 Introduction

In order to address the shortcomings of existing approaches to mission energy prediction, the algorithm presented here takes advantage of prior mission information regarding terrain types and the interaction between a particular UGVs propulsion system with given terrains over a range of climatic conditions in addition to live information about propulsion energy consumption and wheel slip to generate more accurate results.

Previous work by Sadpour [32] uses prior knowledge of rolling resistances for known terrain types to be encountered for a given mission to allow for improved accuracy of mission resource requirements. This approach only takes advantage of prior knowledge regarding terrain types. No consideration is given to the effects of weather on the terrains, and the impact that this can have on energy consumption.

As shown in Chapter 3, data from typical UGV sensors can be used to determine both the rolling resistance and type of the terrain type being traversed. It is suggested that improved mission energy prediction will be achieved by predicting the future state of terrain types apropos moisture content and resulting energy demands.

This chapter describes the design and test of a novel mission energy prediction algorithm that compares live sensor data relating to power and wheel slip to that of previously collected empirical data to assess the moisture content of the terrain presently being traversed, and then to predict of the likely rolling resistance of the yet un-traversed terrains of a mission in order to achieve improved accuracy.

6.2 Aims and Goals

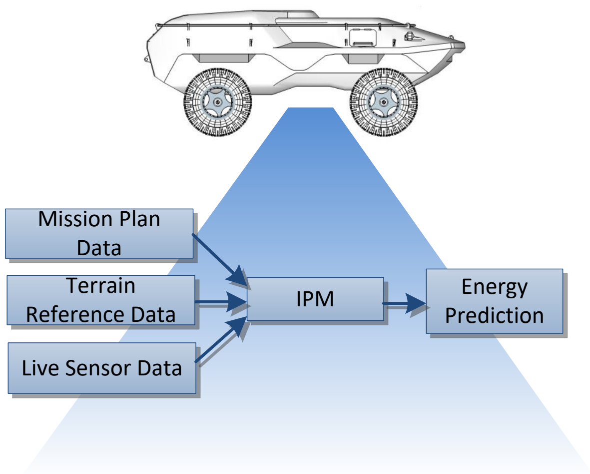
The overall aim of the algorithm is to achieve improved mission energy prediction accuracy compared to existing approaches, using only the data sources than would be provided by typical existing on-board UGV sensors.

An initial goal of the algorithm is to synthesise data describing the moisture content of the terrain being traversed using on-board sensors. In this case we sample live propulsion current and wheel slip level, combined with prior terrain behaviour knowledge (from previously collected empirical data) to estimate the moisture level in the ground.

With the initial goal achieved, a secondary goal of the algorithm is to exploit the estimated moisture level to predict the likely resistance of future mission terrain in order to provide a mission energy prediction that is more accurate than previous efforts.

6.3 Algorithm Data

To circumvent the complexities of modelling wheel terrain interaction over varying terrains (which has been previously discussed in Chapter 3) the Intelligent Power Management (IPM) algorithm is reliant on having available two terrain reference data sets that are derived from empirical data (representing slip and power), mission plan information and terrain reference data, that are synthesised with sensor data during a live mission to achieve prediction.



6.3.1 Mission Plan Data

Mission data consists of information that is provided by mission planners. It details primarily the mission route and can be broken down from this to provide information regarding distance for mission route segments, Figure 6.1 shows how the mission route is divided into segments, each segment representing a portion of the mission route where the terrain is of the same type.

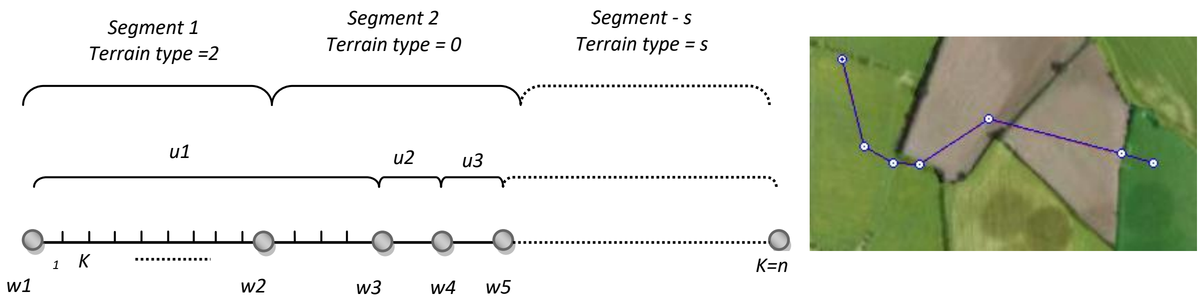


Figure 6.1: UGV mission data

It is important to note that many military missions are fluid in nature, and mission goals are likely to change during the live mission, but the pre-mission data forms a starting point for the prediction. The data sets required by the algorithm are:

$$\vec{u} = \{u_i \mid i = (1:n)\} \tag{13}$$

$$\vec{w} = \{w_j \mid j = (1:n)\} \tag{14}$$

$$\vec{D} = \{D_k \mid k = (1:n)\} \tag{15}$$

$$Tt = \{Tt_m \mid m = (1:n)\} \tag{16}$$

Vector *w* describes the planned velocities that the UGV should travel at between waypoints. In practice *w* would have been defined during the mission planning phase. Vector *u* represents the set of actual velocities achieved, which are based on the intended set of velocities described by *w*, but subject to real world effects such as terrain interaction and UGV performance. Vector *D* represents the set of distances between the waypoints (in metres) and finally the set Tt described the terrain types of the segments.

6.3.2 Terrain Reference Data

The terrain data sets represent terrain/UGV interaction behaviour for all expected terrain types to be encountered on a particular UGV mission. The data sets represents a UGVs behaviour in relation to its current draw (power) and wheel slip ratio over the range of possible UGV velocities and for 3 given moisture content conditions. The data sets *W* and *S* are power versus velocity and slip versus velocity over the three terrain conditions (*j*). Where *i* are sample values for Slip Ratio and Power for the three terrain conditions (and n the total number of samples), *k* represents terrain types (and *x* the total number) and *u* represents the reference velocities.

$$\overrightarrow{W_{ijk}} = \{W_{ijk} \mid i = (1:n); j = (d, m, s); k = 1:x\} \tag{17}$$

$$\overrightarrow{S_{ijk}} = \{S_{ijk} \mid i = (1:n); j = (d, m, s); k = 1:x\} \tag{18}$$

$$\vec{u} = \{u_i \mid i = (1:n)\} \tag{19}$$

Empirical reference data was collected as described in Chapter 5. An example data set for the test UGV on sand of varying moisture content is shown in Figure 6.2:

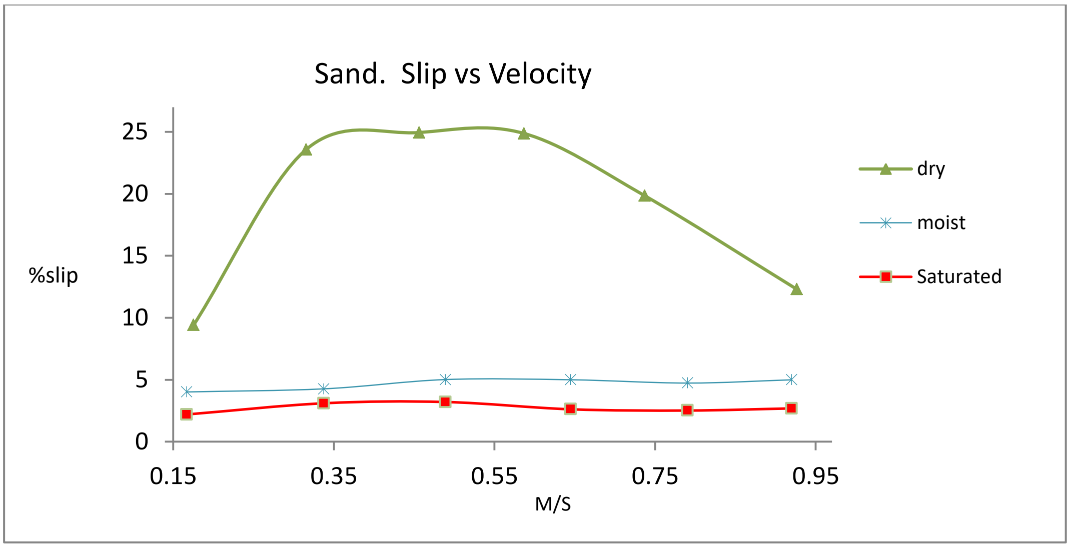


Figure 6.2: Example of empirical slip data for UGV on sand of varying moisture content

A goal of the algorithm is to find the dependent variable (*P or %slip*) for values not equal to the independent variables used as reference points for the data collection (i.e. discrete values of velocity or slip stored in the result set).

As discussed earlier it is clear that the problem of energy prediction is non-linear by nature. A number of possibilities exist for non-linear analysis to be used in the prediction. However, due to the fact that a particular function presented by the empirical data (and the fact that vehicle/terrain interaction is considered a complex relationship) may have any number of minima/maxima, Non-Linear Polynomial Regression has been chosen. This allows for off-line analysis of the empirical data to conclude the number of minima/maxima and select the best order polynomial and allow for any type of function to be represented (opposed to limiting to logarithmic or exponential).

$$y_i = a_0 + a_1 x_i + a_2 x_i^2 + \cdots + a_m x_i^m$$

$$(m - 1 = maximun\ num\ of\ maxima/minima) \quad (20)$$

$$\vec{\vec{a}} = (\boldsymbol{X}^T \boldsymbol{X}) y^{-1} \boldsymbol{X}^T \vec{y} \quad (21)$$

Using (20) with *Wd*, *Wm* and *Ws* and ordinary least squares estimation (21), it is possible to generate polynomial coefficients for prediction with 95% confidence levels (standard error) derived from (22).

$$C = \sqrt{\left(\sum_{1}^{n}(Iimp_i - Ip_i)/n\right) T\ inv} \tag{22}$$

6.3.3 Live Sensor Data

As well as mission prior data, the algorithm uses live sampled UGV sensor data for comparison with the reference data to calculate future energy prediction.

Power is calculated with sampling of the battery terminal voltage (BV) and current drawn by the left and right drive motors (LI, RI). To counter for instantaneous fluctuations of current due to rapid slip encountered due to periods of excessive acceleration, samples are to be stored, for required filtering by the algorithm.

Velocity is monitored by the sampling of angle encoder data from the left, right and rear wheel sensors (*LV, RV, REV*). Wheel slip is calculated by comparing the difference in velocity between driven and non-driven wheels.

6.4 Algorithm Design

6.4.1 Sensor Data Processing and Filtering

Although instantaneous power may be sampled directly, momentary wheel slip fluctuations are anticipated and will lead to short term errors in prediction. The need for some filtering of sensor data is apparent. The chosen method to allow for this was the inclusion of a low pass finite impulse response filter in the form of:

$$P_f\{k\} = \frac{1}{M}\sum_{j=-(M-1)/2}^{(M-1)/2} P\{k+j\} \tag{23}$$

Where $P_f\{k\}$ is filtered power sample, M is the number of samples to be included in the filtering, P is the live sample data.

Wheel slip is calculated by comparing the angular velocity of the redundant rear wheel encoder data with that of the drive wheels:

$$\%Slip = \left(\frac{(LeftDistTrav + rightDistTrav)/2}{mS\_elapsed} - \frac{rearDistTravelled}{mS\_elapsed}\right) \tag{24}$$

There is also a requirement to filter the slip results in order to eliminate similar short term anomalies from producing erroneous predictions. The filter used for power data filtering is reused here:

$$S_f\{k\} = \frac{1}{M} \sum_{j=-(M-1)/2}^{(M-1)/2} S\{k+J\} \tag{25}$$

Where $S_f\{k\}$ is filtered wheel-slip data, M is the number of samples to be included in the filtering, P is the live sample data. For the remainder of this chapter, references to live wheel slip and power data refer to the filtered sensor data.

6.4.2 Energy Prediction

The overall mission energy may be calculated by integrating the instantaneous power use over the mission duration:

$$E_m = \int_0^T P(t)dt \tag{26}$$

Where E_m is total energy required for the mission duration, *T* is the duration of the mission, *P(t)* is instantaneous power and *dt* is the interval between samples. Using discrete time intervals for use within the algorithm can be expressed as:

$$E_m = \sum_{i=1}^{N} f(v_i) \ \Delta t \tag{27}$$

Where Δt is sample interval duration, v_i velocity for sample *i*, N the total sample intervals steps and $f(v_i)$ the discrete function of $(v_0, P_0 \ldots v_N, P_N)$ from empirical data. For on-line power prediction and at any moment during a mission, the total energy prediction for propulsion can be expressed as:

$$\hat{E}_m(k) = E_c\,(k) + \hat{E}_{rs_i}(k) + \sum_{x=i+1}^{x=N} \hat{E}_{s_x}\,(k) \tag{28}$$

$\hat{E}_m(k)$ is total predicted energy required, this can be broken down into three distinct expressions, $E_c(k)$ is energy (actual) consumed at point *t.* $\hat{E}_{rs_i}(k)$ is predicted energy for the remainder of current segment, and $\hat{E}_{s_x}$ energy required for the remainder of whole segments. With reference to Figure 6.3 it can be seen that there are a number of conditions that may exist for any given point in a mission. A segment in this context is considered a portion of the mission route where with a continuous terrain type, so, when considering the current position, any future terrain segments (segment-s) may either be "terrain type is previously traversed" or "terrain type not previously traversed".

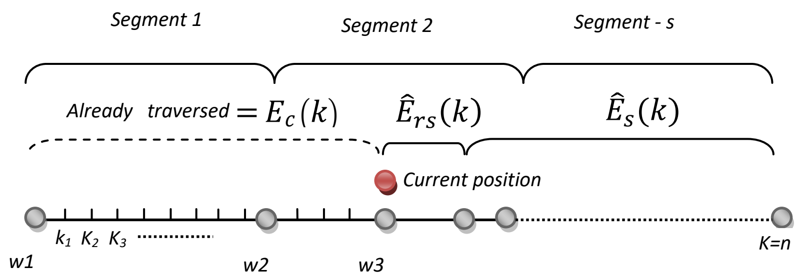


Figure 6.3: Energy prediction example

6.4.3 Prediction of Energy Requirement for Remaining Current Segment

To make a prediction for $\hat{E}_{rs_i}(k)$ (energy required for remainder of current segment) the empirical data for terrain behaviours are not required as actual live data from sensors are used. Instantaneous values at sample period Δt for left (*LI*) and right (*RI*) motor currents and battery terminal voltage (*BT*) allow for the instantaneous power to be calculated:

$$\overrightarrow{LI} = \{k_i \mid i = (m-n+1:m)\} m > n \tag{29}$$

$$\overrightarrow{RI} = \{ki \mid i = (m-n+1:m)\} m > n \tag{30}$$

$$\overrightarrow{BT} = \{ki \mid i = (m-n+1:m)\} m > n \tag{31}$$

6.4.4 Prediction of Energy Requirement for Future Segment

For $\hat{E}_{sx}(k)$ (future segments of non-traversed terrain types) filtered sensor data $P_f\{k\}$ from the current terrain is compared to the three (dry, moist and saturated) "terrain vs. current reference data" curves (from empirical data) for the current terrain type (see Chapter 5) to evaluate the relevant power for each terrain condition:

$$P_d = a_{d0} + a_{d1}u_d + a_{d2}u_d^2 + a_{d3}u_d^3 \tag{32}$$

$$P_m = a_{m0} + a_{m1}u_m + a_{m2}u_m^2 + a_{m3}u_m^3 \tag{33}$$

$$P_s = a_{s0} + a_{s1}u_s + a_{s2}u_s^2 + a_{s3}u_s^3 \tag{34}$$

$$(P_{i,1})\,(w) + (P_{i,2})\,(1-w) \tag{35}$$

$$where\ 0 \leq w \leq 1$$

Where the filtered sensor data ($P_f\{k\}$) lies between two of the polynomial curves in the terrain reference data (388) is used to determine the future segments moisture content.

$$P_{i,1} = a_{0,1} + a_{1,1}v_i + a_{2,1}v_i^2 + a_{3,1}v_i^3 \tag{36}$$

$$P_{i,2} = a_{0,2} + a_{1,2}v_i + a_{2,2}v_i^2 + a_{3,2}v_i^3 \tag{37}$$

$$(P_{i,1})\,(w) + (P_{i,2})\,(1-w) \tag{38}$$

$$where\ 0 \leq w \leq 1$$

This linear interpolation method yields a result that represents a likely value of a dependent variable (in this case instantaneous power use) based on the proximity of the independent variables (slip, current and velocity) to the available result sets for different moisture contents. Effectively, the utility of the empirical results collected in Chapter 5 is extended to consider a complete range of terrain moisture rather than three discrete levels.

In situations where $P_{i,1}$ and $P_{i,2}$ are indistinguishable due to intersection of the power consumption result curves, the slip curves are used as an alternative. This method provides the possibility for increased confidence by cross referencing the two empirical data sets.

6.4.5 Algorithm Definition

The following flowchart (Figure 6.4) shows a complete formal definition of the power prediction algorithm discussed in the previous sections. Annotations show where the model refers to empirical data or previously explained formulae.

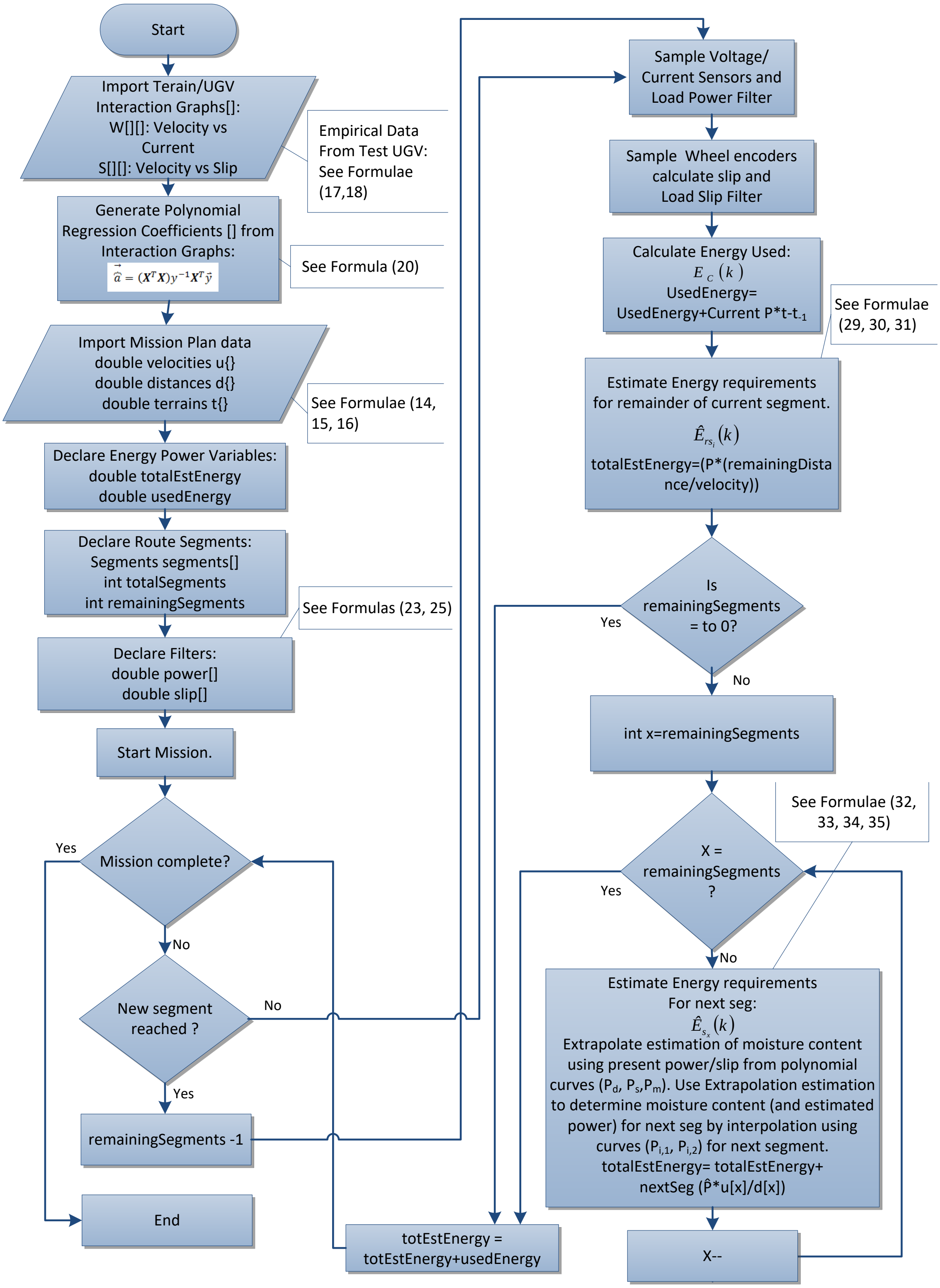


Figure 6.4: Algorithm Flowchart.

6.5 Experiment Set 1 – On-Road 'Baseline' Prediction Methods

In order to establish a baseline for comparison of prediction methods, an experiment that reproduces current research approaches to mission energy prediction is presented.

The experiment presented here compares the two prediction methods proposed by Sadpour [32]. Sadpour's work considers UGVs that traverse routes that comprise of prepared surfaces, this allows for the problem to be considered linear in nature (opposed to routes that include off-road terrain).

In Sadpour's work the first approach generates a prediction based on live sensor data using a linear regression technique with no consideration of prior terrain type knowledge. The second approach also uses live sensor data and a linear regression technique, but also considers prior terrain knowledge (the type of terrain along the mission route and its cost in terms of power consumption per unit distance) with a Bayesian estimation method. Both methods use sensor data to calculate the present rolling resistance coefficient to be used in the prediction.

The experiment uses the linear regression algorithm described in section 6.4, but for comparison, in the first approach no prior knowledge of terrain types is known, opposed to the second approach that has pre-mission knowledge relating to terrain types.

The experiment considers traversal of two types of road surface. These terrains are not considered "off road" and are not affected by weather in terms of energy cost for traversal. [32]

6.5.1 Experiment Design

The experiment is based upon the developed Resource Management Simulation Platform, fully described in Chapter 4.

The terrain data sets for the prepared road surfaces are shown in Table 15 and were used as a terrain reference to describe the energy consumption of the UGV over a range of velocities. This data was acquired from empirical data collected using methods described in Chapter 5. The effects of weather conditions on energy use are assumed to be negligible due to the use of prepared road surfaces.

VEL (M/S)	TERRAIN 0 (P) VERY ROUGH	TERRAIN 1 (P) ROUGHLY PAVED
0.16	3.83819	4.44260
0.33	5.03459	6.18037
0.5	6.77362	7.53522
0.66	8.23905	8.88017
0.83	9.76585	10.3615
1	11.8529	12.24235

Table 15: Empirical data describing UGV energy use at given set of velocities on road surfaces

The experiment uses the mission plan shown in Figure 6.5, that describes a journey conducted over two 722m length segments of terrain with type 'Very Rough' and 'Roughly Paved'.

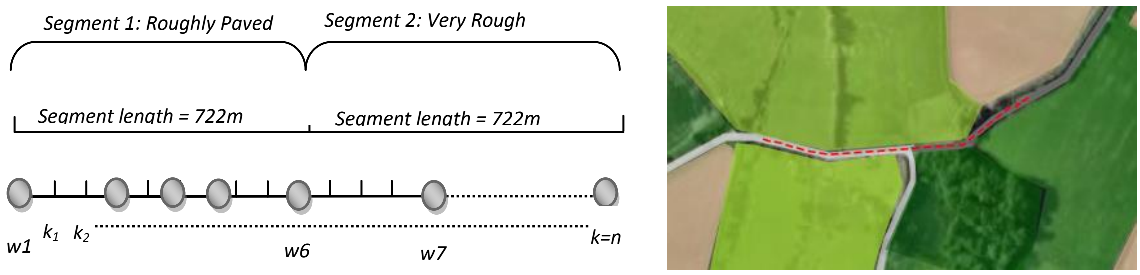


Figure 6.5: Mission plan for experiment 1 based on road surfaces

The first prediction experiment relies simply on the live sensor data regarding current consumed to make a prediction of the energy required for the duration of the mission. It does not take into account terrain reference data (prior knowledge) on any future route segments to enhance the prediction.

$$\hat{E}_m(k) = E_c\ (k) + \hat{E}_{rs_i}(k) \tag{39}$$

The algorithm detailed in section 6.4 is used but with the total energy predicted as shown (equation38), where $\hat{E}_m(k)$ is total predicted energy required, $E_c(k)$ is energy (actual) consumed and $\hat{E}_{rs_i}(k)$ is predicted energy for remainder of the mission.

A second prediction approach uses live sensor data regarding energy use, combined with (prior) terrain reference and mission plan data in the form of terrain type segments and pre-mission rolling resistance values, to generate predictions for the same mission. The algorithm described in section 6.4 is used but with total energy predicted using (28) where the algorithm generates a prediction based not only on current energy use information, but also likely energy use with consideration for yet to be traversed terrain types.

6.5.2 Results and Observations

Figure 6.6 shows the actual velocity of the UGV throughout the mission duration.

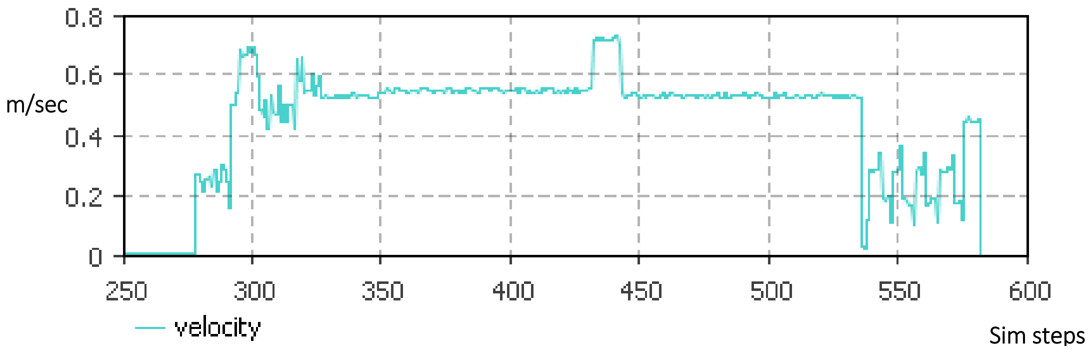


Figure 6.6: Experiment 1 - Mission velocity profile results

Figure 6.7 presents a comparison of the two algorithms under test. The two chart series represent each algorithm's prediction of complete mission energy requirement at each step of the simulation (i.e. the prediction is continually reassessed). The graph shows that prediction without prior knowledge over-estimates the mission energy requirement by approximately 10% between 300 and 480 seconds (until waypoint 4 is reached). In contrast, the prior knowledge algorithm predicts with a higher level of overall accuracy.

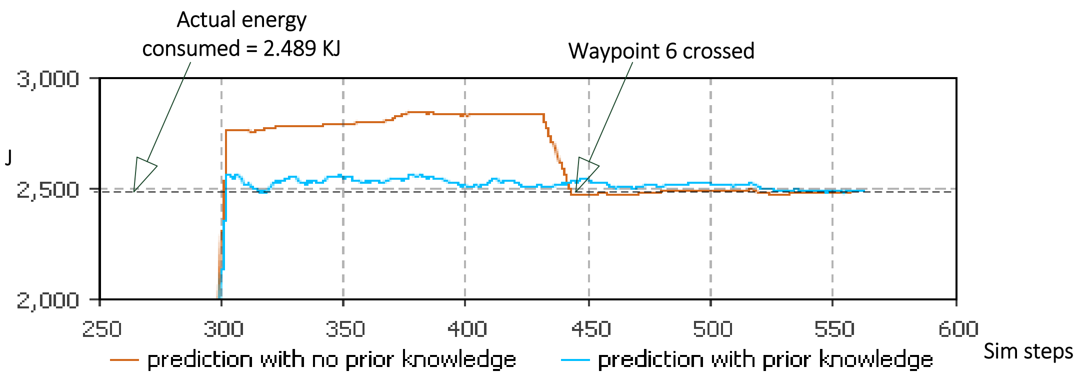


Figure 6.7: Experiment 1. Energy prediction comparison of prior knowledge vs. no prior knowledge algorithms

The results in Figure 6.7 show the prediction with prior knowledge of terrain types does improve overall prediction under the described conditions. It can be seen that the "prediction with no prior knowledge" over-estimates total energy required prior to *"w6"* being crossed as it assumes that the current rolling resistance will be the same for the remainder of the mission. In contrast, the "prediction with prior knowledge" approach knows that an upcoming terrain change in the mission plan will result in less energy consumption in that segment.

6.6 Experiment Set 2 – Off-Road Prediction with Linear Regression Algorithm

The focus of this thesis is energy prediction in off-road unmanned vehicles. Therefore, a second set of experiments that considers the application of energy prediction algorithms for off-road missions is presented. The empirical result collection conducted in Chapter 5 indicates the significant effect of weather conditions on off-road terrain and accordingly the simulated missions presented here are subject to varying weather conditions. However, the varying weather conditions are not used to enhance energy prediction.

6.6.1 Experiment Design

Terrain reference data for a range of off-road terrains is presented in Tables Table 16, Table 17 and Table 18 (reproduced from empirical terrain data collection experiments in Chapter 5). Each terrain type is described by the energy consumption required for traversal at a set of velocities for three given moisture contents (dry, moist, saturated).

Vel (m/s)	Terrain 0 Sand					
	P			Slip Ratio (%)		
	dry	moist	saturated	dry	moist	saturated
0.16	6.45276	4.24689	4.93303	10.04264	4.01641	2.2435
0.33	8.32035	6.02469	6.23286	23.57438	4.26749	3.10461
0.5	10.03216	7.65238	7.80368	24.94497	5.01676	3.20481
0.66	10.94731	9.11656	9.44545	24.86856	4.99929	2.61651
0.83	12.56868	10.36774	10.28488	19.84937	4.6333	2.51774
1	13.66227	12.7091	13.01879	12.24118	4.89505	2.68995

Table 16: Mean values for empirical data for sand

Vel (m/s)	Terrain 1 Top Soil					
	P			Slip Ratio (%)		
	dry	moist	saturated	dry	moist	saturated
0.34	6.452652	8.163752	9.49472	12.57747	17.45619	21.03528
0.46	9.981672	10.54532	11.55123	14.98947	17.04102	16.77833
0.58	12.49824	12.63966	13.64535	14.8124	19.69437	19.88019
0.69	13.45291	14.56233	16.45868	14.41729	19.4774	20.14693
0.82	14.75672	16.93408	17.85816	15.72096	20.12156	20.64302

Table 17: Mean values for empirical data for top soil

Vel (m/s)	Terrain 2 Short Grass					
	P			Slip Ratio (%)		
	dry	moist	saturated	dry	moist	saturated
0.16	4.53135	5.53938	7.29854	3.67943	4.43717	5.56714
0.33	6.52197	6.99718	8.14436	3.78652	4.76389	6.27916
0.5	8.58376	8.9723	10.04574	4.84853	6.01897	7.092
0.66	10.22574	11.49059	12.04312	5.3816	6.75405	7.82147
0.83	12.03069	12.2783	14.12125	6.44262	6.97855	8.78619
1	14.76247	14.92047	15.34183	6.44831	7.521	8.60489

Table 18: Mean values for empirical data for grass

The mission plan data describes a mission consisting of three segments of off-road terrain. These are short grass, loose dirt and short grass of distances 95m, 117m and 20m respectively, see Figure 6.8. In addition, the simulation is configured to increase the moisture content of terrains by 10% during the mission.

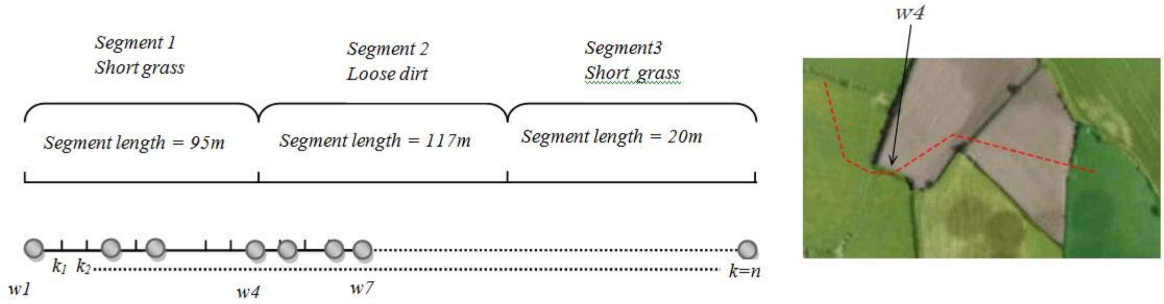


Figure 6.8: Mission plan for experiment 2 based on off-road surfaces

The two previously presented algorithms (prior knowledge vs. no prior knowledge in Experiment Set 1, section 6.5) are re-simulated and compared over the newly defined off-road terrains and mission plan.

6.6.2 Results and Observations

Figure 6.9 shows the actual velocities achieved throughout the mission duration. Compared to the 'on-road' results presented in Figure 6.6 the velocity profile for this mission exhibits considerably more jitter.

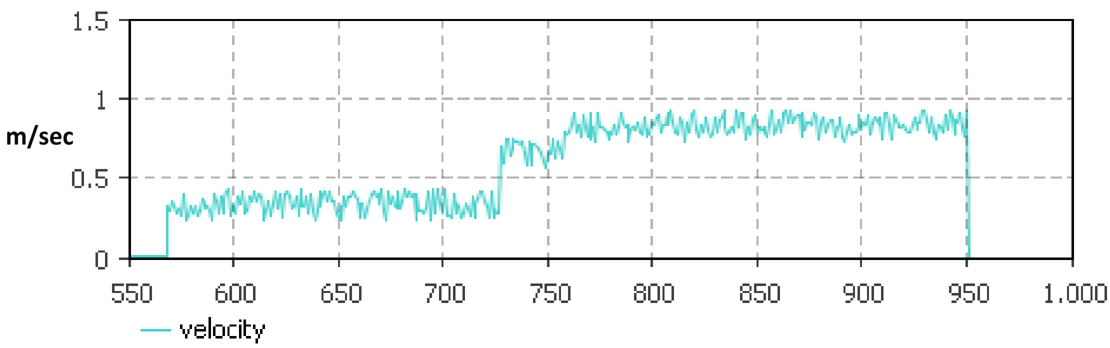


Figure 6.9: Experiment 2 - Mission velocity profile results

Figure 6.10 shows a comparison of the algorithm's performance in predicting total mission energy requirements, throughout the mission. The "prediction with no prior knowledge" algorithm underestimates in its prediction by approximately 20% until waypoint 6 is crossed. It then over predicts the energy requirement between waypoints 7 and 8 by approximately 4%.

The 'prediction with prior knowledge' algorithm also underestimates energy required until waypoint 6 is crossed, but by a smaller amount (~10%). It then adjusts to generate prediction within ~1% accuracy.

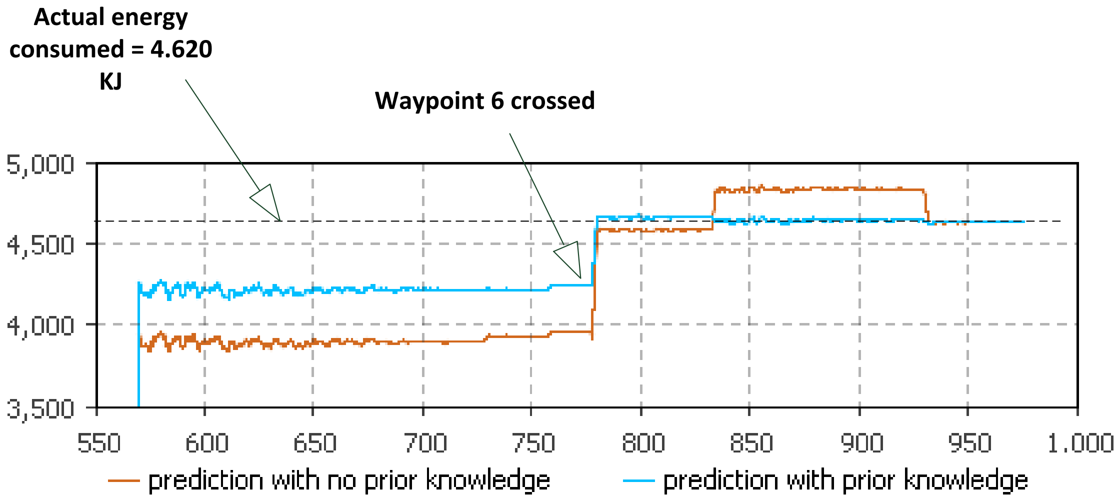


Figure 6.10: Experiment 2. Off-road energy prediction comparison of prior knowledge vs. no prior knowledge algorithms

Once again, prediction with prior knowledge improves the overall prediction accuracy compared to prediction with no prior knowledge. Although the prediction with prior knowledge takes into account the increased resistance for "Segment 1" it fails to compensate for the prevailing climatic conditions. This is a significant shortcoming in the consideration of off-road terrains. The empirical results gathered in Chapter 5 provide a real world reference to the magnitude of such errors.

6.7 Experiment Set 3 – Off-Road Prediction with Polynomial Non-linear Regression Algorithm

The third set of experiments compare the existing mission energy prediction approaches to the novel Polynomial Non-linear Regression algorithm, presented as a focus of this thesis and fully described in section 6.4.

6.7.1 Experiment Design

Experiment set 3 uses the same terrain reference data (Table 16) and mission plan (Figure 6.8) as Experiment set 2.

The previously employed linear regression prediction with prior knowledge algorithm is reused, but in this experiment is compared with the novel Polynomial Non-linear Regression algorithm, fully described in section 6.4. The Energy prediction is reproduced below for reference (40).

$$\hat{E}_m(k) = E_c\,(k) + \hat{E}_{rs_i}(k) + \sum_{x=i+1}^{x=N} \hat{E}_{s_x}\,(k) \tag{40}$$

Where $\hat{E}_m(k)$ is total predicted energy required. This can be broken down into three distinct expressions, $E_c(k)$ is energy (actual) consumed at point *t*. $\hat{E}_{rs_i}(k)$ is predicted energy for remainder of current segment, and $\hat{E}_{s_x}$ energy required for the remainder of whole segments.

6.7.2 Results and Observations

The results in Figure 6.11 show a comparison of the algorithm's performance in predicting total mission energy requirements throughout the mission. The "prediction with prior knowledge" algorithm underestimates in its prediction by approximately 9% until waypoint 4 is crossed. The Polynomial Non-linear Regression algorithm provides a more accurate prediction throughout the mission.

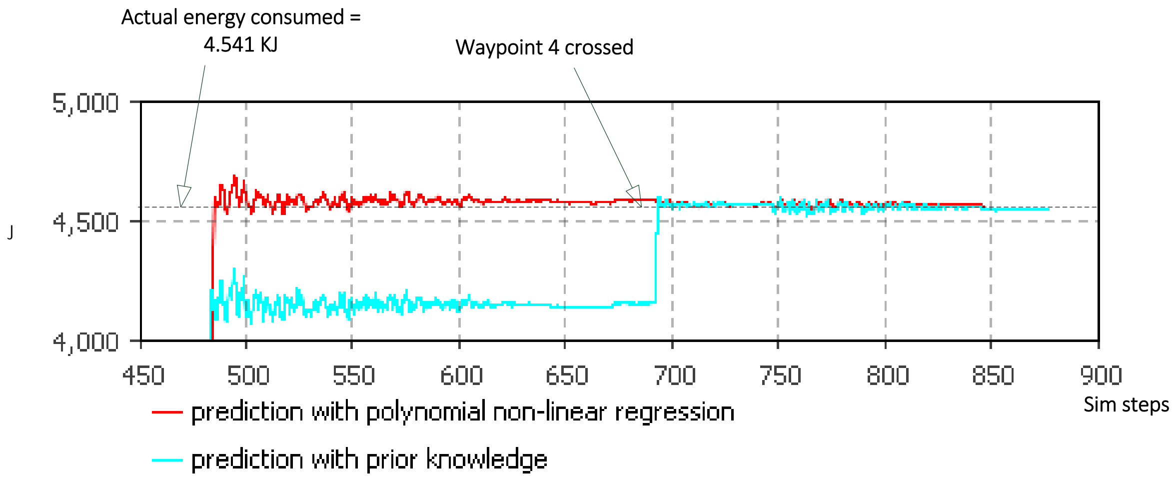


Figure 6.11: Experiment 3 Off-road energy prediction comparison of prior knowledge vs. non-linear regression algorithms

Once again, the 'prior knowledge algorithm' underestimates the required mission energy for a considerable period of the mission as it does not compensate for prevailing terrain moisture content levels. This is an obvious disadvantage considering the typical deployment of UGV type vehicles on a wide variety of terrain types. Using the same simulation parameters the implementation of polynomial non-linear regression as described above along with the method of predicting future terrain rolling resistances results in an improved overall prediction as shown.

6.8 Discussion

The experiments presented here provide a comparison of current mission energy prediction approaches with the novel 'polynomial non-linear regression' algorithm for simulated off-road missions with varying climatic conditions.

The overall aim of the new algorithm is to exploit knowledge about the current terrain moisture content to predict the likely resistance of future mission terrain in order to provide a mission energy prediction that is more accurate than previous efforts.

In common to previous work by Sadpour [32] in the area of energy prediction, the algorithm uses mission prior knowledge in the form of storage vectors that map terrain behaviour which describe energy consumption for given terrain types. Mission parameter data is also common with the two approaches such that velocity profiles for a given mission are defined along with terrain type information. The previous work defines the terrain as road surfaces that are segmented as to their consistent surface condition and focuses on surfaces that result in a linear response regarding a UGVs rolling resistance.

Sadpour's work fails to take into consideration the impact that environmental conditions can have on energy usage, this is mainly ignored due to the fact that the work focuses on forgiving terrains such as prepared road surfaces which are affected little by moisture content. However the work of Odedra [22] suggests that typical UGV missions will include traversal of a wide variety of terrains many of which are effected by climatic conditions. The empirical results collected in Chapter 5 clearly show that climatic conditions are likely have a large effect on the energy consumption of UGVs deployed 'off-road'.

The algorithm presented here improves on the existing work as it addresses the impact of prevailing environmental conditions on the off-road terrain that comprise the mission route. The algorithm exploits current live sensor data to not only reassess the rolling resistance of current terrain but that of yet to be traversed terrains, while not requiring excessively large amounts of stored pre-mission data or redundant hardware in the form of sensors.

Sadpour highlights the fact that pre-mission data relating to rolling resistance coefficients may not be entirely accurate, and therefore leads to inaccuracies of mission energy prediction. He also highlights the fact that a mission consists of varying terrains with varying rolling resistance coefficients.

This work addresses the issue of inaccurate pre-mission data by using live sensor data to calculate rolling resistance coefficients to recalculate mission energy requirements during a live mission. However, the overall mission prediction is only improved by re-assessing the rolling resistance coefficient for the terrain that is currently being traversed, any terrain type that has yet to be traversed, is assumed to have the same rolling resistance coefficient as prior to the mission starting.

Where previous work focuses on idealised terrains (prepared surfaces) the method presented here encompasses off-road terrains. It is important to note that, not only are off-road terrains more affected by prevailing weather conditions and, hence weather influences cannot be ignored but, energy consumption cannot be considered a linear function as is possible with prepared surfaces.

In order to address the non-linear nature of the problem with regards to the relationship between slip and current over a range of velocities for off road UGVs, the algorithm utilises a Non-Linear Polynomial Regression method to describe terrain behaviour. This allows for off-line analysis of the empirical data to conclude the number of minima/maxima and select the best order polynomial and allow for any type of function to be represented (opposed to limiting to logarithmic or exponential).

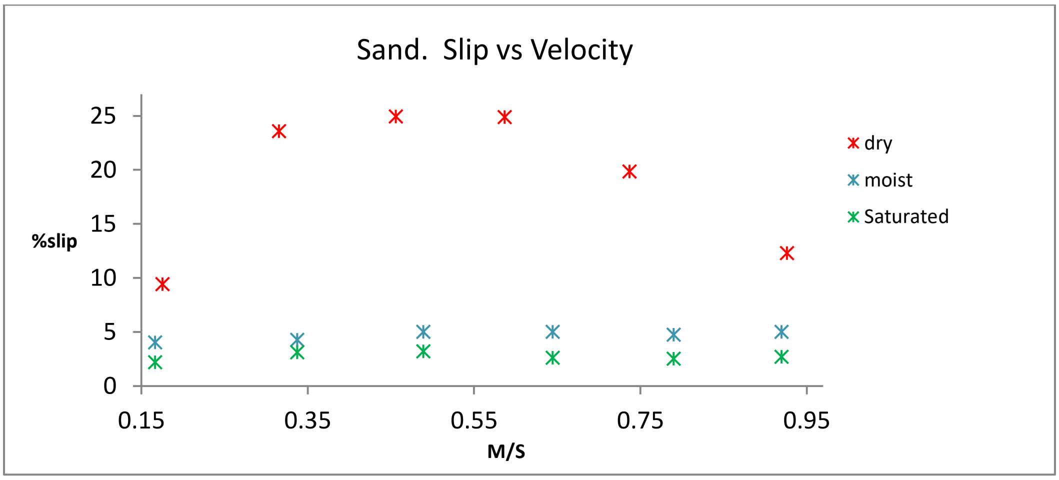


Figure 6.12: Dependent variables of polynomial curves for one terrain type

If consideration is given to one terrain type (Figure 6.12) it can be seen that pre-mission data for the polynomial regression only requires minimal data as only the dependent variables are required to be stored (6 per moisture content condition in the case described in this work), along with the polynomial coefficients. By limiting the order of the polynomial the sensitivity to minor changes is reduced. To allow for a point of inflection that is present on some of the data curves, a polynomial of order of three was chosen, which still considers the sensitivity issue. There is only a requirement for one vector to store the independent variables (velocity reference points) for all polynomial curves for all terrain types as the data was previously sampled at the same reference velocity points.

Figure 6.13 depicts an example where a terrain type is presently being traversed (sand in this example), it can be seen that the using minimal stored data it is possible to build a "relationship between curves". It is possible to represent the present sensor data along with the pre-mission polynomial coefficients (depicting %slip in this example), which will allow for plotting of the present prevailing condition between two of the polynomial curves (in this example dry and moist).

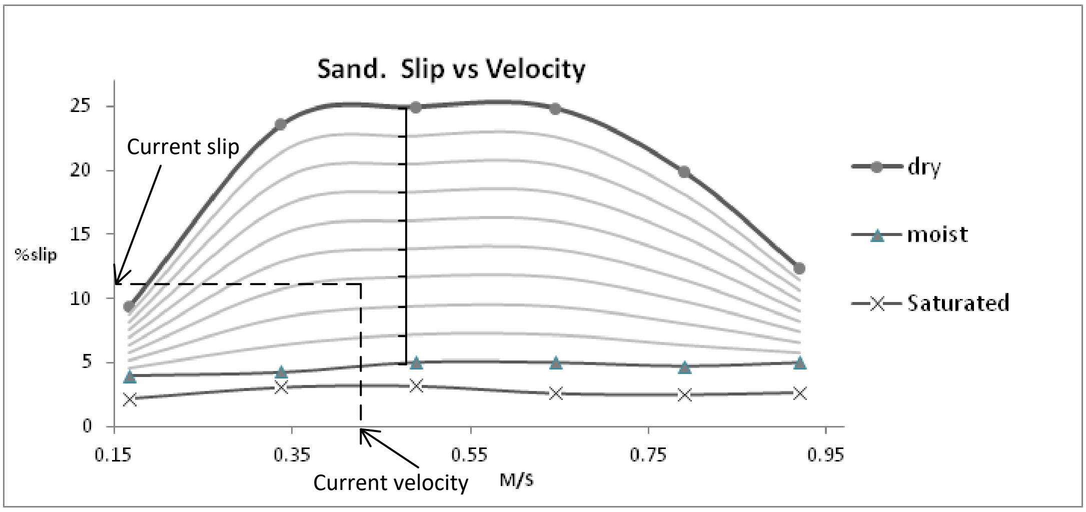


Figure 6.13: Example of operating point when between two polynomial curves

With the measured present velocity and slip ratio it is possible to ascertain the present operating point of the UGV and between what two polynomial curves the current operating point lies. Using the polynomial coefficients from the terrain reference data, it is then possible to ascertain the terrain condition between two of the polynomial curves.

The algorithm can then use the terrain condition reference data of future terrains to be traversed to predict energy consumption. Figure 6.14 depicts the method used by the algorithm. Again, by using the polynomial coefficients and dependent variables of a particular future terrain combined with using the weighting value, the terrain condition for the terrain can be found. This method is then applied to all future terrain segments.

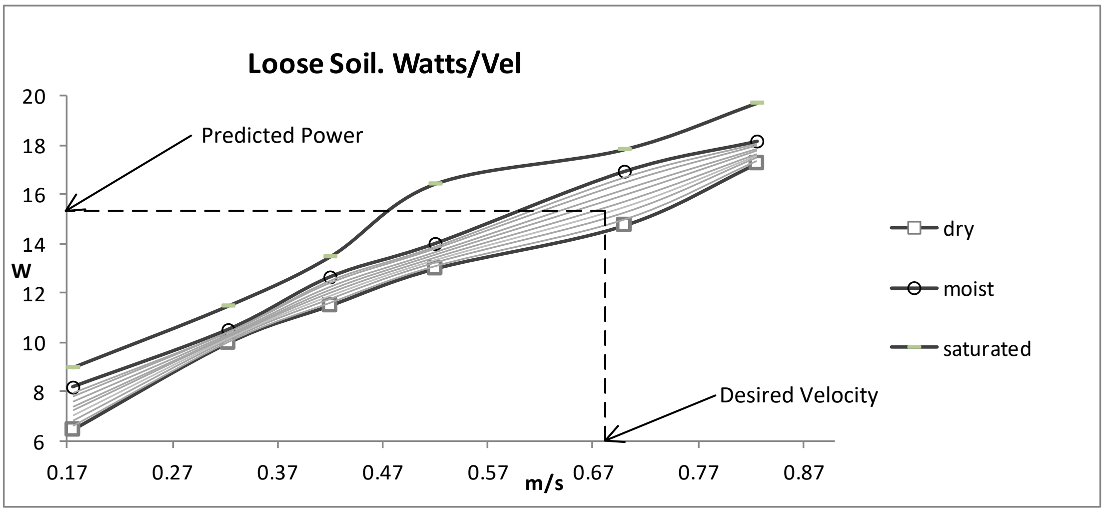


Figure 6.14: Method for future terrain power prediction

The terrain behaviour graphs (shown in Figures Figure 6.13 and Figure 6.14) show curves that are distinguishable from each other as in there is no overlap. Ojeda [53] highlights the problem of sensing terrain types from sensor data when a particular behaviour is undistinguishable from one source of sensor data (in his example, current versus “rate of turn”). This is also the case for moisture detection of terrains. The algorithm addresses this problem with the inclusion of more than one source of independent data. Power versus Velocity is the obvious choice and is used in the first instance. This is complemented with terrain behaviour graphs that represent Slip versus Velocity. Prior to a prediction being made, a comparison is made to ascertain which set of curves offers the best distinguishable dependent variables.

6.9 Conclusion

The algorithm addresses significant shortcomings in current approaches to energy prediction for off-road UGVs. Current methods focus on missions comprising terrains that are considered favourable such as tarmac or concrete. While this serves as a starting point for investigation for UGV energy prediction, it is considered unrealistic due to the expectations of current UGV missions.

A significant issue with current prediction methods is that energy consumption for propulsion is considered to be linearly related to velocity, which is not the case when traversal over off-road is considered. The algorithm addresses this with the use of Non-Linear Polynomial Regression. This method appeared well suited to representing current/velocity curves that were produced from empirical sampled data, and sufficient curves could be produced with minimal dependent variables while using a third order polynomial. Should more complex curves be required, the order of polynomials and the number of dependent variables may be increased.

If consideration is given to the varying rolling resistance coefficients of terrains and the differing impact of climatic conditions on these coefficients, then an improvement can be made on existing methods by using present live sensor data to predict future terrains. Chapter 5 highlights the dramatic difference in energy consumption that terrain moisture content can have. Current methods, only adjust predictions for the present terrain. The IPM algorithm improves on these methods by using current sensor data to predict future terrain rolling resistance, providing pre-mission information regarding terrain interaction is available.

In order to improve the probability of making a reliable prediction the algorithm does not rely on one single source of data. Previous work by Ojeda [53] has shown that it is not always possible to rely on one data source to differentiate between terrain types. The Algorithm addresses this by employing live sensor data from two independent data sources where an informed choice can be made as to what data source provides the greatest discretion regarding terrain conditions.

Where other methods exist that may be used for prediction such as modelling the wheel terrain interaction, it is important to note that these methods may be prohibitive for application during live missions due to required processing resources and time constraints. The algorithm presented addresses the previously discussed issues of energy prediction on off-road terrains while taking into consideration the economics of power consumption as only minimal additional data storage and processing power is required.

If a prediction system requires the addition of sensor hardware, processing power or large data storage, then, requirements for overall consumption of a UGV will negatively be effected. Also the physical size (and, hence weight) is increased, both these factors defeat the overall aim of increased effective capability, so a trade-off exists between accurate prediction and effective utilisation of stored energy.

The algorithm presented above is described in isolation of any computational environment and would require incorporation into a host system such as a simulation or physical UGV.

7 Conclusions and Future Work

The main objective of this thesis is to improve the management of UGVs limited energy resources through improved overall mission energy requirement prediction. It presents a novel system approach to the solution of the energy prediction problem, consisting of a physical test-bed UGV system, an algorithm development and simulation platform, and novel energy prediction algorithms that improve upon the current state of the art.

The following conclusions discuss the significant and novel contributions to research delivered through 1) a new energy prediction algorithm that improves upon current state of the art approaches (section 7.1), 2) a novel UGV energy prediction algorithm simulation and development environment (section 7.2), and 3) a novel UGV with accompanying methods and tools for the collection, synthesis and validation of terrain / vehicle drive-train interaction reference data sets (section 7.3).

7.1 Energy Prediction Algorithm

The thesis presents a significant contribution to research in the form of a novel mission energy prediction algorithm that improves upon the existing state of the art algorithms by 9% in overall accuracy terms over the series of presented off-road mission experiments.

The approach used by the prediction algorithm is novel in the assumption of terrain types for the mission route as prior information in contrast to existing approaches that typically attempt to identify terrain dynamically. Technological advances in GIS mapping, and big data availability of map data make this a viable position for current and future platforms.

The improved algorithm characterises the terrain being traversed with consideration of prior knowledge of the terrain type to make a determination about ground moisture content and subsequent energy requirement for traversal.

Using knowledge of current terrain type, the algorithm is able to exploit typical on-board UGV sensor data to make accurate predictions about the prevailing moisture content of the terrain. This in turn allows improved prediction of the energy required to travel over the current and future terrains. As the algorithm can be executed during a live mission, the energy prediction for the mission can be updated dynamically to address changes in prevailing weather conditions.

The algorithm also addresses the non-linear nature of the problem whilst keeping data storage and computation requirements to a minimum by employing a non-linear polynomial regression approach. Physical experimentation revealed that the relationships between wheel slip, instantaneous current draw and velocity are non-linear in nature for off-road terrains, as opposed to existing research on paved or grass type terrain. The presented solution introduces the concept of multiple sets of polynomial reference maps that relate the current UGV velocity to the wheel slip or motor current data for a range of different terrains and a range of moisture contents.

The maps are described by vectors that relate sample velocities to related levels of slip or power consumption for a given terrain with a given moisture content. The result is a novel method of relating sensor data to moisture content given a known terrain type and current velocity.

As well as pragmatic data storage and computation resource considerations, the utility of the approach is also increased significantly by restricting the variables used by algorithm to those representing typically available UGV sensors which ensures that the solution is exploitable by current UGV platforms with minimal hardware investment.

7.2 Algorithm Development and Simulation Environment.

The Resource Management Systems Simulation (RMSS) presented in chapter 4 represents a significant contribution to research through a novel approach and implementing and tool set for the design, implementation, performance analysis and comparative evaluation of the proposed algorithms. The RMSS approach provides software and methods that allow a user to rapidly develop and test algorithms over simulated UGV missions, and to collect performance results. The new approach provided significant improvement in terms of the complexity and time taken to develop and test new energy prediction algorithms compared to available existing approaches.

A particularly novel aspect of the system is that it operates in cooperation with the Experimental Platform described in section 7.3 in order to furnish the system with empirical data from a real-world UGV, allowing the simulation behaviour to be validated against a real world UGV.

The use of the simulated environment allows for a fast and iterative design approach to algorithm development and testing to be employed. The efficiency of the development cycle is improved significantly through the creation of domain specific tool features such as UGV, environment and terrain interaction models as well as automatic simulated mission execution.

The simulation tool also allows experimentation with a range of variable weather conditions, terrains, power system configurations and mission plans. This enables a wide range of experiments to be conducted with minimal time and cost.

The simulation tools are validated by direct comparison between simulated and physical experiment results collected from the UGV experimental platform. The validation process revealed close fidelity between the simulated system and the physical reality of a UGV traversing its environment.

7.3 Experimental Platform

The creation of an experimental UGV platform including a data collection facility that provides stimulus for a simulation platform and automatically synthesises datasets describing terrain behaviour in terms of common sensor inputs, which is a novel approach to both algorithm development and testing. The significant research contribution is a UGV / simulation cooperation approach that closely and efficiently couples the simulation environments to real world result collection achieving intrinsic simulation behaviour validation.

The collected results have two primary functions. As a core function the system is used to create terrain / energy consumption reference data sets of known terrains with given moisture contents (assuming trafficability). These data sets used by the prediction algorithms provide a definitive reference describing the behaviour of a real UGV in a variety of conditions.

Another important use of the platform is to validate the results of the simulation outputs by comparing the simulated outputs with physical reality. The results output by the simulation over a mission are compared to the results collected by the UGV on a real world mission. The output of the simulation is therefore validated by direct comparison, proving confidence of the validity of the simulated work.

The test UGV system operates with minimal human intervention and as such can be rapidly deployed in order to create new reference data sets making the system inherently extendible and to able consider new terrains or conditions as required.

7.4 Thesis Achievements and Implications

This thesis describes three significant contributions to research in the area of mission energy prediction for off-road unmanned ground vehicles. A new energy prediction algorithm that improves upon current state of the art approaches (section 7.1), a novel UGV energy prediction algorithm simulation and development environment (section 7.2), and finally a novel UGV with accompanying methods and tools for the collection, synthesis and validation of terrain/vehicle drive-train interaction reference data sets (section 7.3).

The improved mission energy prediction algorithm represents an opportunity for increased effective capability delivery for UGV operators. More accurate forecasting of mission energy requirements allows a more efficient allocation of available energy to the goals of the mission. Emergent opportunities arising during missions can be accepted or rejected at lower risk as accurate energy forecasting can be quickly performed. Similarly, the impact of any unexpected adversity encountered during a mission can be quickly evaluated in terms of energy cost, allowing mission controllers to quickly develop and assess mitigation plans.

The improvement in prediction directly increases UGV performance by avoiding a need for excessive energy depletion safety margins, typically manifested through the carrying of unnecessary extra batteries or by premature mission termination as resources are conservatively estimated. This in turn has positive implications for the achievement of mission goals as more payload or increased duration is achieved.

The creation of an energy prediction algorithm development methodology and implementing toolset, consisting of a physical UGV test platform and cooperating simulation environment, provides an effective basis for future development and improvement of energy prediction approaches.

7.5 Future Work

Although the primary focus of the work presented in this thesis is power prediction and power prediction algorithms, additional further work important to improving the overall power prediction problem has been identified. These related areas such as terrain classification, UGV data collection and power resource simulation are also recommended for future research work.

7.5.1 Algorithm Development

The work presented here relied upon terrain condition categorisation based upon limited sensor data, using typical on-board UGV sensors. Although this proved effective on the terrain types selected for the experiments carried out, this may not be the case for differing terrains that were not sampled. Also, weather conditions were limited to moisture content alone.

It has been noted that further sensor data may be required to differentiate varying weather conditions on certain terrain types, however, it’s important to note that additional sensors represent extra cost and complexity, and ironically place extra burden on limited power resources. As such, typical existing UGV sensors should be employed as far as possible.

Analysis of the results revealed differing signal noise characteristics across differing terrains and weather conditions. This differing variance may provide a further reference set of empirical data that could be used for differentiation of weather conditions while excluding the requirement for extra hardware or sensors to be added. Further to this, the distribution of the data may also provide further indication as it was shown that not all data sets produced the same distribution.

The sensing of weather conditions on prepared surfaces such as asphalt has not been researched in this work. As vehicle tyres and prepared surfaces are designed for minimising slip and rolling resistance the methods described in this work are not suitable for sensing weather conditions on prepared surfaces. This is due to minimal slip being present regardless of moisture content, However there is a minimal increase of current when there is a layer of water present on the surface, presenting a resistance. Additional algorithm facilities that allow sensing upon prepared surfaces would be required in order to offer a complete on and off-road solution.

It was noted during data collection that lateral slip and subsequently the angle of incidence was increased during turns on both prepared and grass surfaces for moist conditions. Further research into this effect and methods of the monitoring and measuring would offer a further reference variable for terrain condition detection.

Experiments conducted for this work considered terrain deformation to be purely horizontal in nature, as slip alone was monitored. When consideration is given to terrains that are prone to shearing (both granular and cohesive soil types) a vertical terrain deformation can be experienced, the extent of the deformation was shown to be largely dependent on the moisture content. If successfully monitored this additional effect would allow for further methods of moisture content prediction. Research into detection methods that could perform this function would further improve power prediction algorithms by providing further methods of detection over a wider range of terrain types.

The experiments carried out in this work considered the terrain surface to reasonably flat, to further the utility of the power prediction algorithms the work should be extended to consider inclines of the predicted UGV routes.

7.5.2 Improved Terrain Classification

Existing research relating to UGV off road terrain traversal appears to have no standard method of classification for the many different terrain types. Researchers tend to employ their own personal methods of classification which are typically inconsistent and incomplete. The methods used tend to have very broad terrain types such as "grass", "gravel", "sand" etc. It is important to note that when considering power prediction and trafficability, the properties of terrain that influence these are similar.

The work presented here highlighted properties of terrains that influence UGVs mobility and hence power consumption which are not usually considered, but would be largely beneficial to be included in a standard classification system for UGV power prediction.

Where Odedra's [26] work goes some way to describe surface properties, it does not consider environmental influences on terrain surfaces. An example being that some terrains cause slippage only when dry. Opposed to describing properties by the effects they cause, it would be beneficial to describe the terrain by properties such as shear strength, cohesiveness, granularity and its ability to drain moisture. These properties are well documented in other areas of engineering and should be applied to a classification method for UGV power prediction and trafficability. Further to this, terrains described for traversal are considered to be single layered, however, this is not the case in reality. An example being grass, under saturated conditions it is possible for the grass to sheer, leaving a surface with differing properties. This further complicates categorisation and should also be considered.

7.5.3 Data Collection

Empirical data collection was limited to a single UGV of a certain mass, which is considered to be of a small UGV. Further tests should be employed of larger UGVs to ascertain relationships of power consumption between UGVs of varying mass that could further assist with power prediction. In addition, further empirical data collection for UGVs with varying locomotion methods would further increase utility of the achievements of this thesis.

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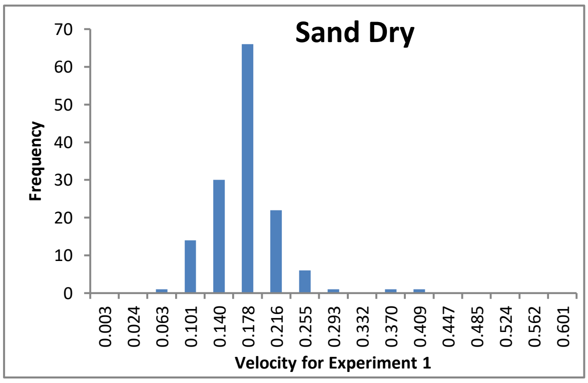
Appendix A. Empirical Data collection Results.

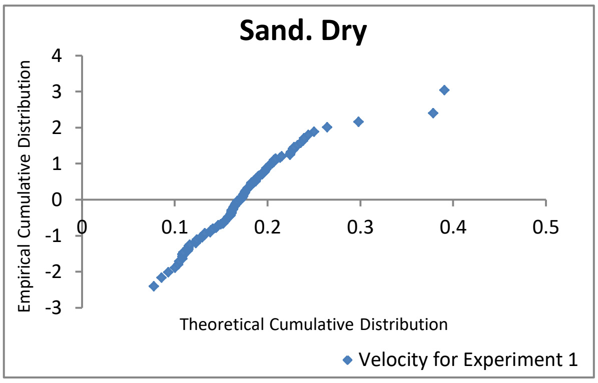
This appendix contains the results of the experiments for Sand, Dirt and Grass under Dry, Wet and Saturated conditions. The column on the left show the histograms and the column on the right shows the P-P Plots for each experiment.

Contents

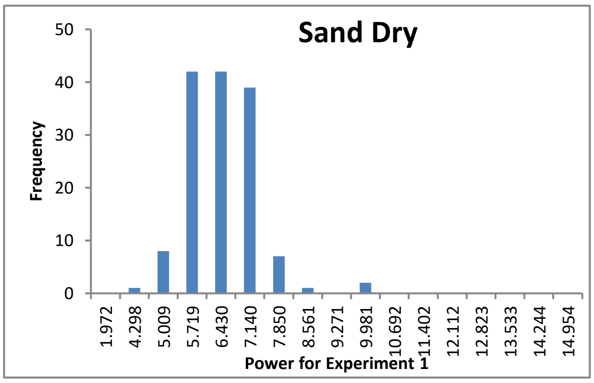
A.1. Experiments for Sand

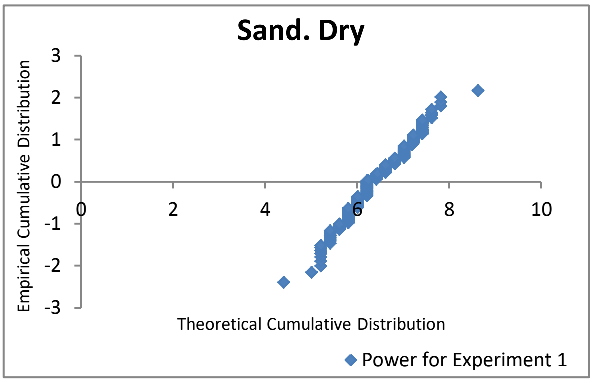
A.1.1. Sand - Dry condition



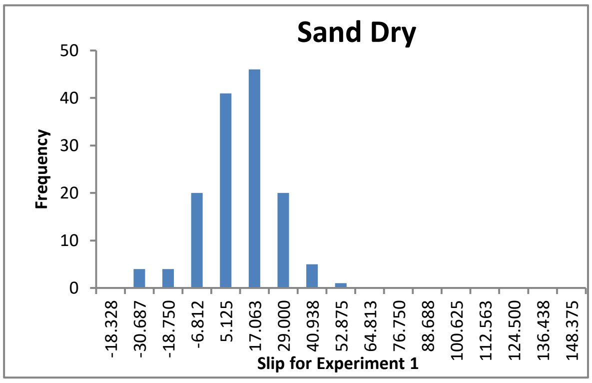


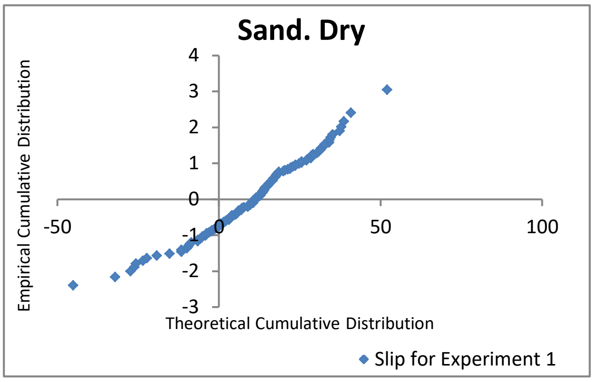
a) Velocity mean = 0.18, standard deviation = 0.05





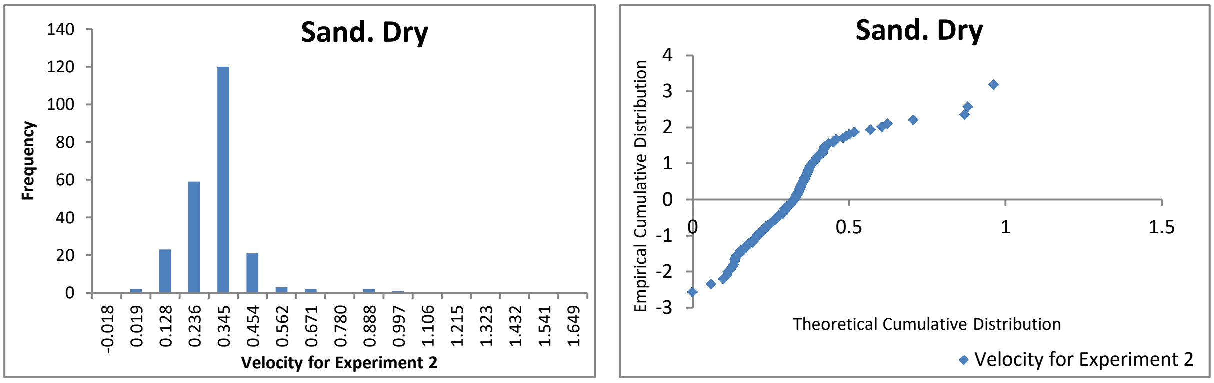
b) Power mean = 6.45, standard deviation = 0.84



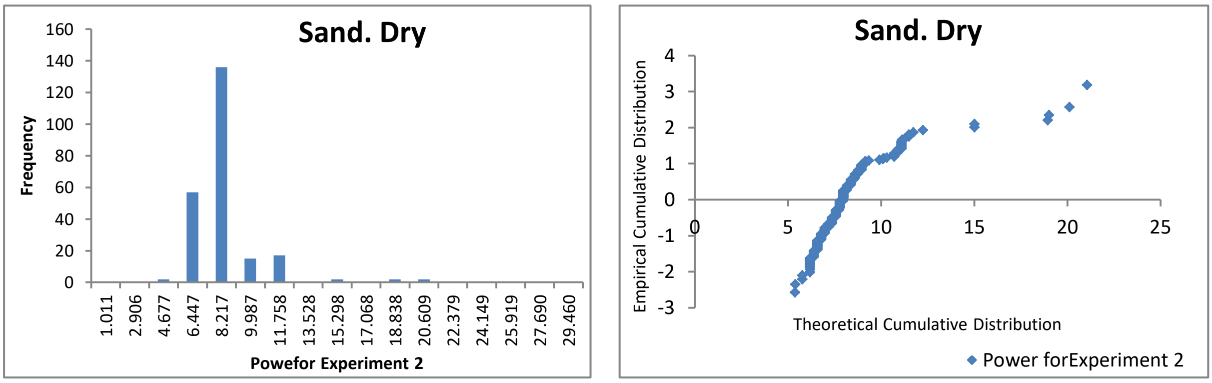


c) Slip mean = 10.04, standard deviation = 15.57

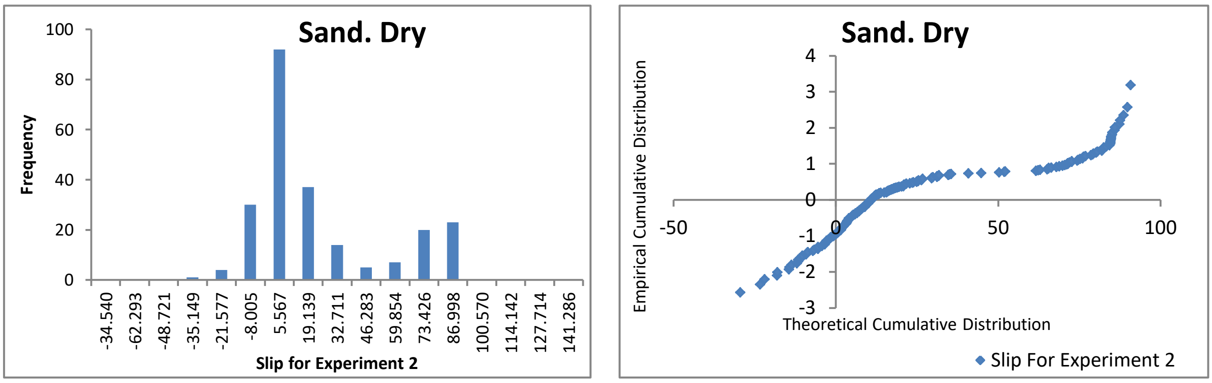
Figure A.1: Experiment 1. Sand.Dry



a) Velocity mean = 0.32, standard deviation = 0.12

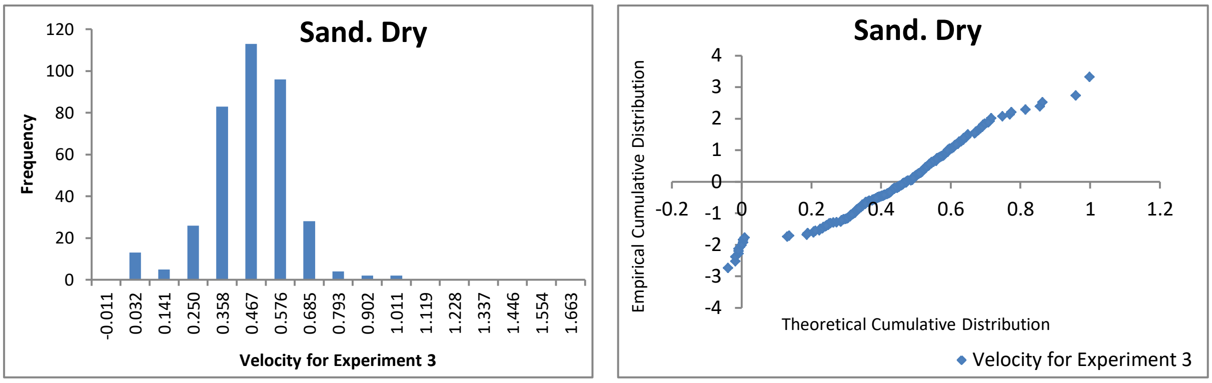


b) Power mean = 8.32, standard deviation = 2.10

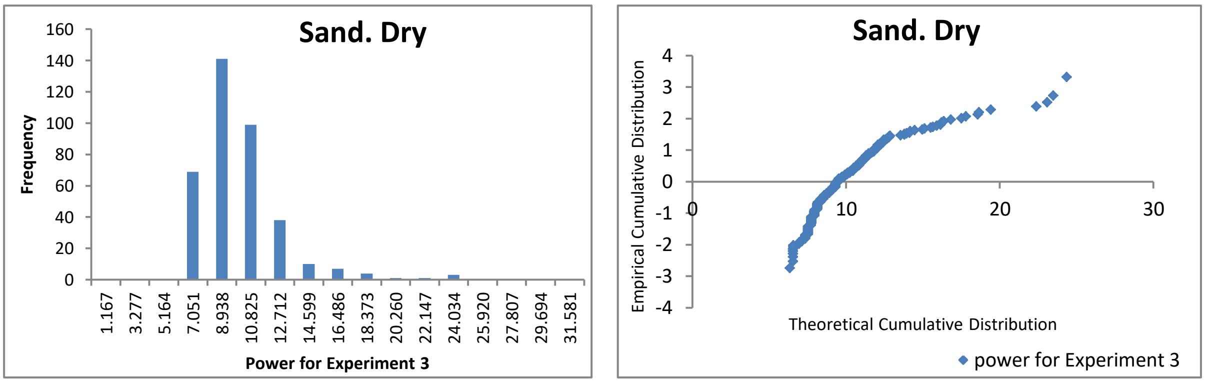


c) Slip mean = 23.57, standard deviation = 30.88

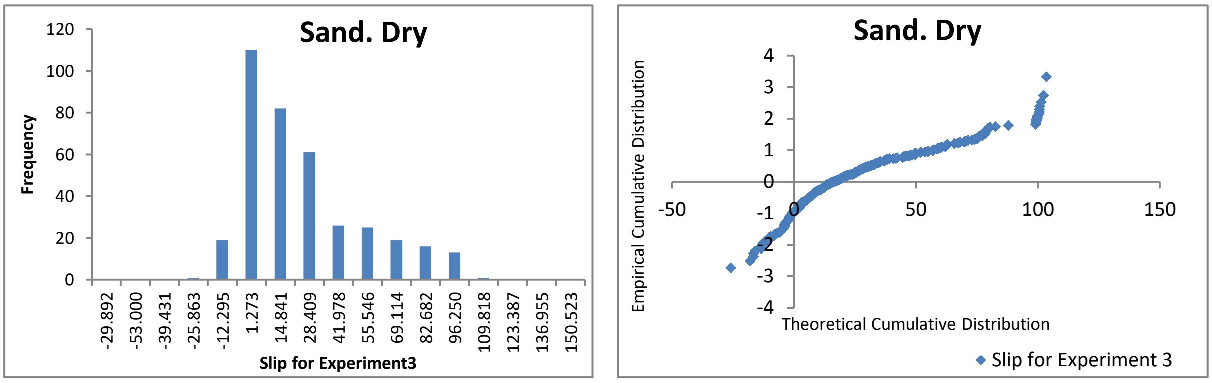
Figure A.2: Experiment 2. Sand.Dry



a) Velocity mean = 0.46, standard deviation = 0.16

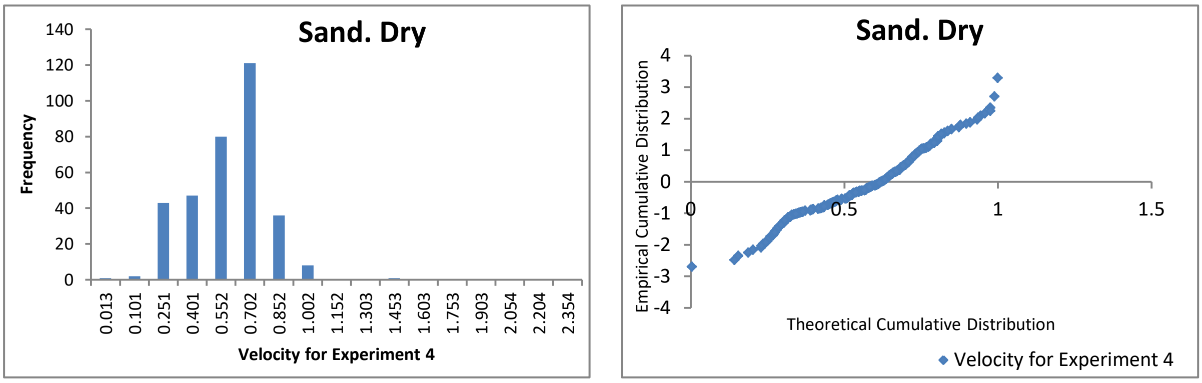


b) Power mean = 10.03, standard deviation = 2.57

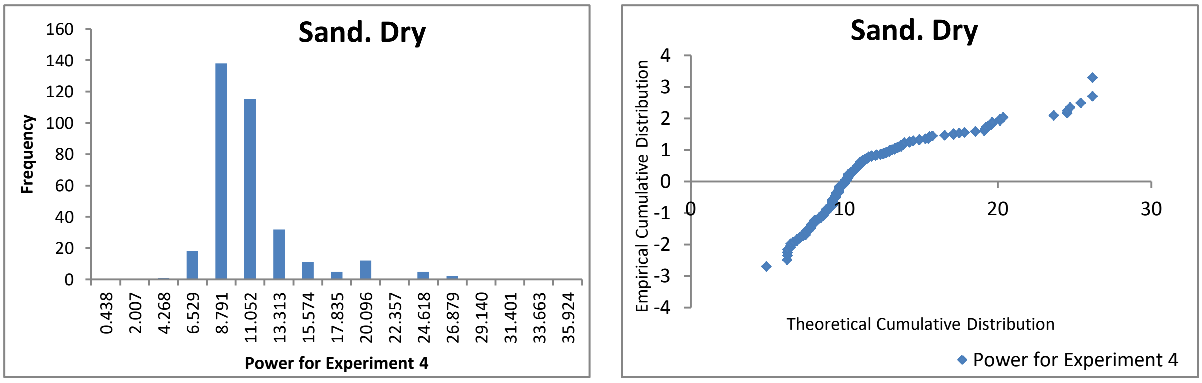


c) Slip mean = 24.94, standard deviation = 28.24

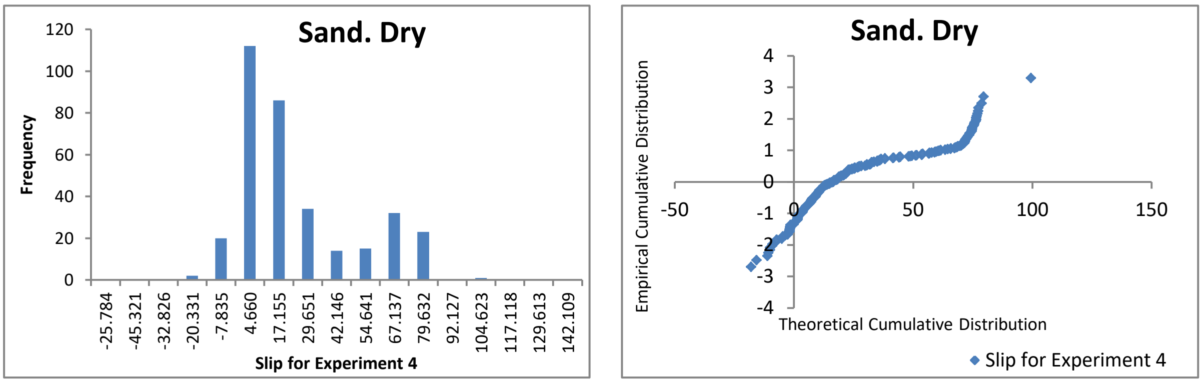
Figure A.3: Experiment 3 Sand.Dry



a) Velocity mean = 0.59, standard deviation = 0.19

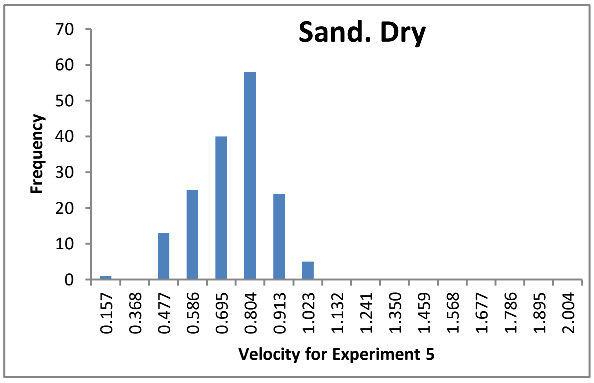


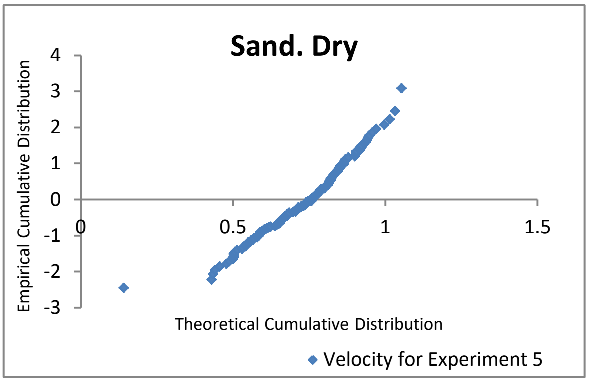
b) Power mean = 10.95, standard deviation = 3.36



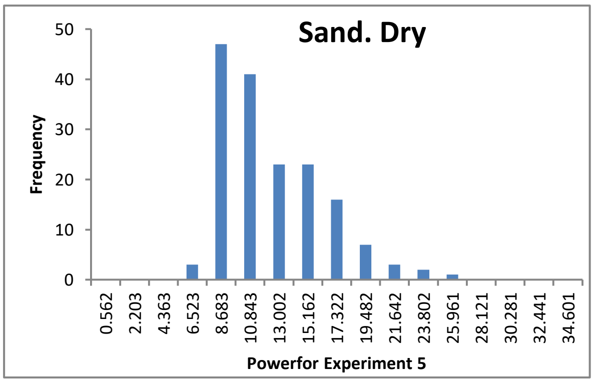
c) Slip mean = 24.87, standard deviation = 25.48

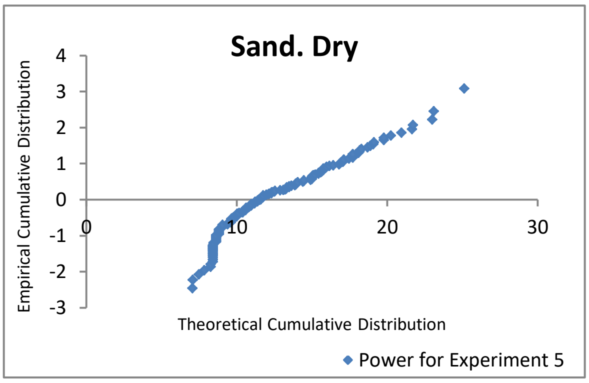
Figure A.4: Experiment 4. Sand.Dry



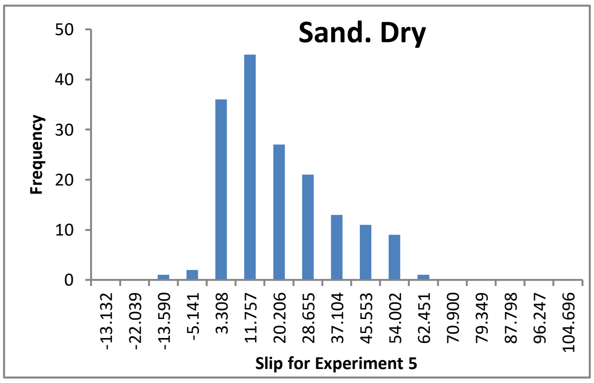


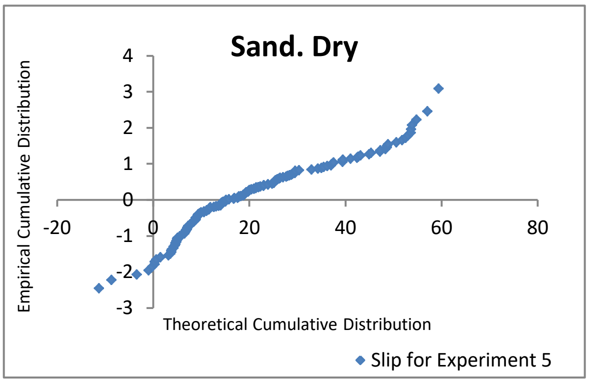
a) Velocity mean = 0.74, standard deviation = 0.14





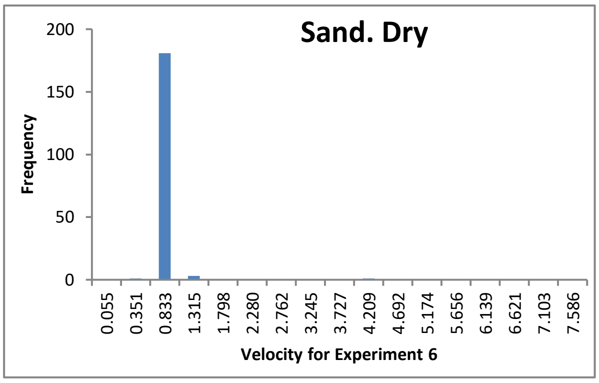
b) Power mean = 12.57, standard deviation = 3.82

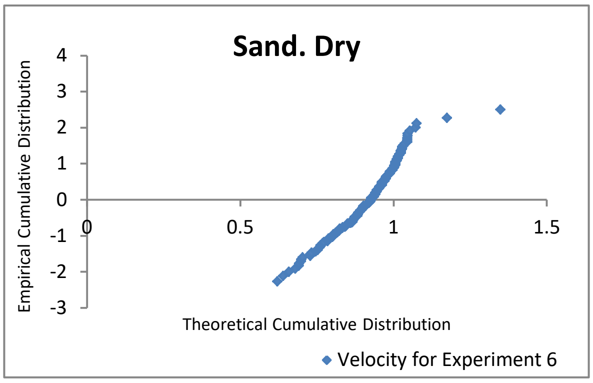




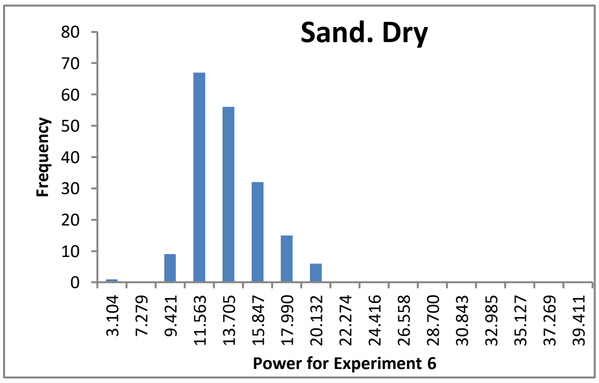
c) Slip mean = 19.85, standard deviation = 15.37

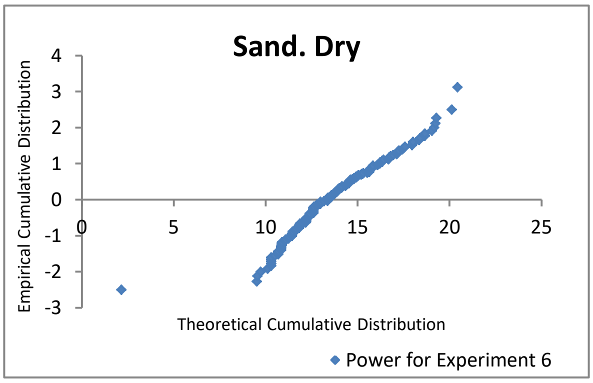
Figure A.5: Experiment 5 Sand.Dry



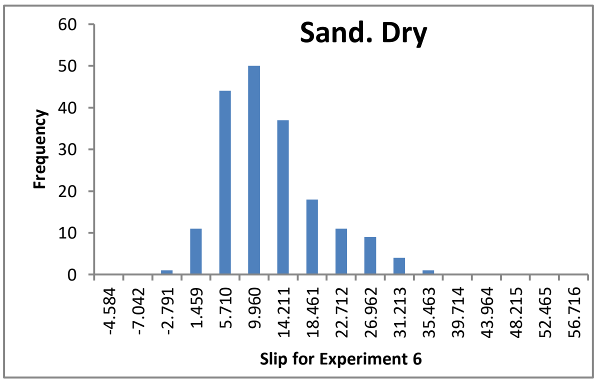


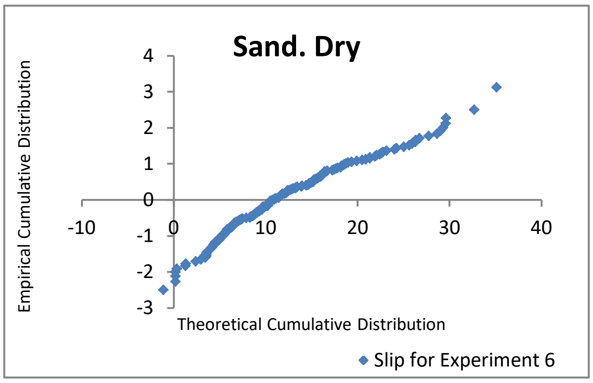
a) Velocity mean = 0.93, standard deviation = 0.27





b) Power mean = 13.66, standard deviation = 2.48

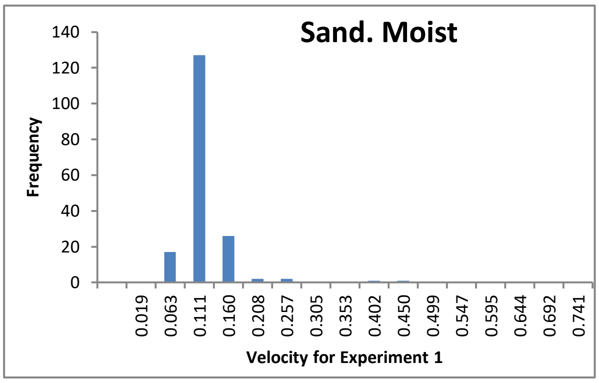


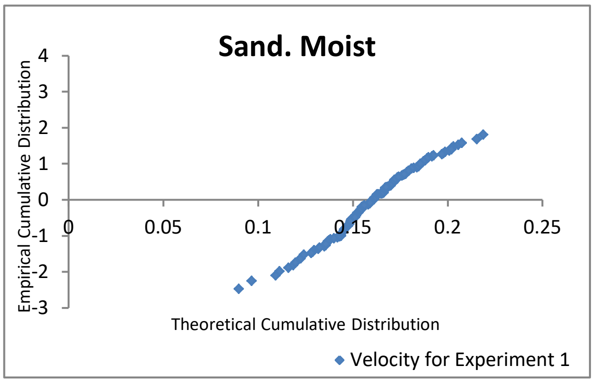


c) Slip mean = 12.24, standard deviation = 7.14

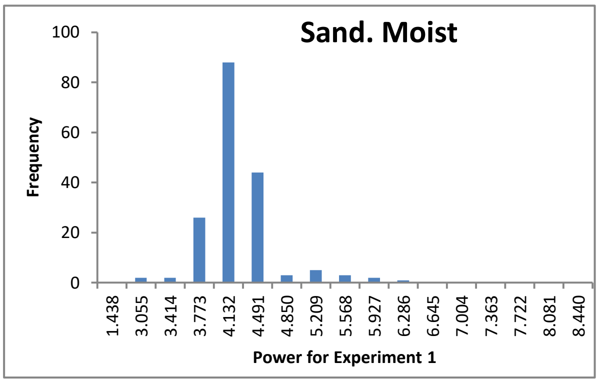
Figure A.6: Experiment 6. Sand.Dry

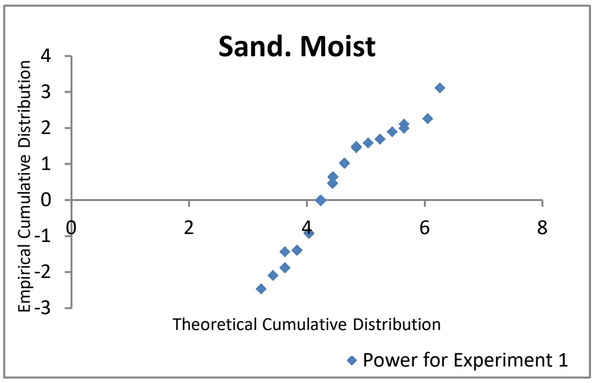
A.1.2. Sand - Moist condition



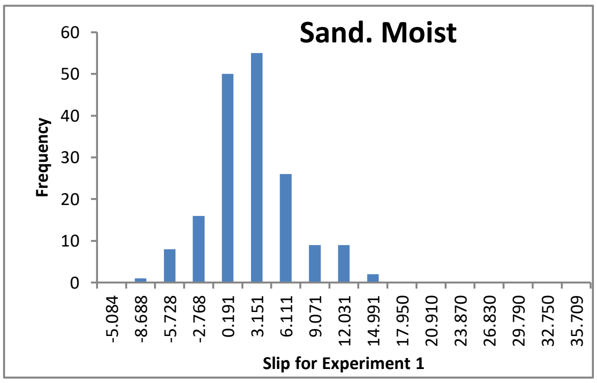


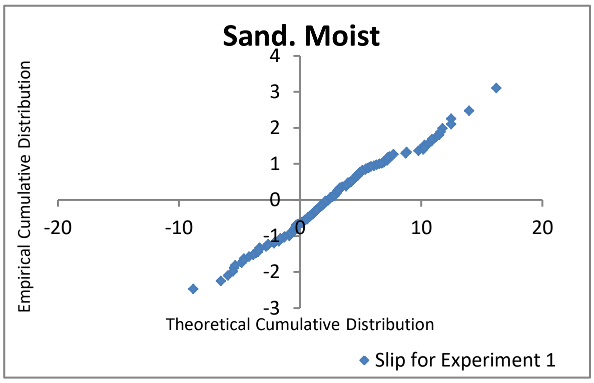
a) Velocity mean = 0.17, standard deviation = 0.04





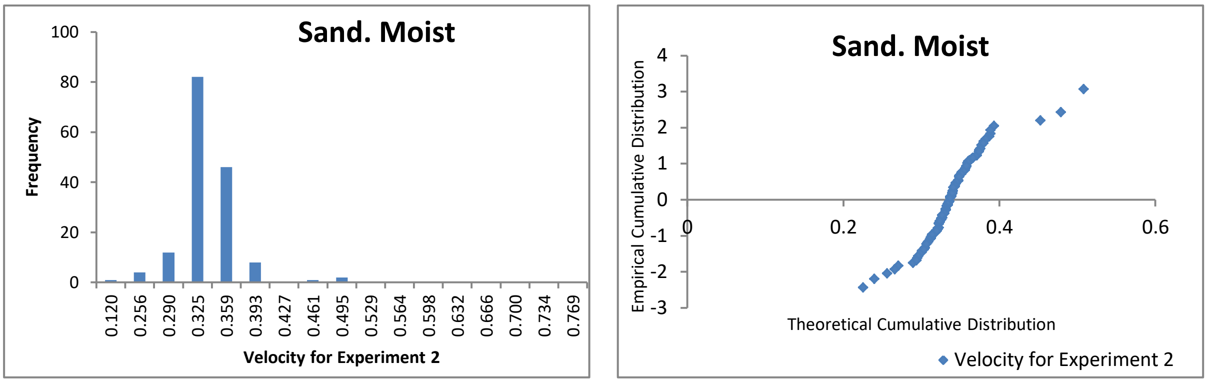
b) Power mean = 4.25, standard deviation = 0.46



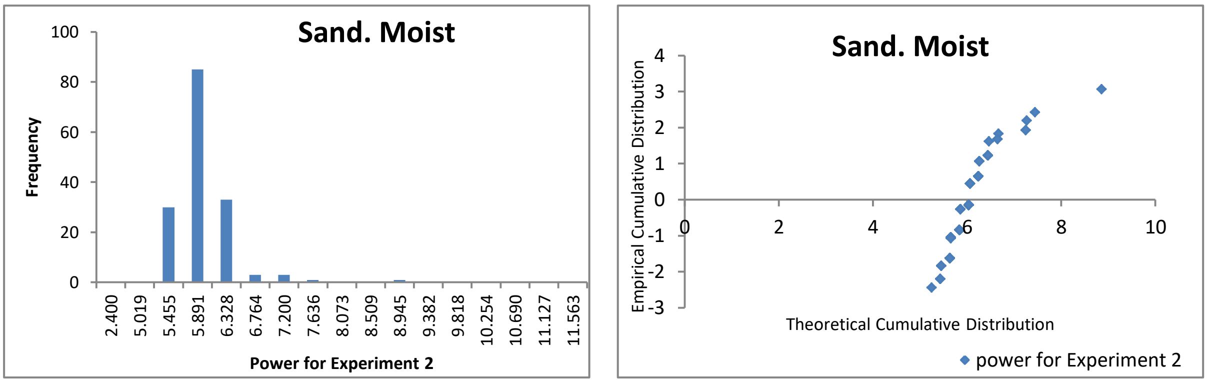


c) Slip mean = 2.63, standard deviation = 4.27

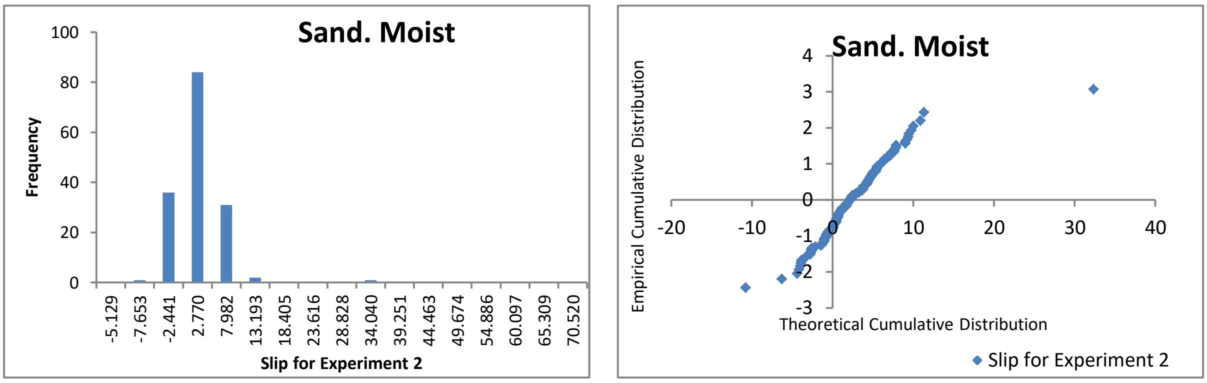
Figure A.7: Experiment 1. Sand.Moist



a) Velocity mean = 0.34, standard deviation = 0.03

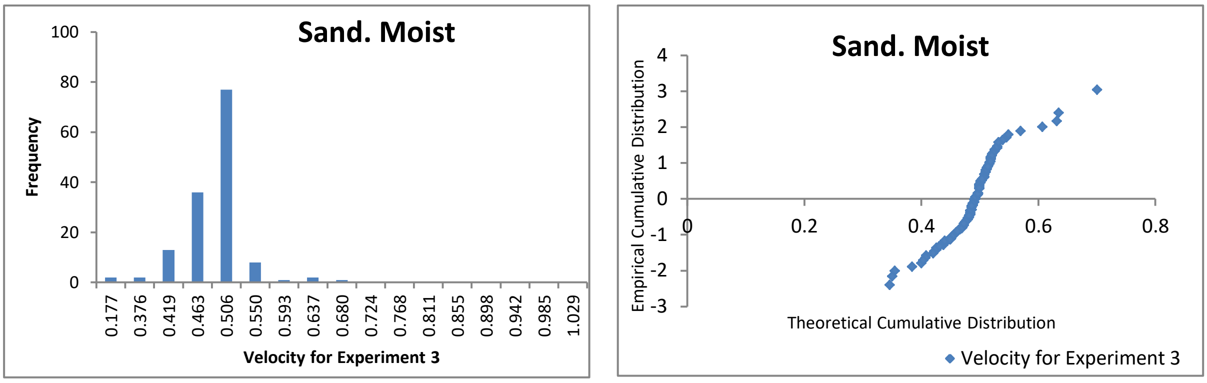


b) Power mean = 6.02, standard deviation = 0.41

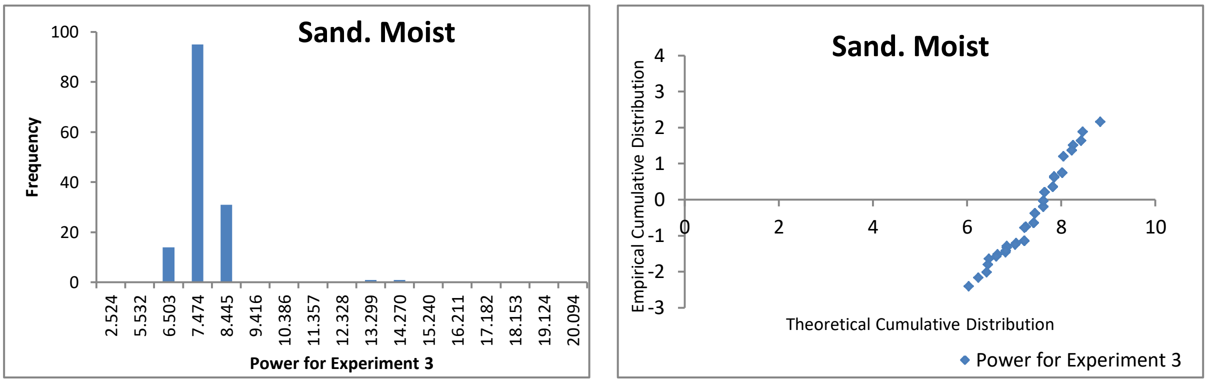


c) Slip mean = 2.65, standard deviation = 4.30

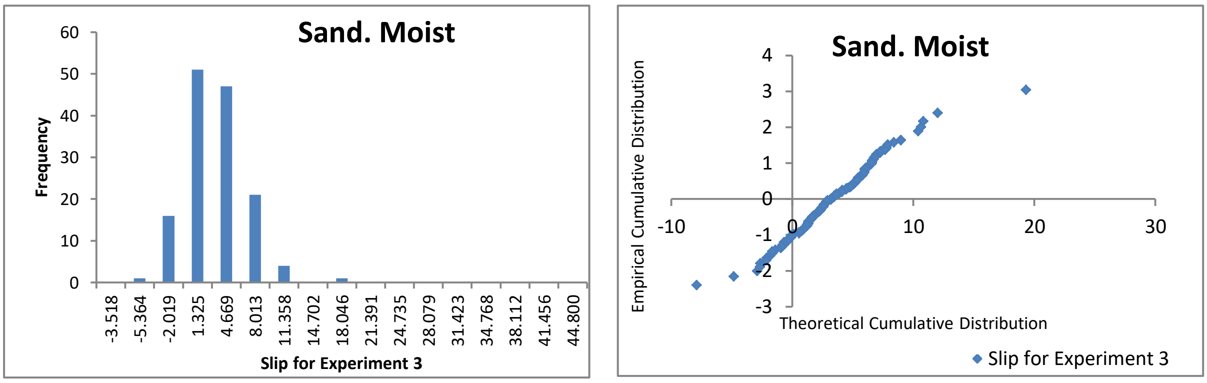
Figure A.8: Experiment 2. Sand.Moist



a) Velocity mean = 0.49, standard deviation = 0.05

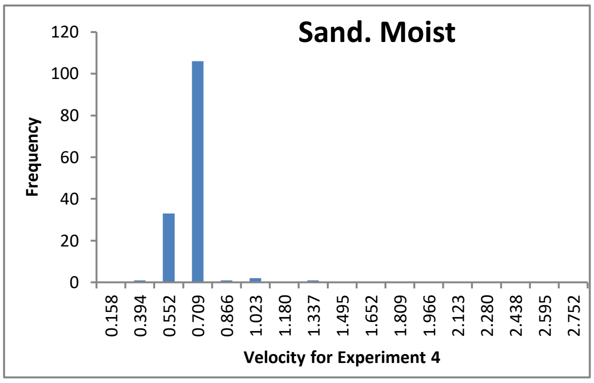


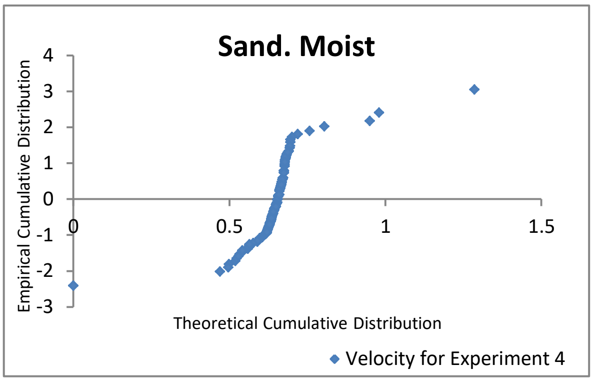
b) Power mean = 7.65, standard deviation = 0.88



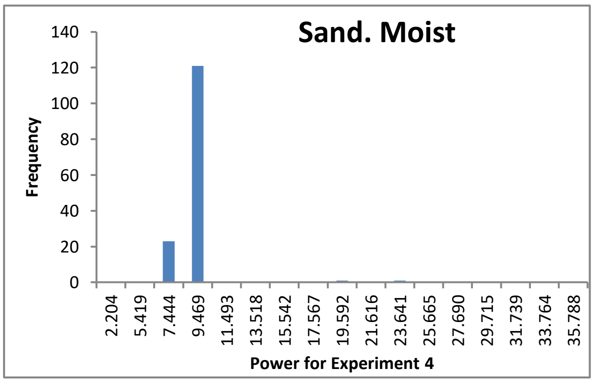
c) Slip mean = 3.47, standard deviation = 3.50

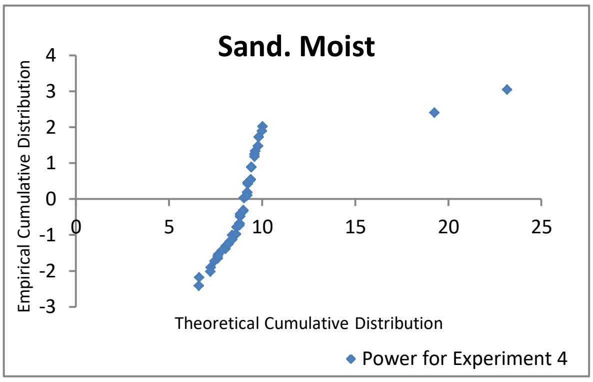
Figure A.9. Experiment 3. Sand. Moist



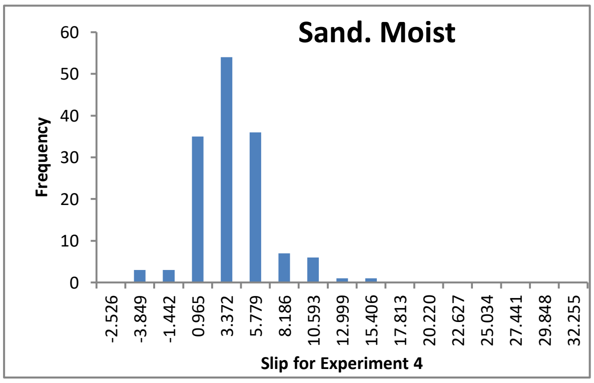


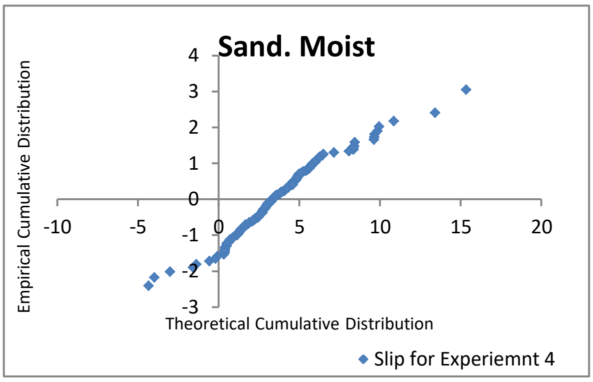
a) Velocity mean = 0.65, standard deviation = 0.11





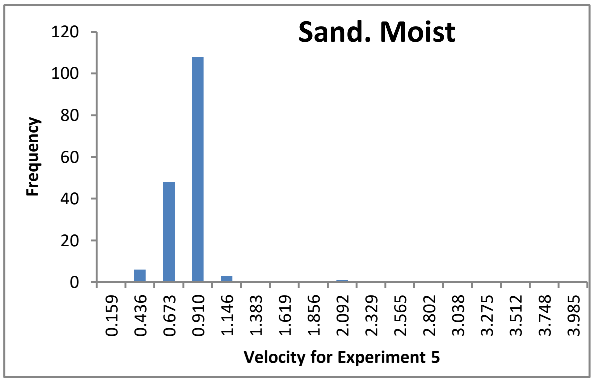
b) Power mean = 9.12, standard deviation = 1.57

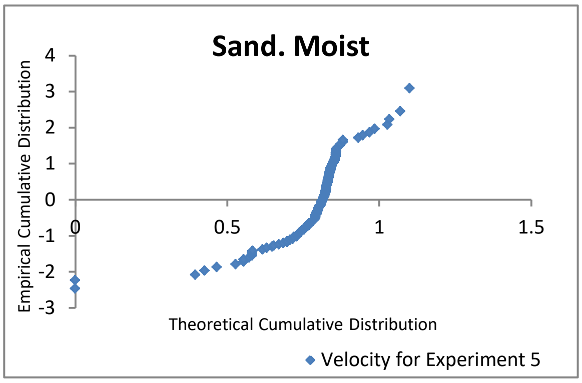




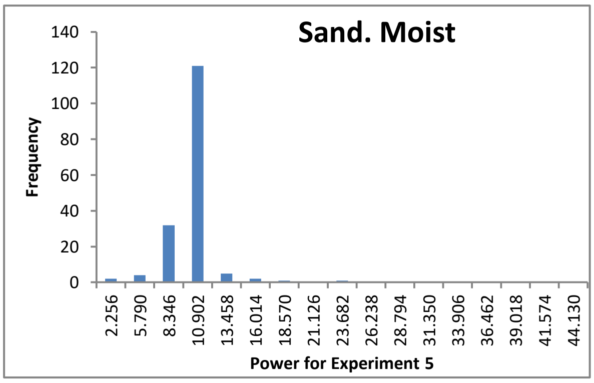
c) Slip mean = 3.68, standard deviation = 2.91

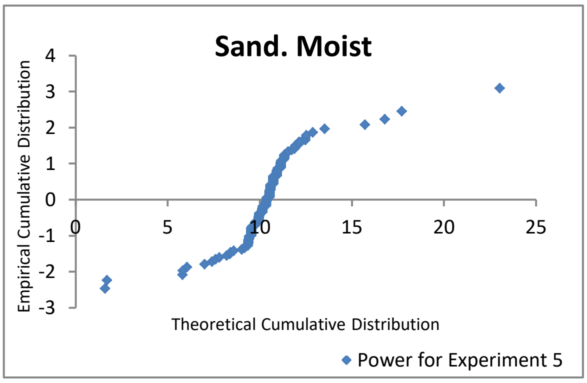
Figure A.10. Experiment 4. Sand. Moist



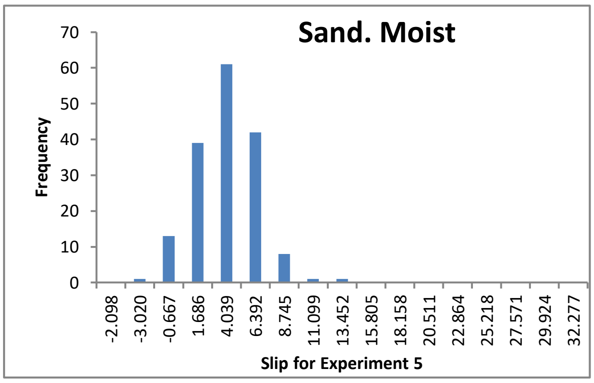


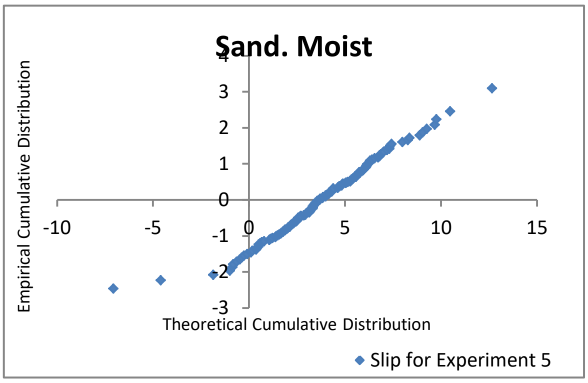
a) Velocity mean = 0.79, standard deviation = 0.16





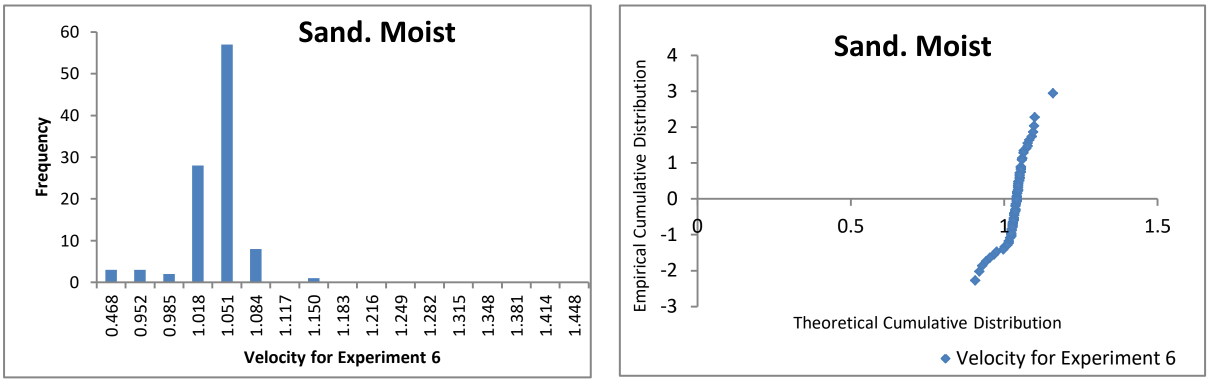
b) Power mean = 10.37, standard deviation = 1.95



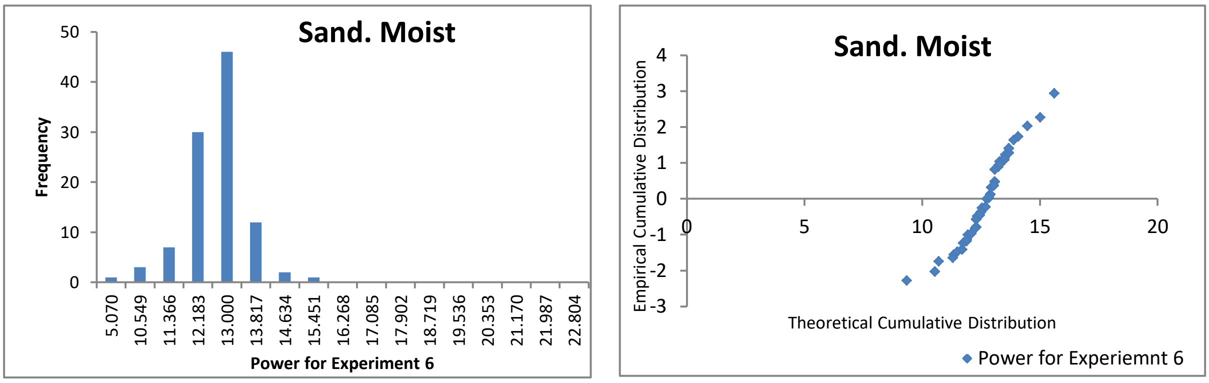


c) Slip mean = 3.85, standard deviation = 2.68

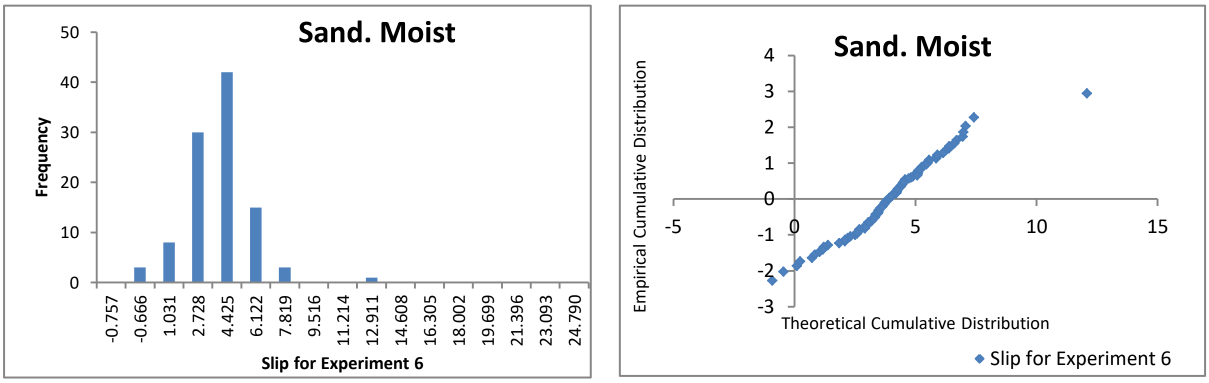
Figure A.11: Experiment 5. Sand. Moist



a) Velocity mean = 1.04, standard deviation = 0.03



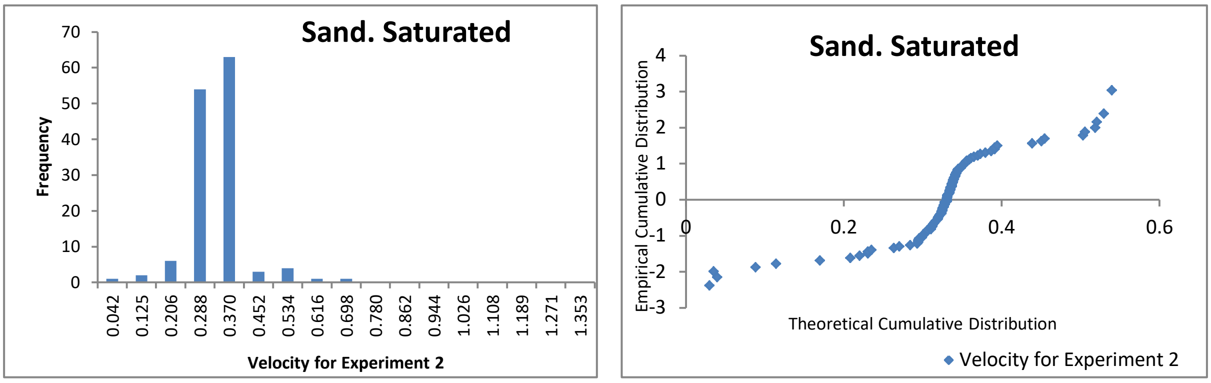
b) Power mean = 12.71, standard deviation = 0.86



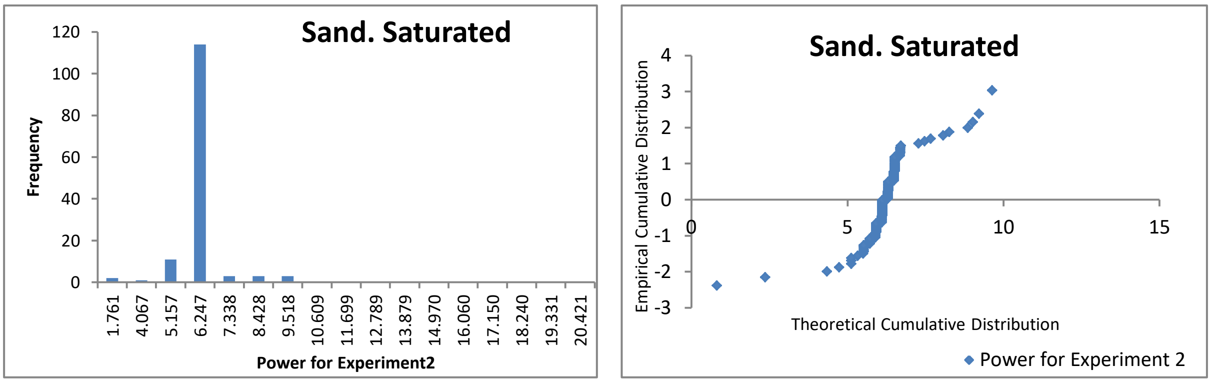
c) Slip mean = 3.97, standard deviation = 1.83

Figure A.12: Experiment 6. Sand. Moist

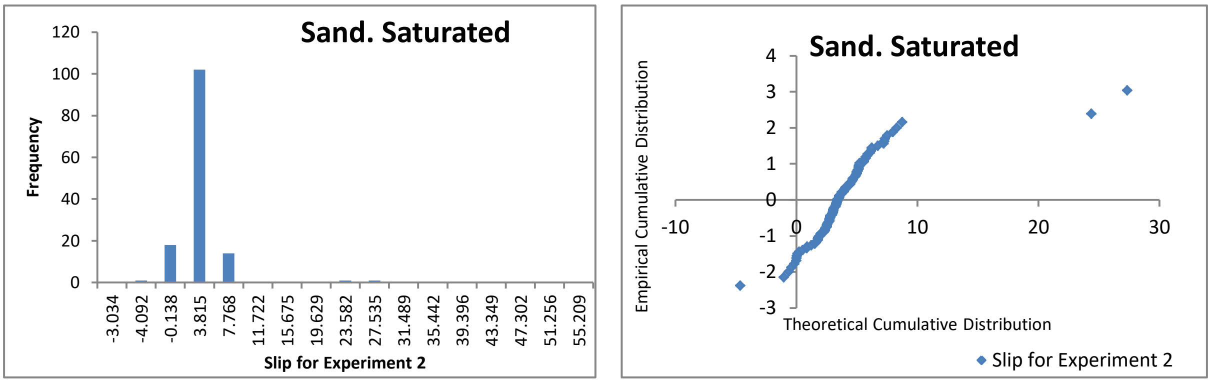
A.1.3. Sand - Saturated condition



a) Velocity mean = 0.33, standard deviation = 0.07

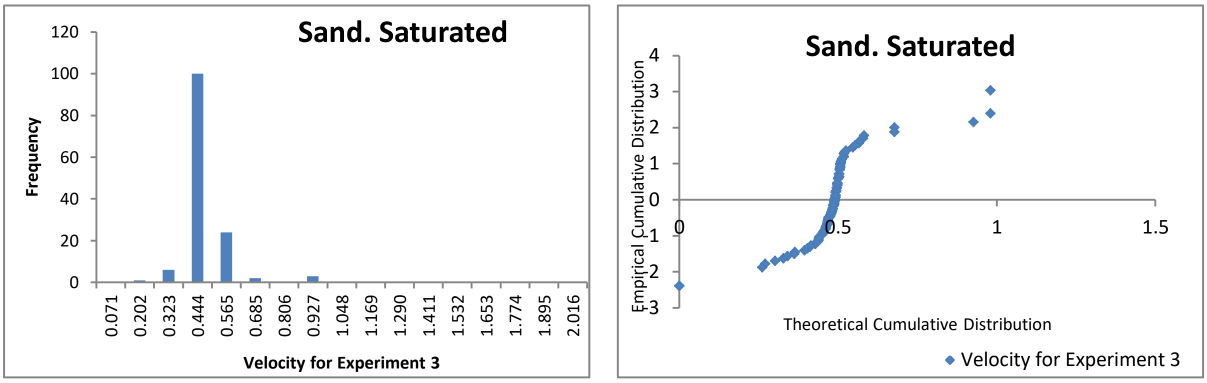


b) Power mean = 6.23, standard deviation = 0.45

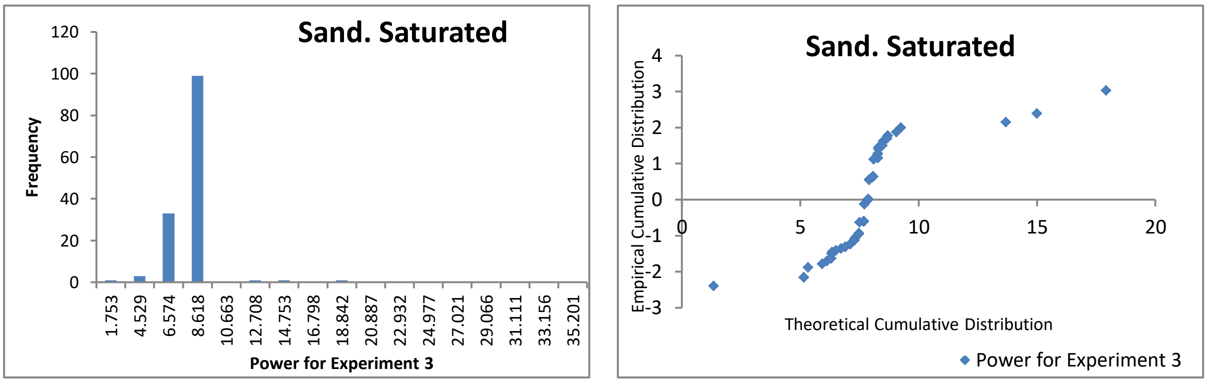


c) Slip mean 3.10 = , standard deviation = 2.99

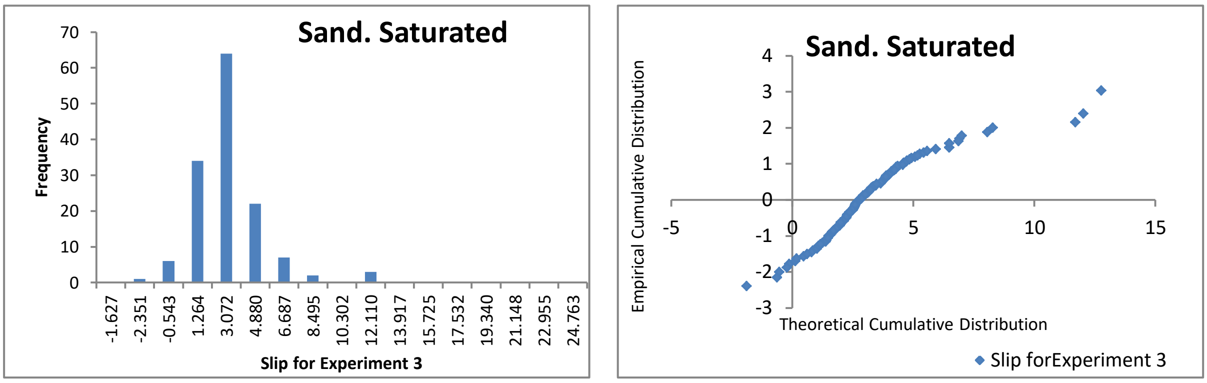
Figure A.13: Experiment 2. Sand.Saturated



a) Velocity mean = 0.48, standard deviation = 0.05

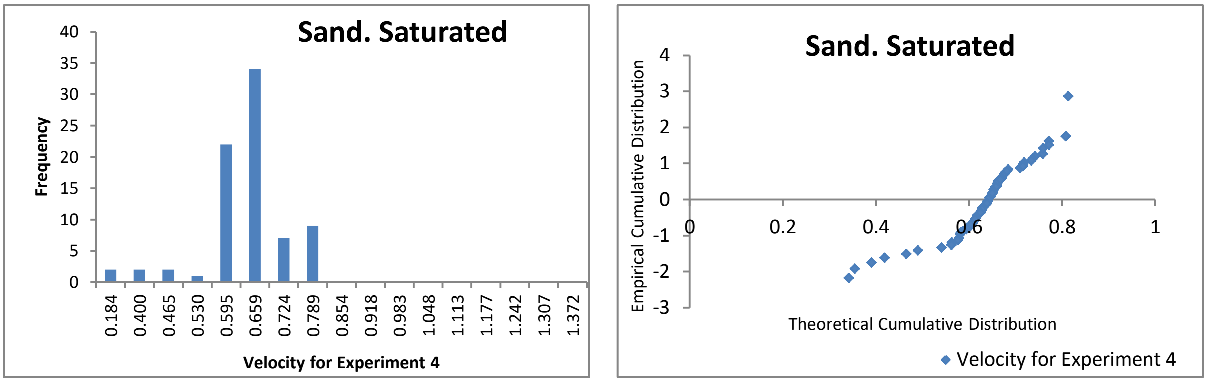


b) Power mean = 7.80, standard deviation = 1.43

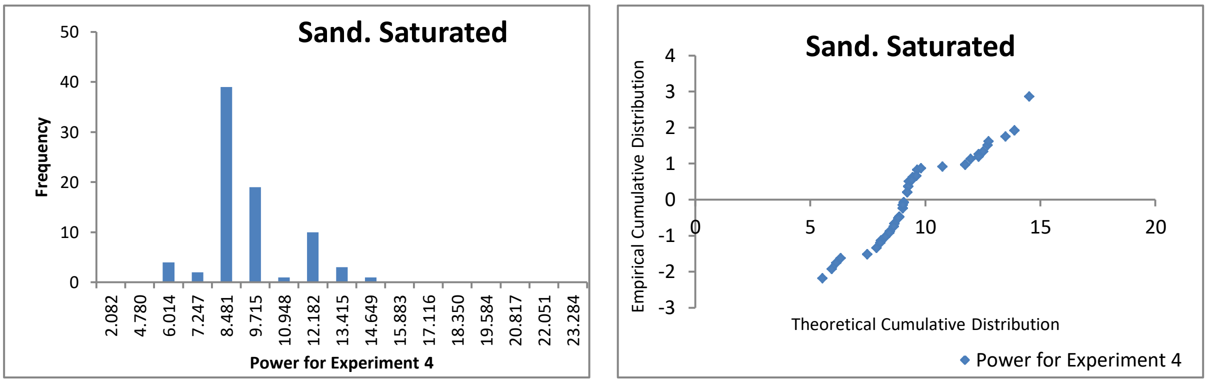


c) Slip mean = 3.20, standard deviation = 2.14

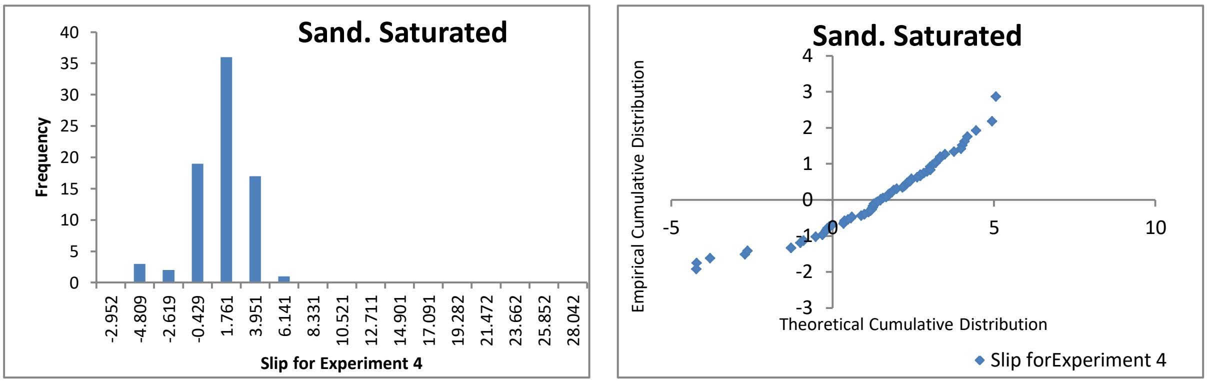
Figure A.14: Experiment 3. Sand.Saturated



a) Velocity mean = 0.64, standard deviation = 0.09

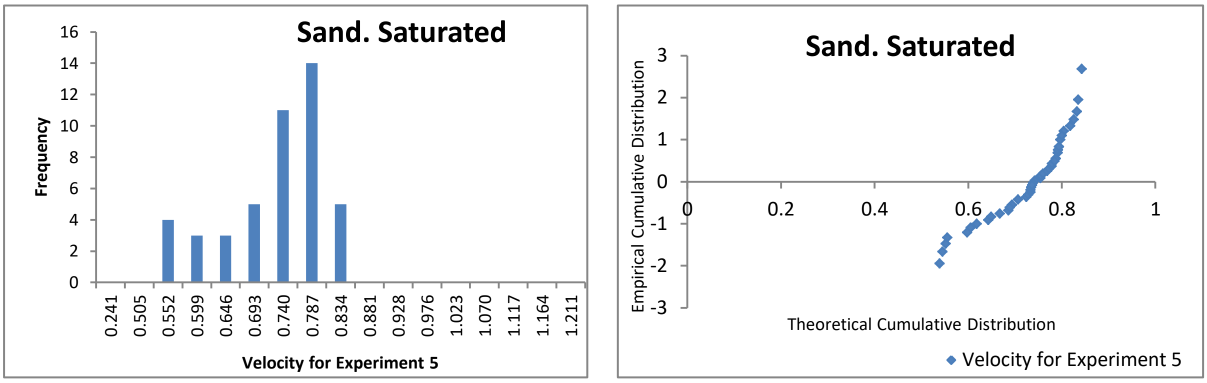


b) Power mean = 9.44, standard deviation = 1.76

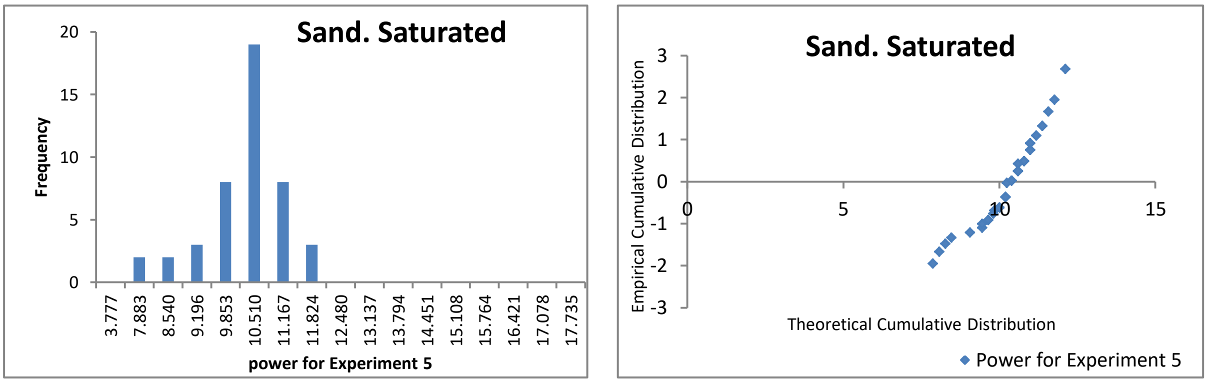


c) Slip mean = 2.62, standard deviation = 2.38

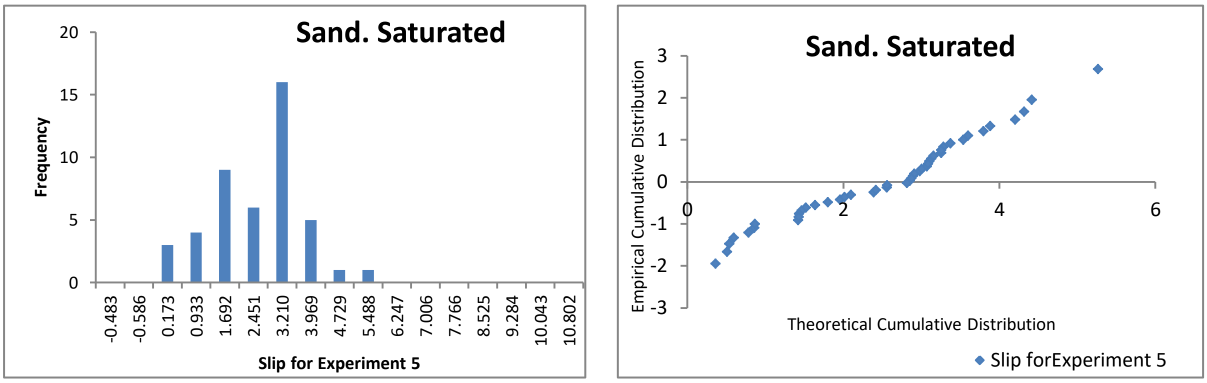
Figure A.15: Experiment 4. Sand. Saturated



a) Velocity mean = 0.73, standard deviation = 0.08

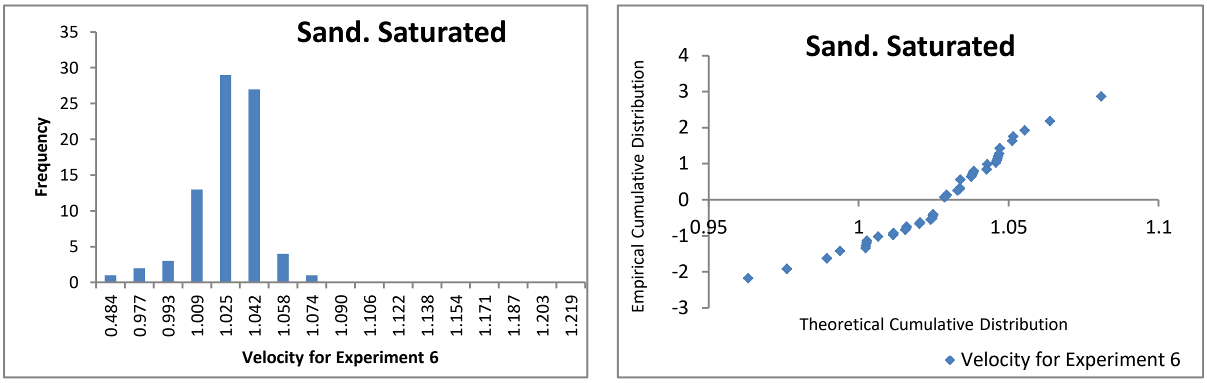


b) Power mean = 10.28, standard deviation = 0.91

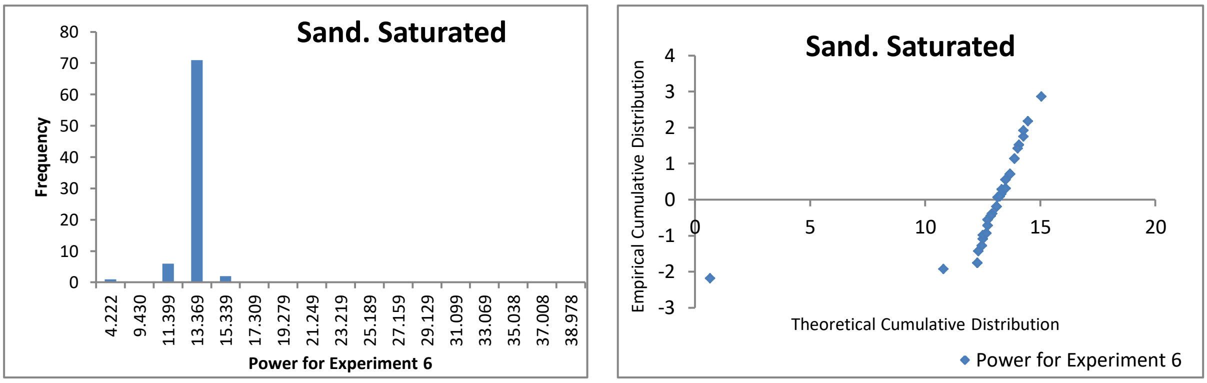


c) Slip mean = 2.52, standard deviation = 1.16

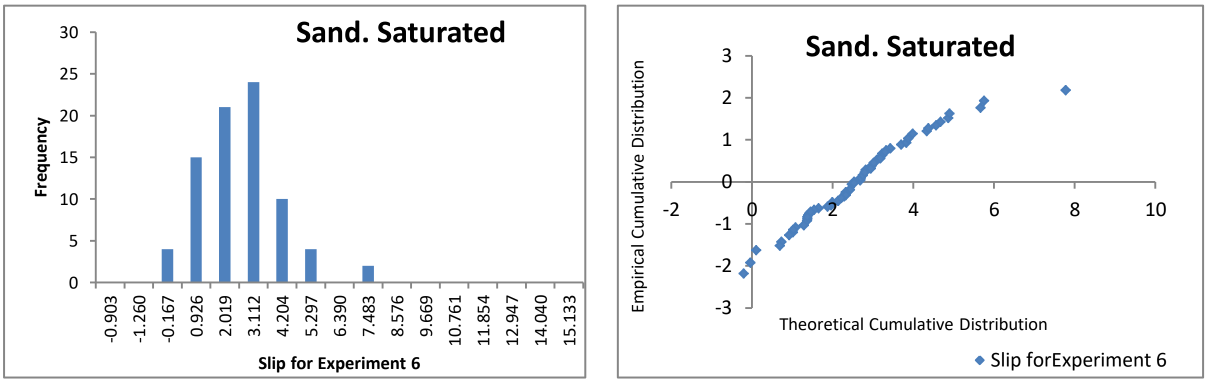
Figure A.16: Experiment 5. Sand. Saturated



a) Velocity mean = 1.03, standard deviation = 0.02



b) Power mean = 13.02, standard deviation = 1.52

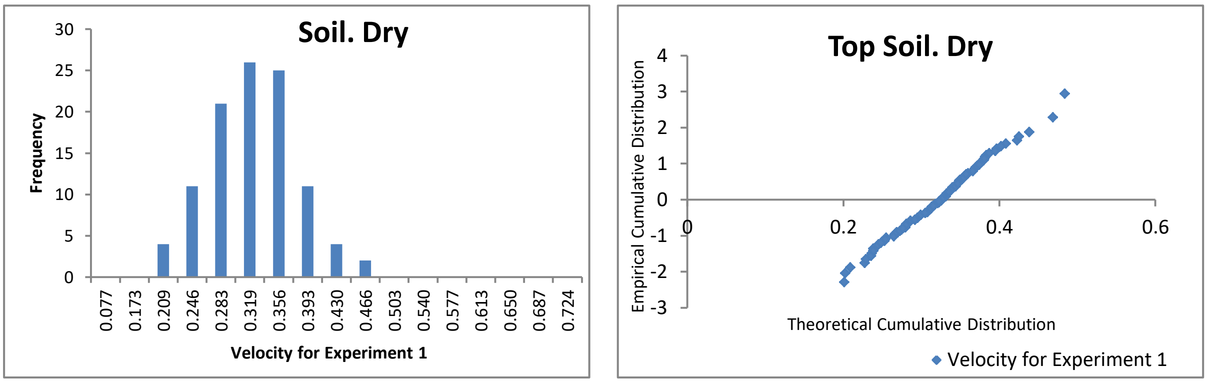


c) Slip mean = 2.69, standard deviation = 1.49

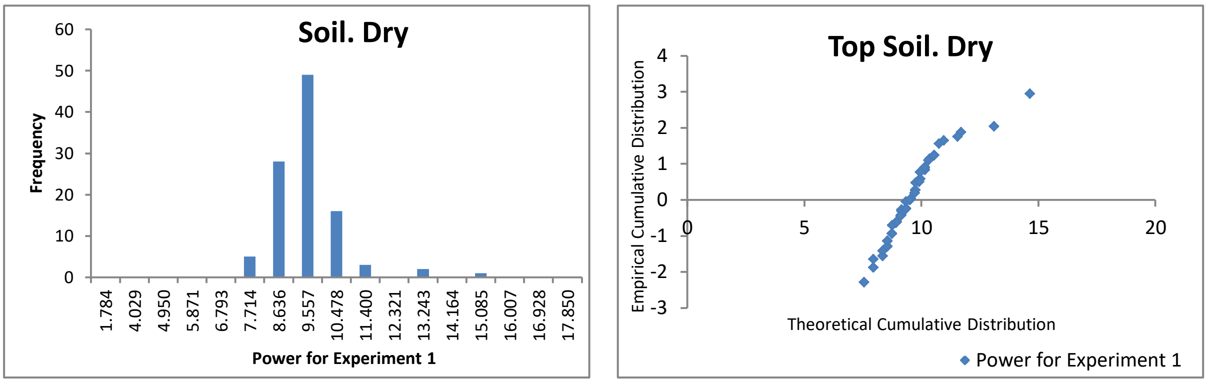
Figure A.17: Experiment 6. Sand. Saturated

A.2. Experiments for Top Soil (Dirt)

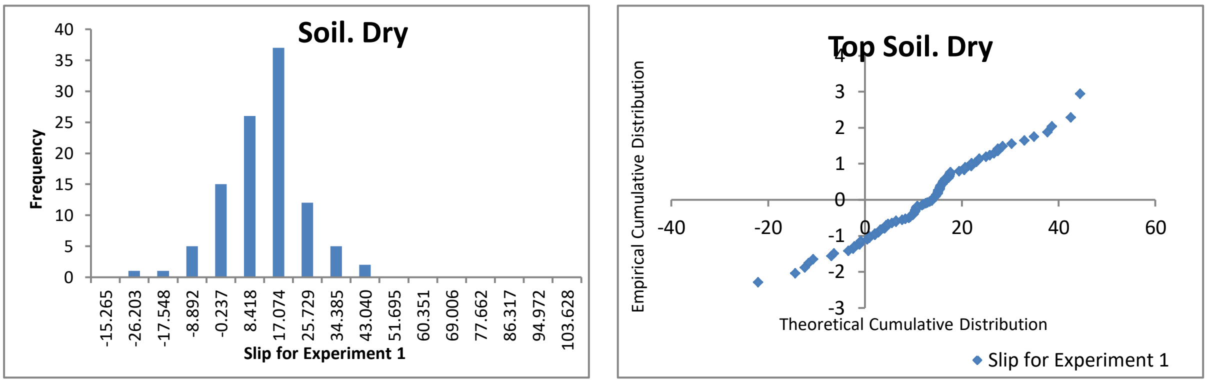
A.2.1. Top Soil - Dry condition



a) Velocity mean = 0.32, standard deviation = 0.06

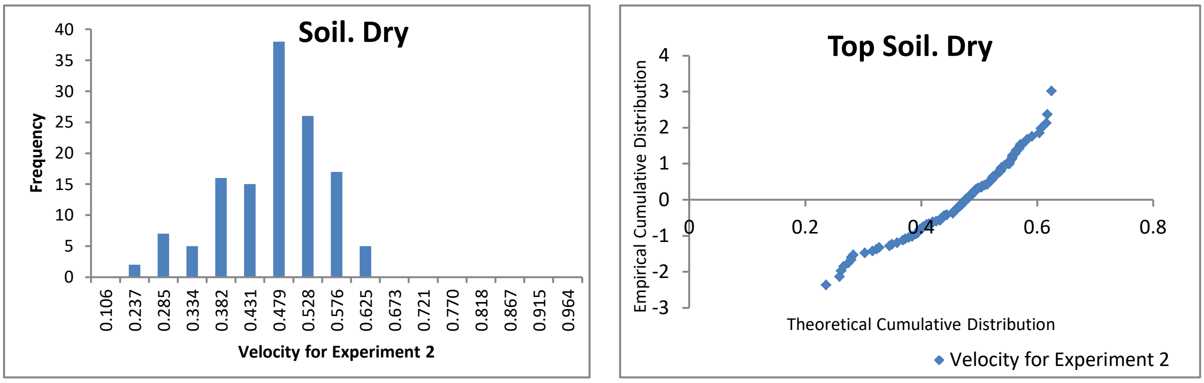


b) Power mean = 9.54, standard deviation = 1.99

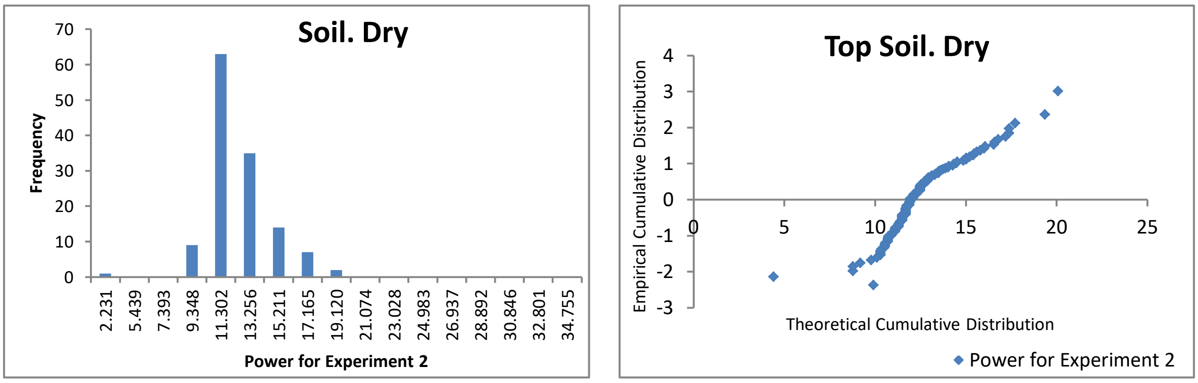


c) Slip mean = 12.58, standard deviation = 14.37

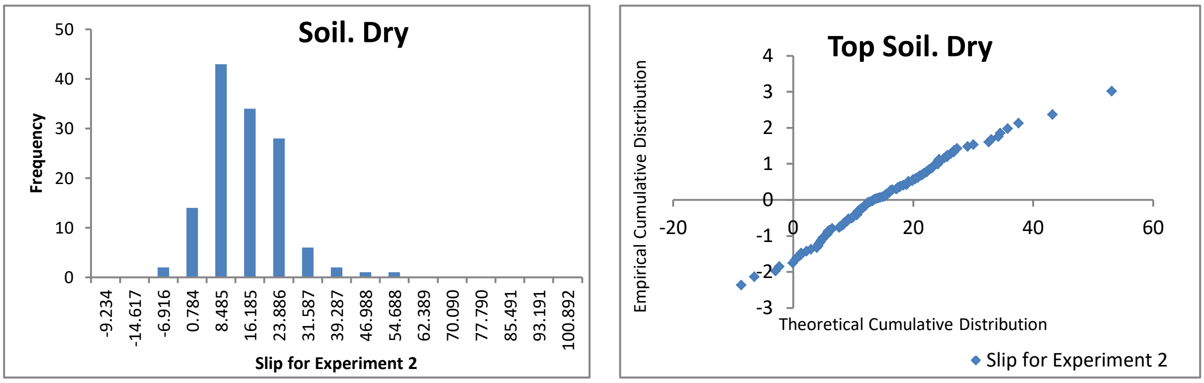
Figure A.18: Experiment 1. Top Soil. Dry



a) Velocity mean = 0.47, standard deviation = 0.08

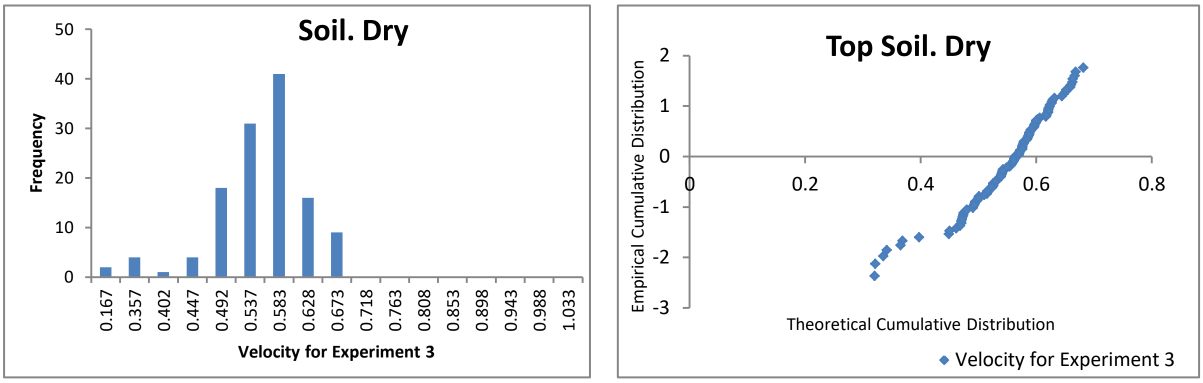


b) Power mean = 11.44, standard deviation = 2.68

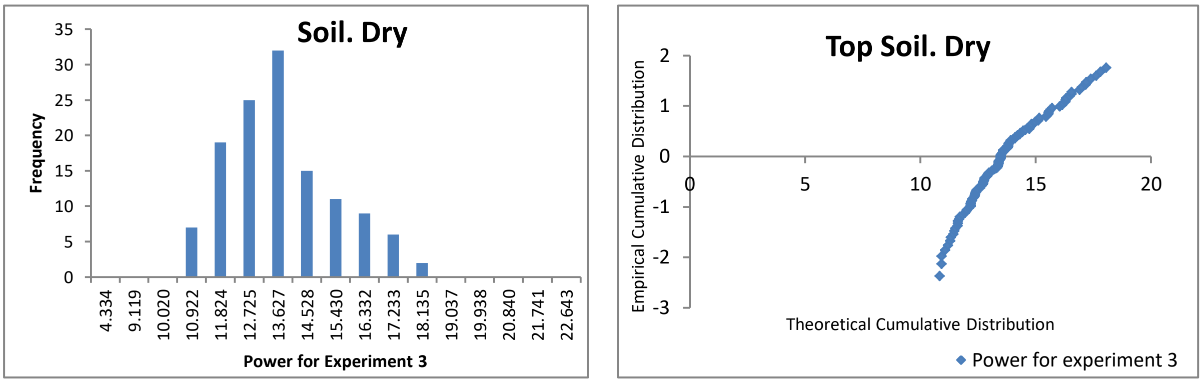


c) Slip mean = 14.99, standard deviation = 11.15

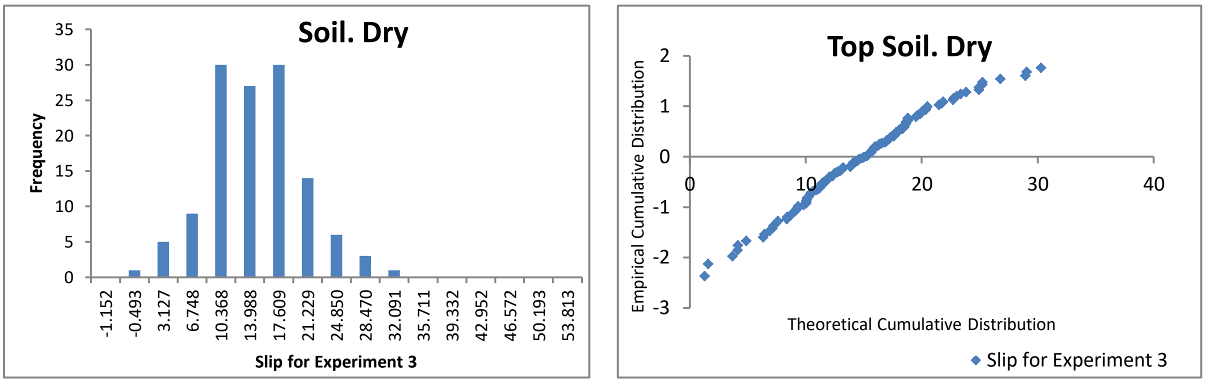
Figure A.19: Experiment 2. Top Soil. Dry



a) Velocity mean = 0.55, standard deviation = 0.07

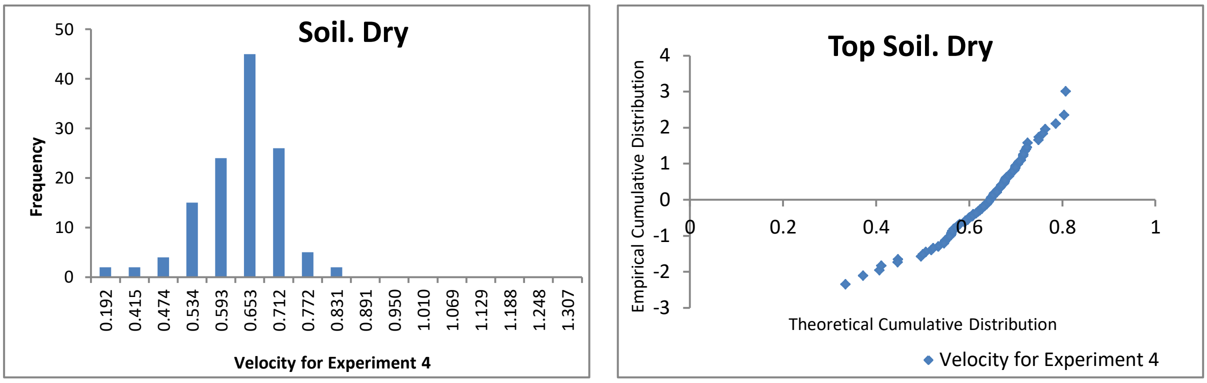


b) Power mean = 13.17, standard deviation = 1.69

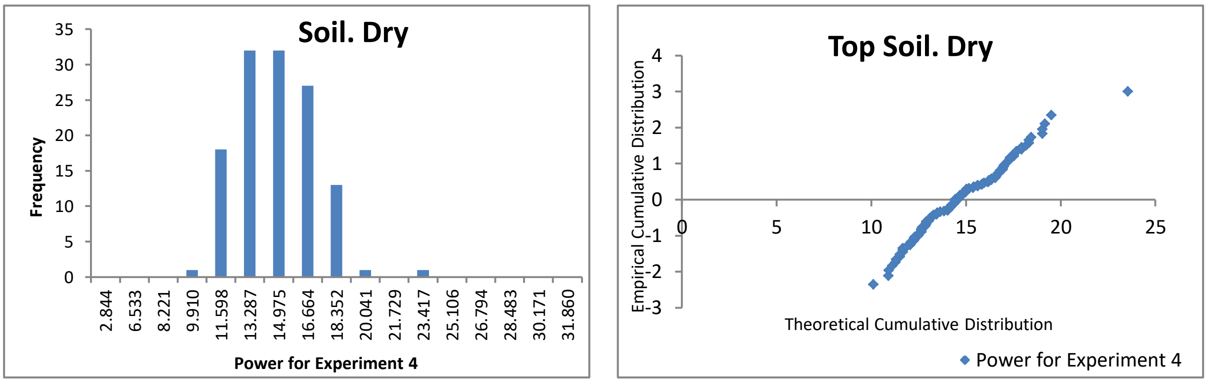


c) Slip mean = 14.81, standard deviation = 5.73

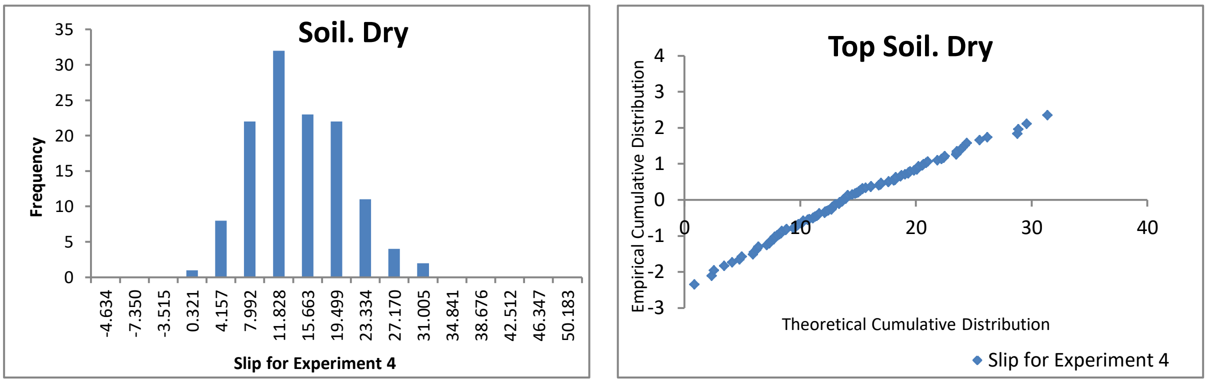
Figure A.20: Experiment 3. Top Soil. Dry



a) Velocity mean = 0.63, standard deviation = 0.08

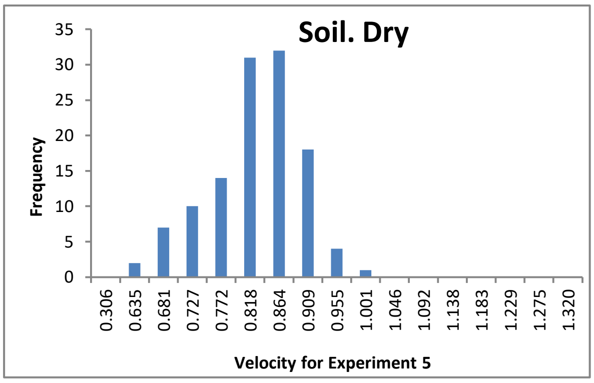


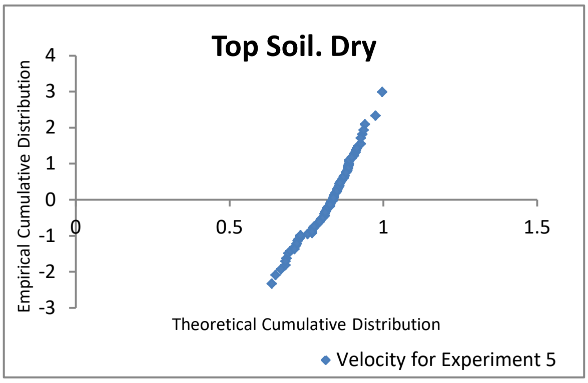
b) Power mean = 14.76, standard deviation = 3.02



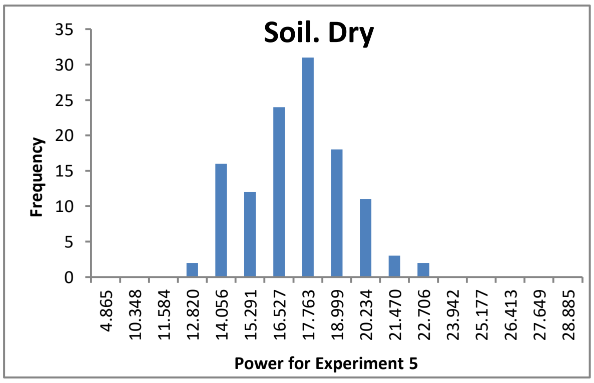
c) Slip mean = 14.42, standard deviation = 7.90

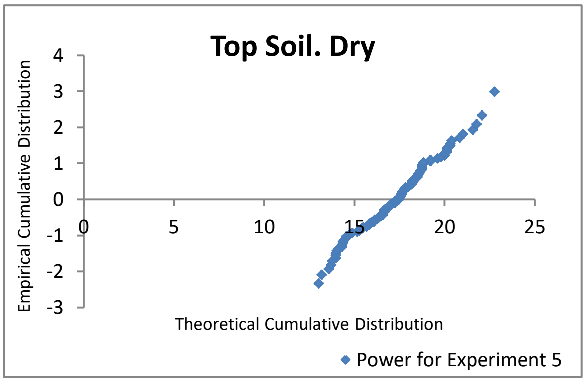
Figure A.21: Experiment 4. Top Soil. Dry



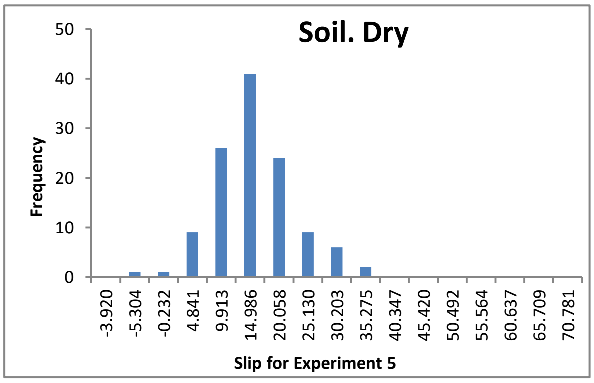


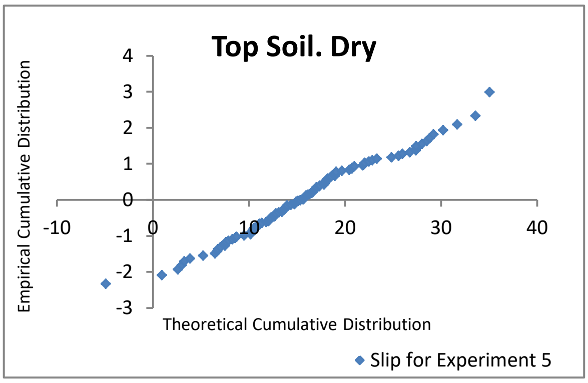
a) Velocity mean = 0.82, standard deviation = 0.07





b) Power mean = 17.27, standard deviation = 2.51

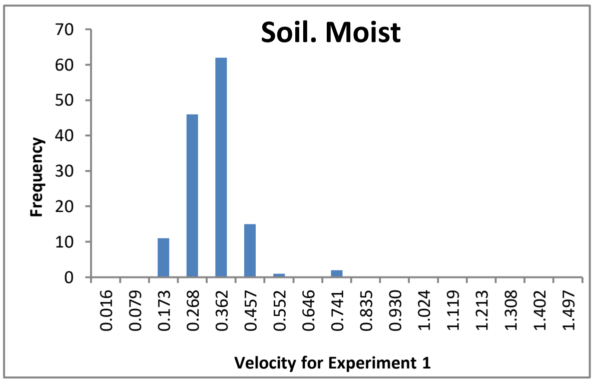


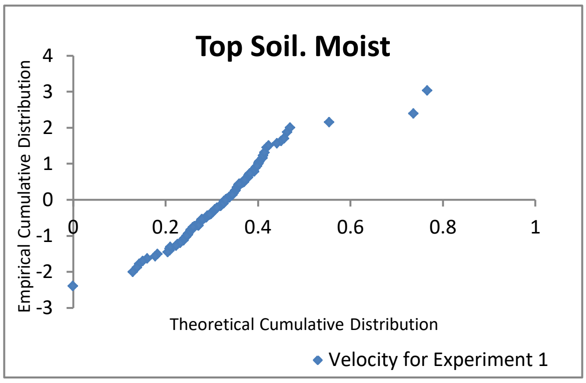


c) Slip mean = 15.72, standard deviation = 7.85

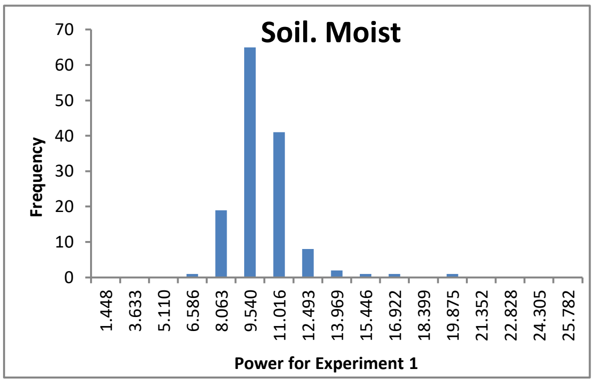
Figure A.22: Experiment 5. Top Soil. Dry

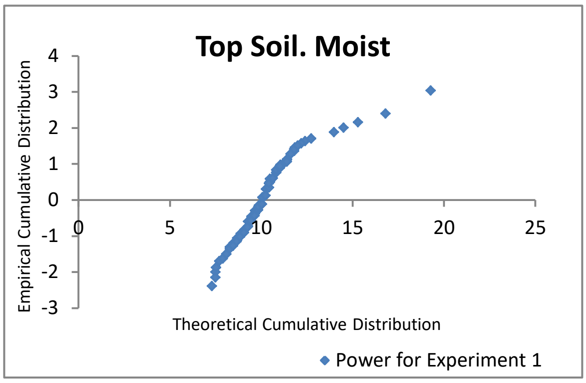
A.2.2. Top Soil - Moist condition



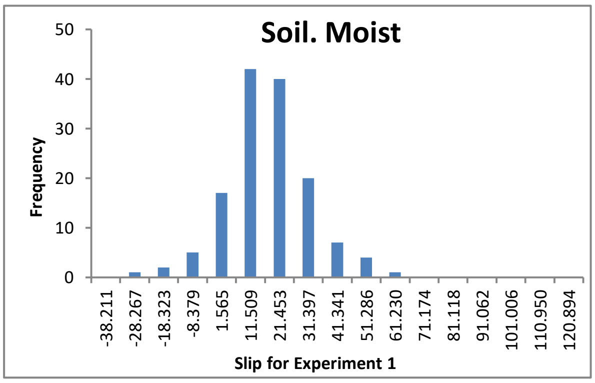


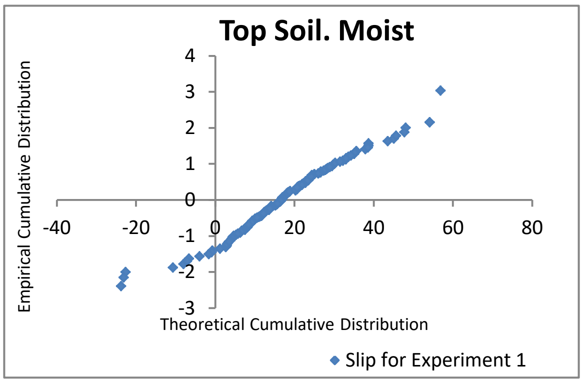
a) Velocity mean = 0.32, standard deviation = 0.07





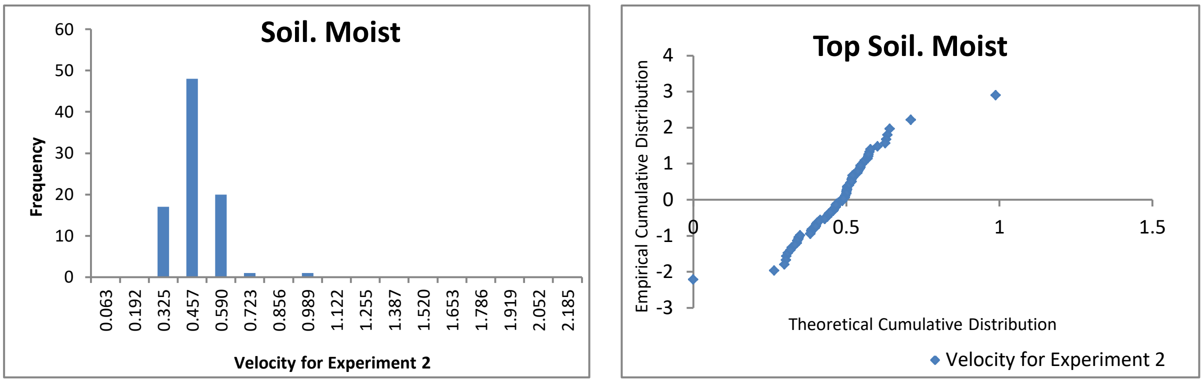
b) Power mean = 10.16, standard deviation = 2.42



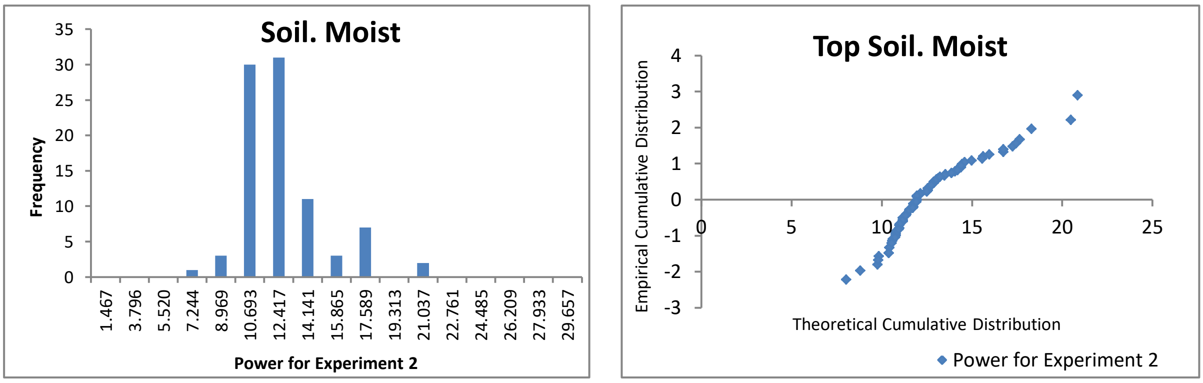


c) Slip mean = X17.46, standard deviation = 16.90

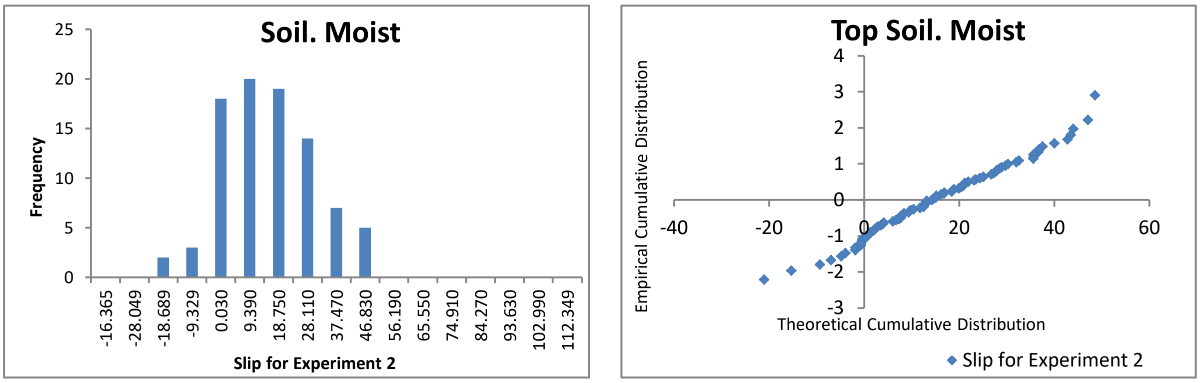
Figure A.23: Experiment 1. Top Soil.Moist



a) Velocity mean = 0.47, standard deviation = 0.09

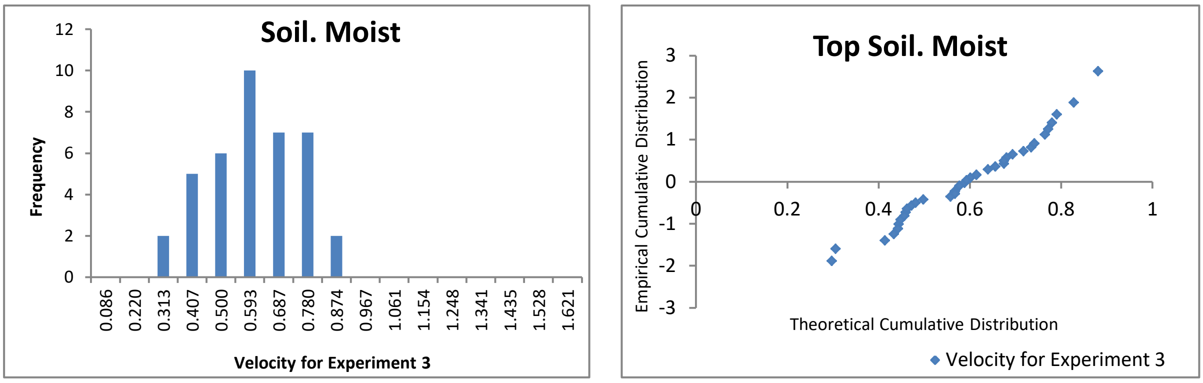


b) Power mean = 12.64, standard deviation = 3.24

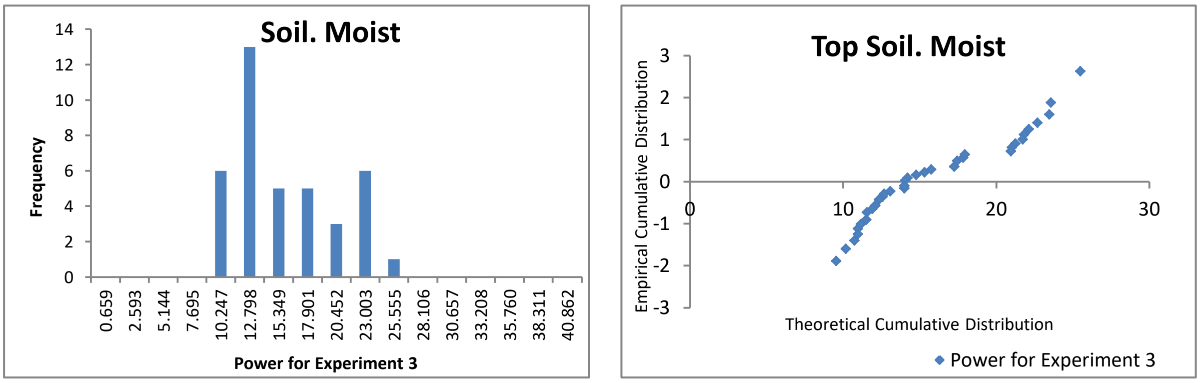


c) Slip mean = 17.04, standard deviation = 16.16

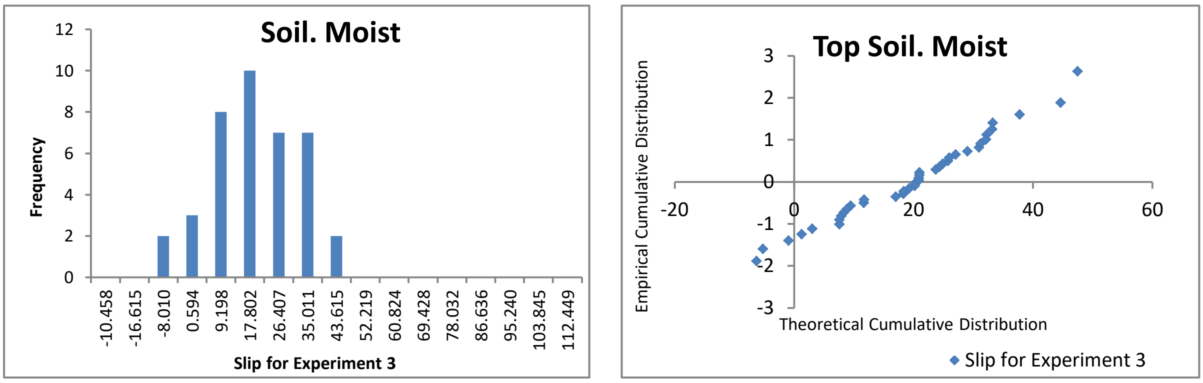
Figure A.24: Experiment 2. Top Soil.Moist



a) Velocity mean = 0.60, standard deviation = 0.14

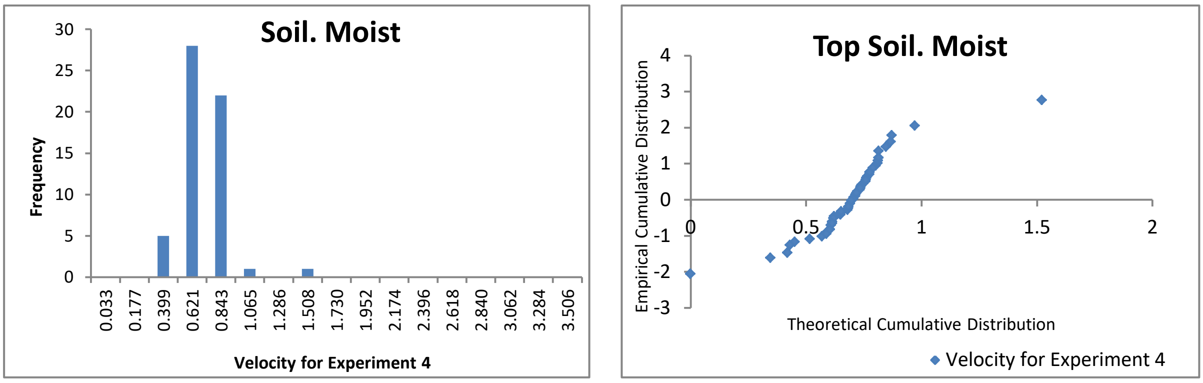


b) Power mean = 15.74, standard deviation = 4.81

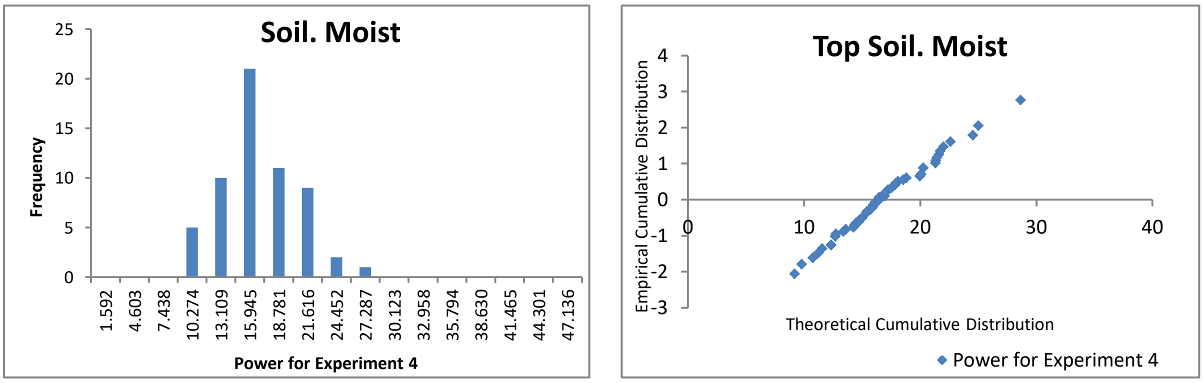


c) Slip mean = 19.69, standard deviation = 13.54

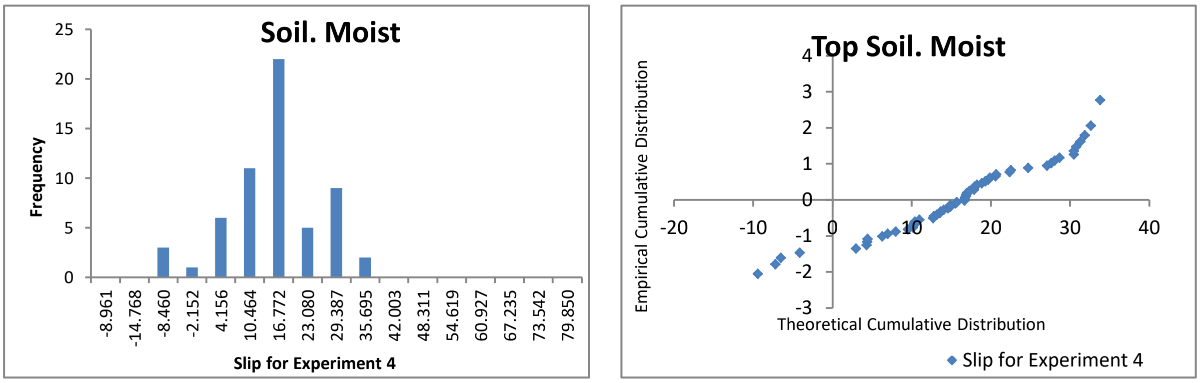
Figure A.25: Experiment 3. Top Soil. Moist



a) Velocity mean = 0.67, standard deviation = 0.15

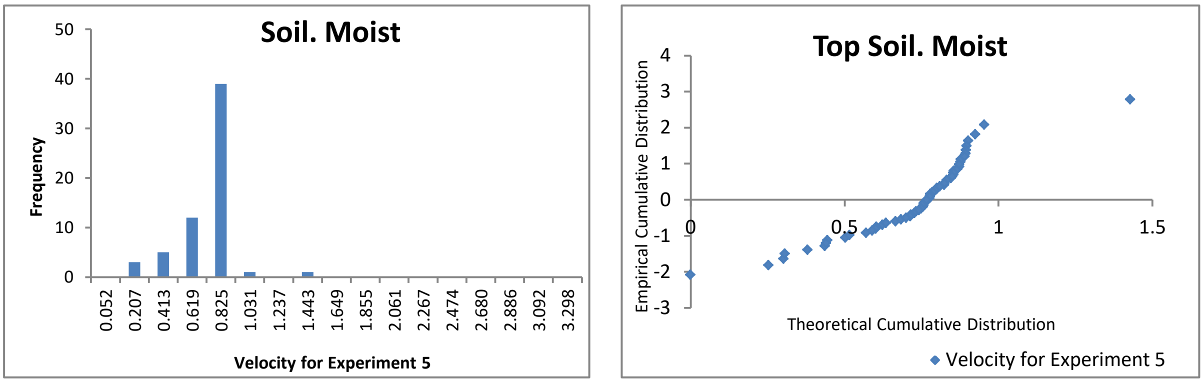


b) Power mean = 16.93, standard deviation = 4.58

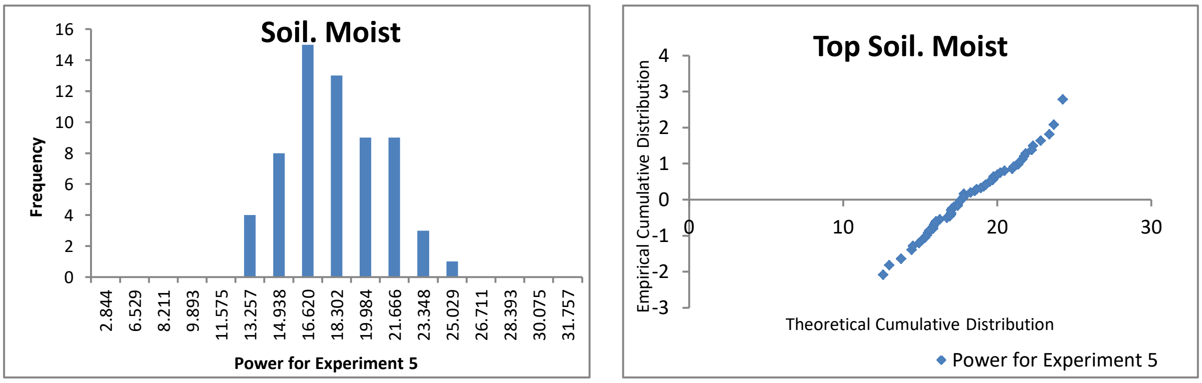


c) Slip mean = 19.48, standard deviation = 11.29

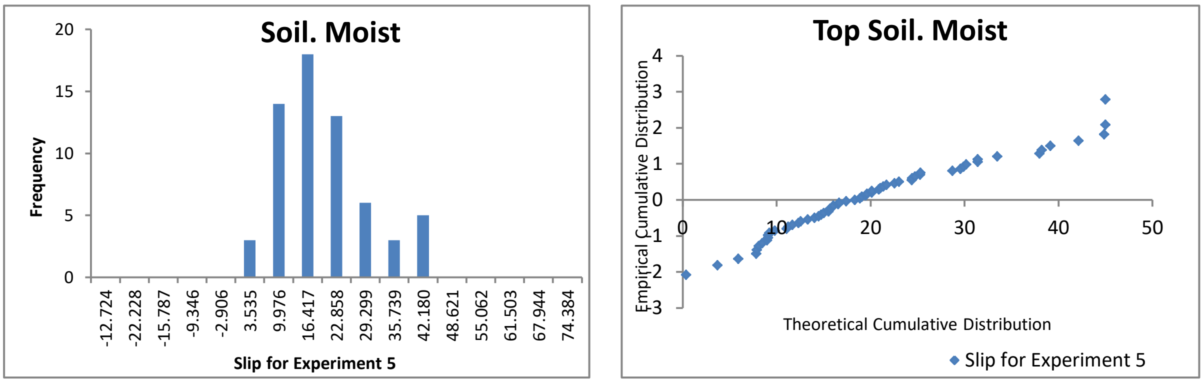
Figure A.26: Experiment 4. Top Soil. Moist



a) Velocity mean = 0.72, standard deviation = 0.16



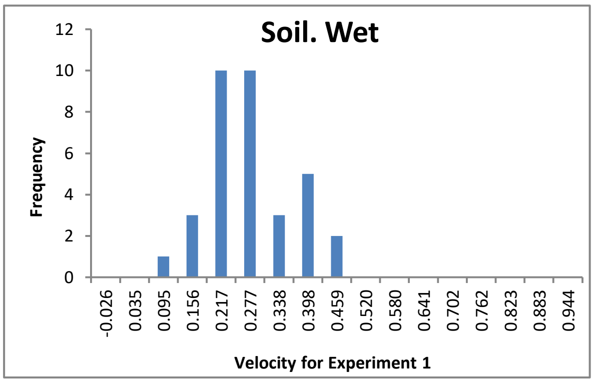
b) Power mean = 18.16, standard deviation = 4.16

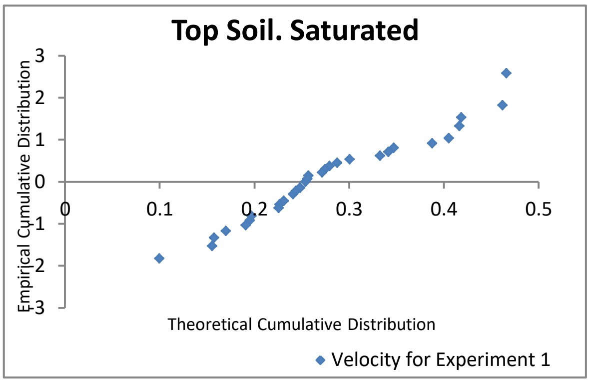


c) Slip mean = 20.12, standard deviation = 15.19

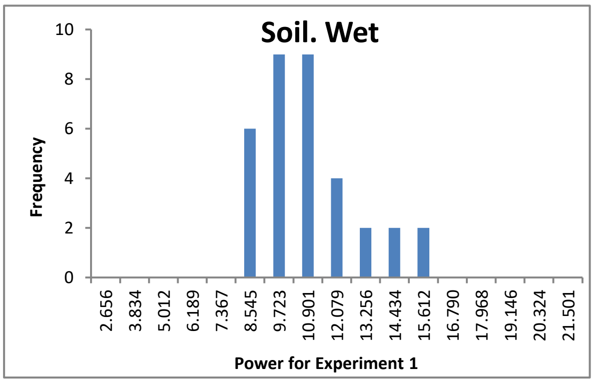
Figure A.27: Experiment 5. Top Soil. Moist

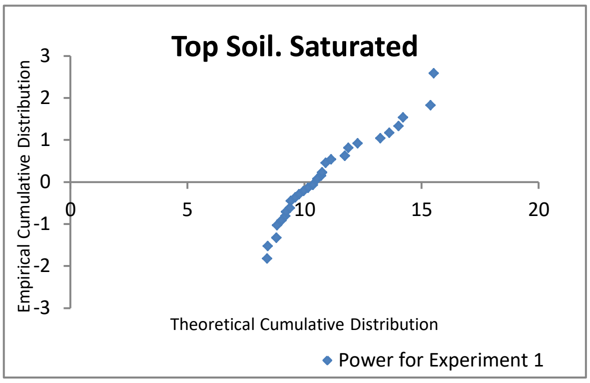
A.2.3. Top Soil - Saturated condition



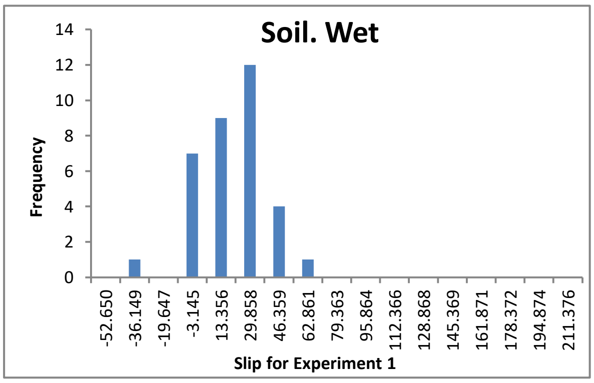


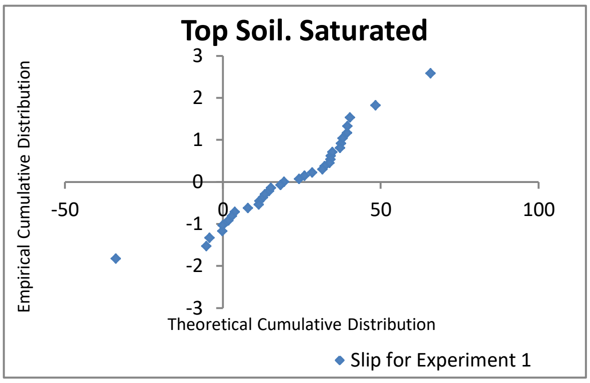
a) Velocity mean = 0.28, standard deviation = 0.09





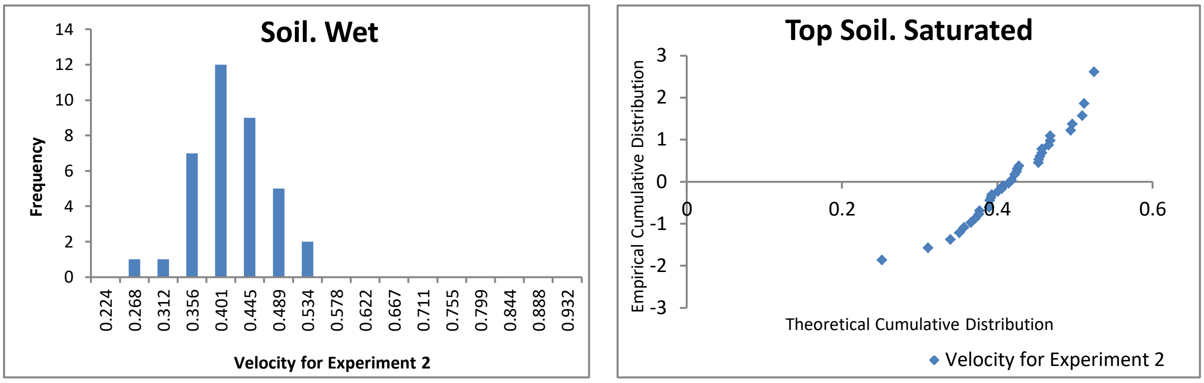
b) Power mean = 10.83, standard deviation = 2.53



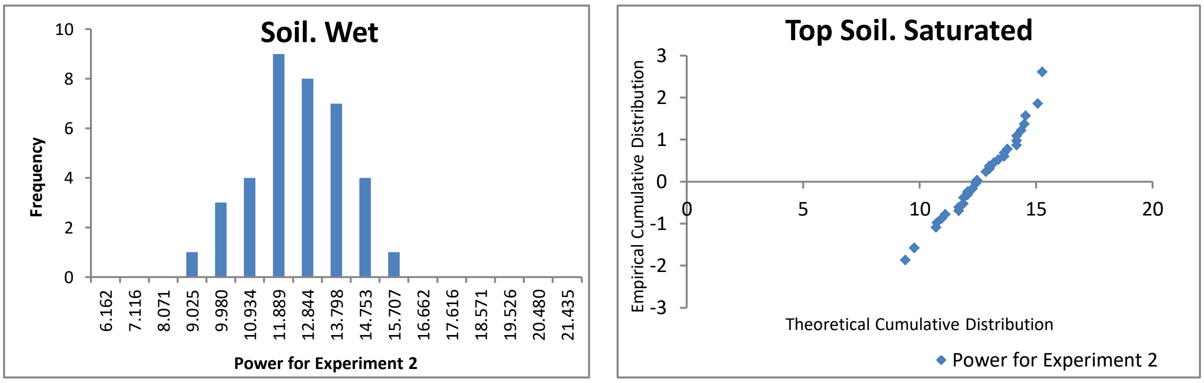


c) Slip mean = 21.03, standard deviation = 21.81

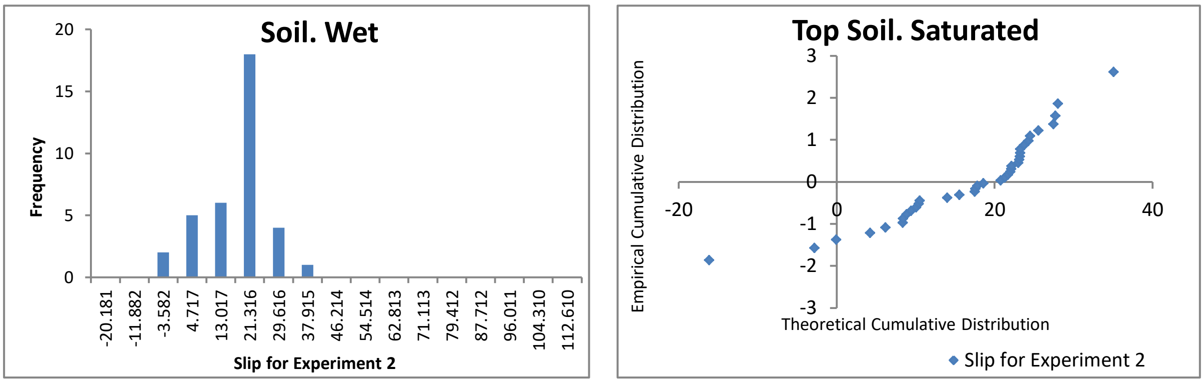
Figure A.28: Experiment 1. Top Soil.Saturated



a) Velocity mean = 0.42, standard deviation = 0.06

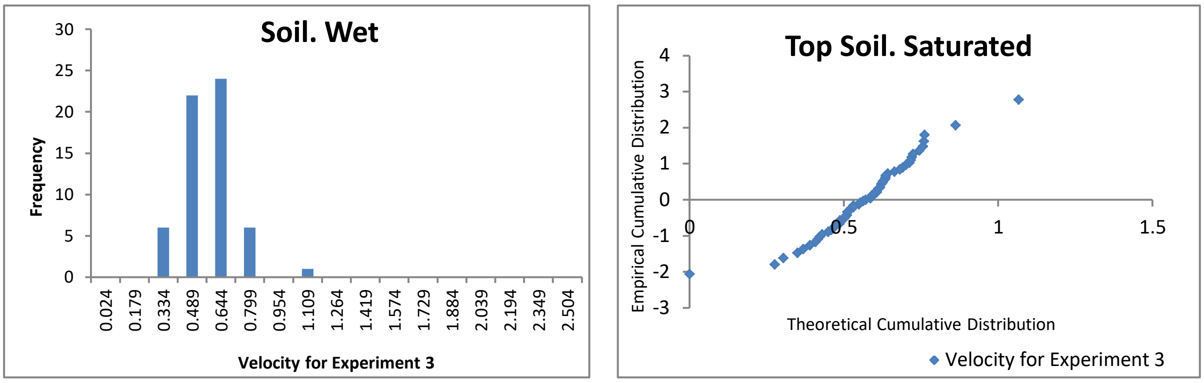


b) Power mean = 12.50, standard deviation = 1.95

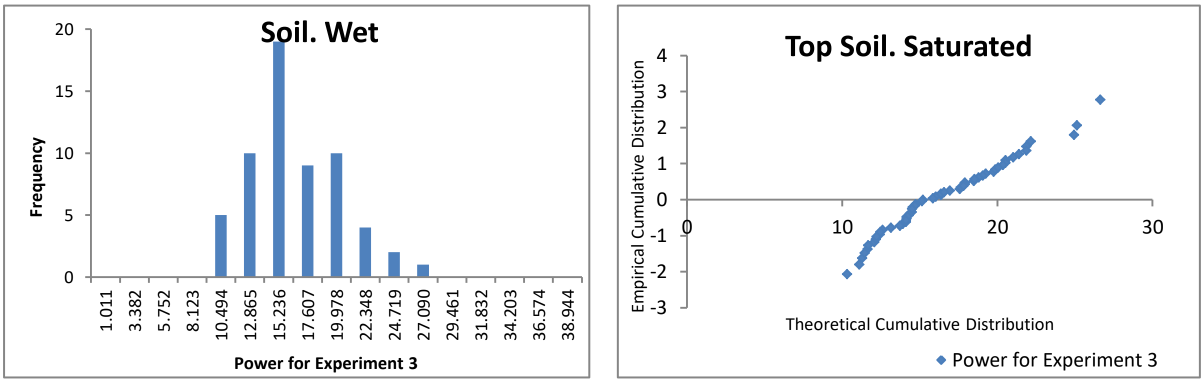


c) Slip mean = 16.78, standard deviation = 10.94

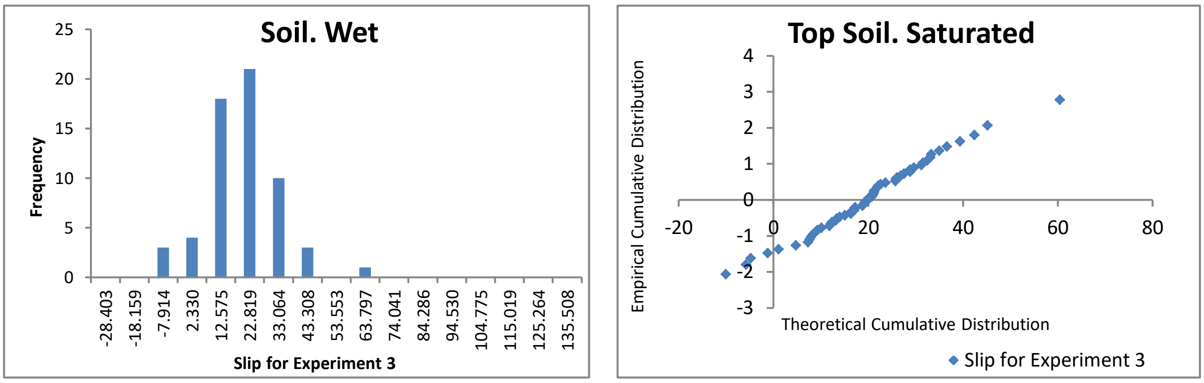
Figure A.29: Experiment 2. Top Soil. Saturated



a) Velocity mean = 0.56, standard deviation = 0.12

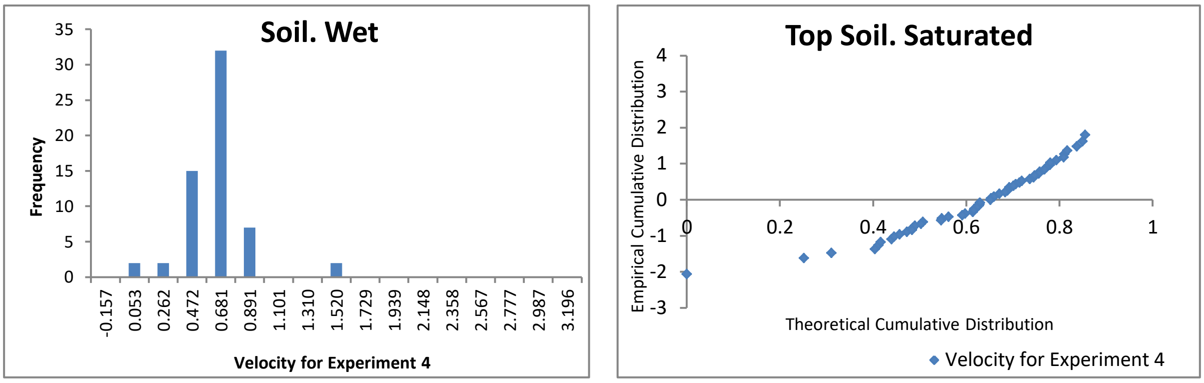


b) Power mean = 16.46, standard deviation = 4.75

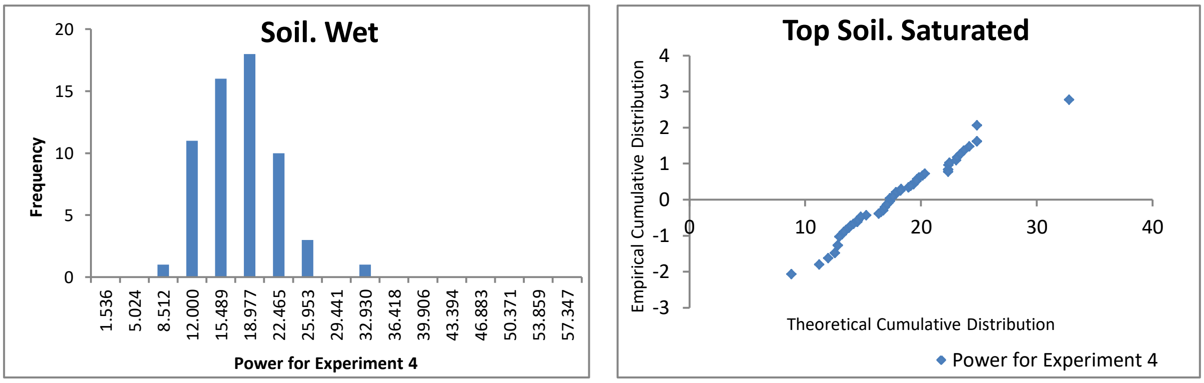


c) Slip mean = 19.88 standard deviation = 14.39

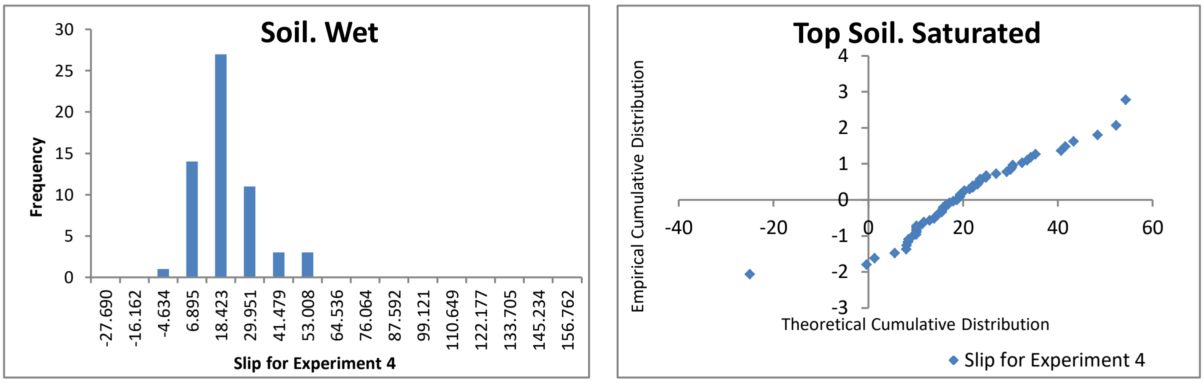
Figure A.30: Experiment 3. Top Soil. Saturated



a) Velocity mean = 0.65, standard deviation = 0.17

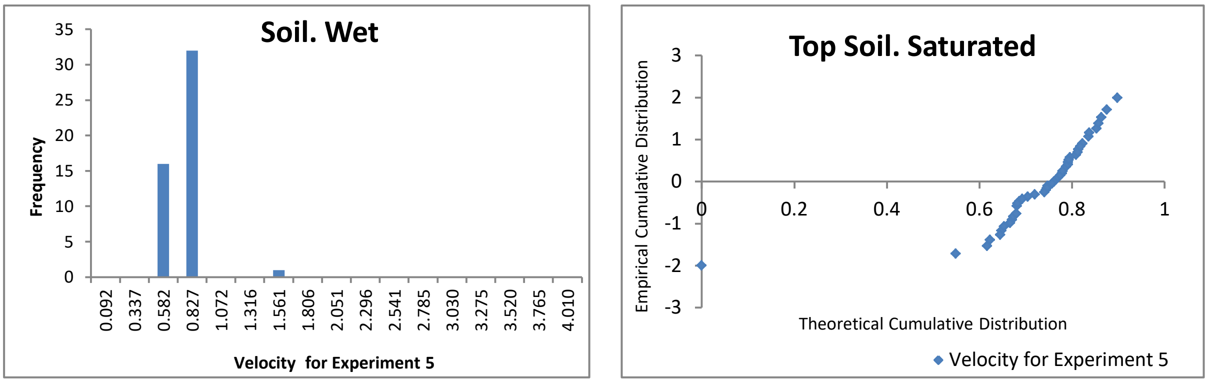


b) Power mean = 17.86, standard deviation = 4.86

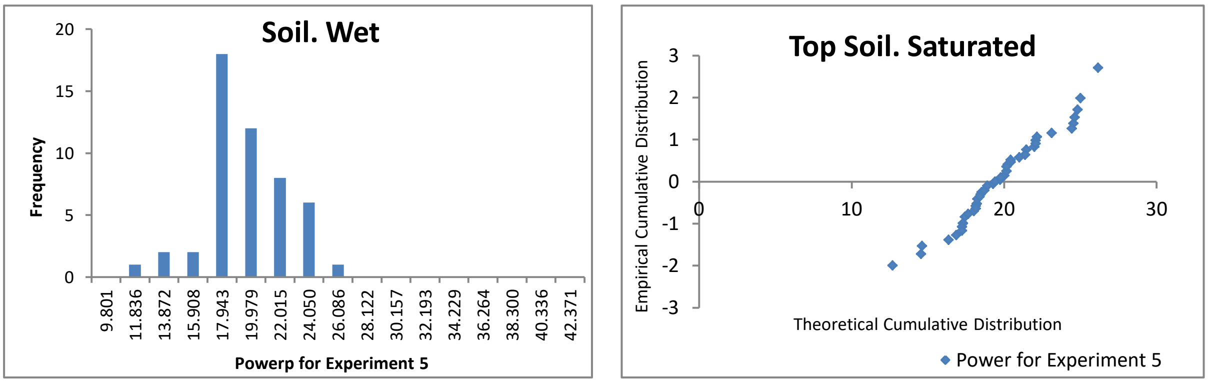


c) Slip mean = 20.15, standard deviation = 14.02

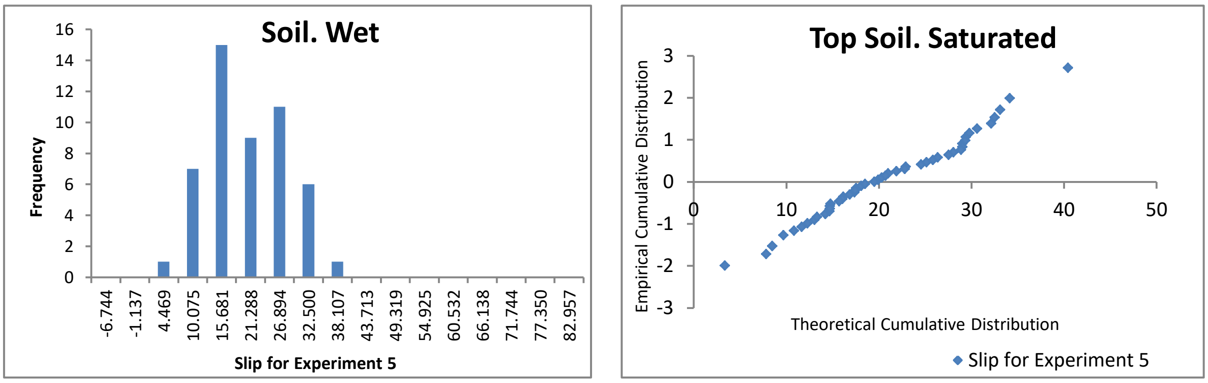
Figure A.31: Experiment 4. Top Soil. Saturated



a) Velocity mean = 0.75, standard deviation = 0.08



b) Power mean = 19.74, standard deviation = 2.97

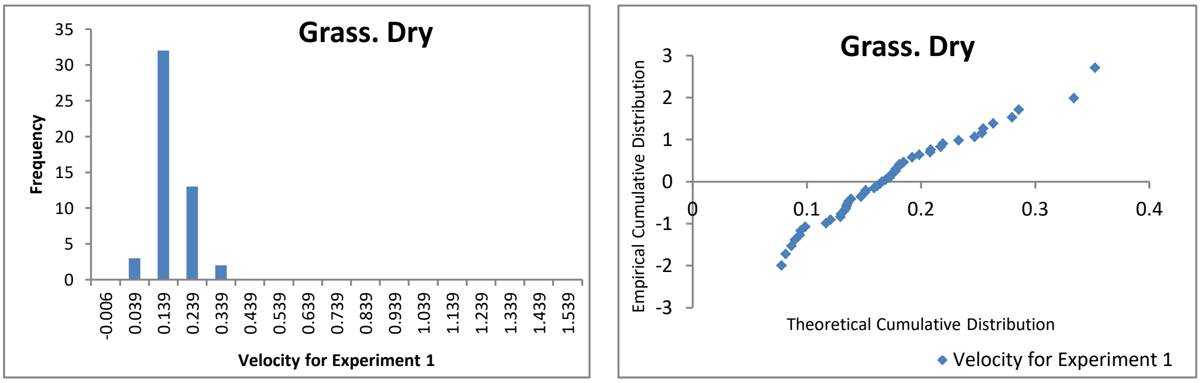


c) Slip mean = 20.64, standard deviation = 8.19

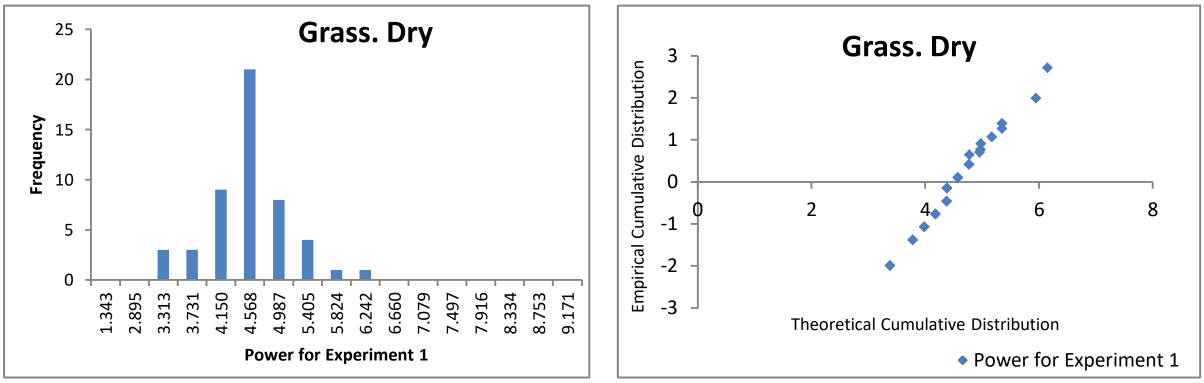
Figure A.32: Experiment 5. Top Soil. Saturated

A.3. Experiments for Grass

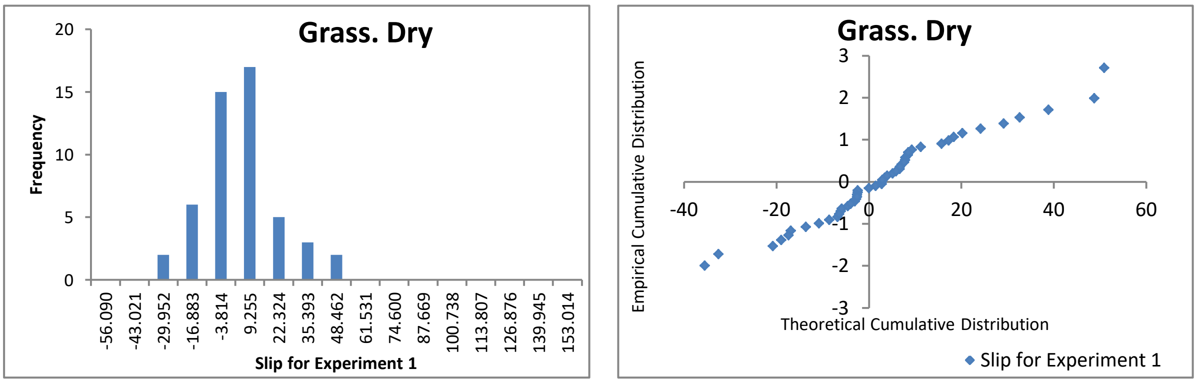
A.3.1. Grass - Dry condition



a) Velocity mean = 1.74, standard deviation = 0.06

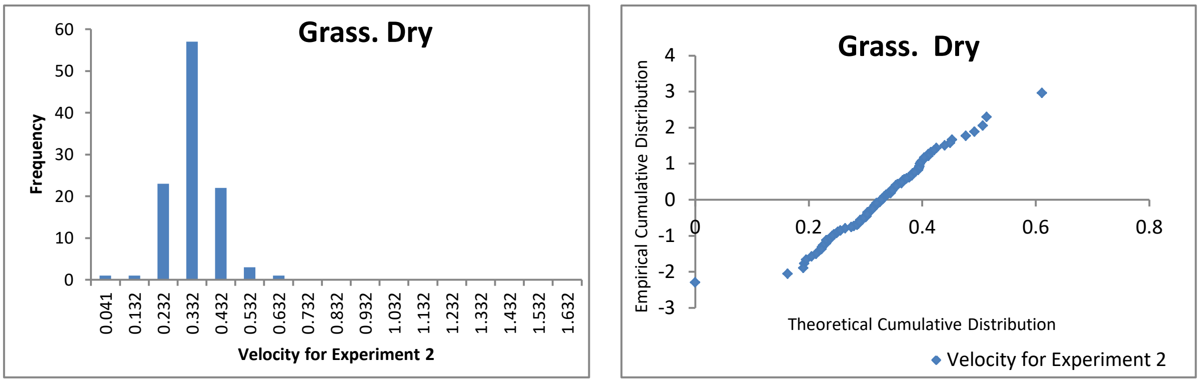


b) Power mean = 4.53, standard deviation = 0.62

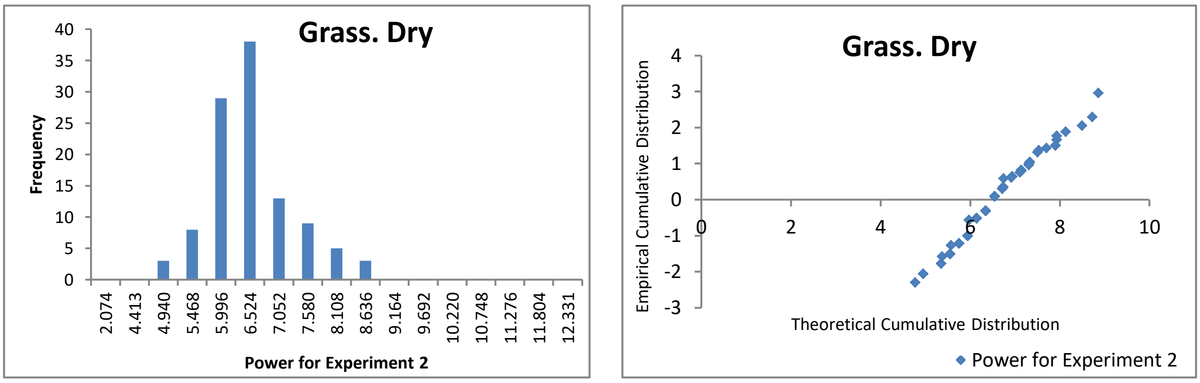


c) Slip mean = 3.68, standard deviation = 17.76

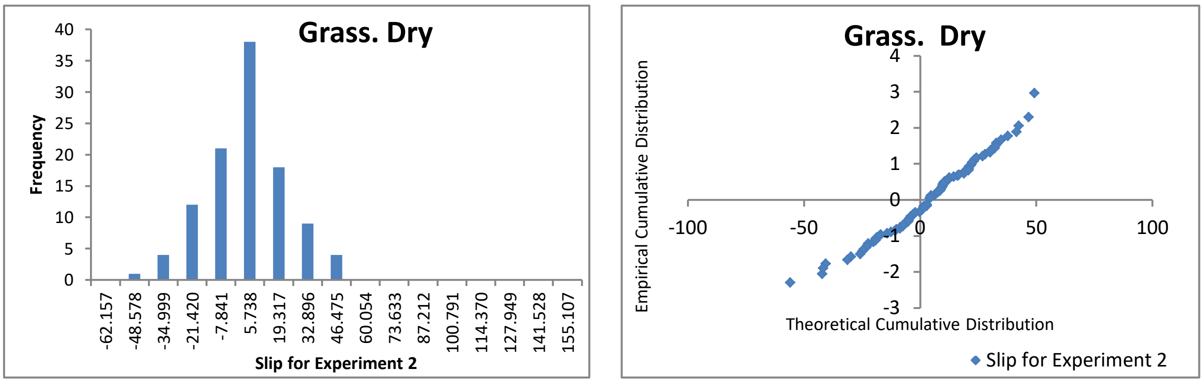
Figure A.33: Experiment. 1 Grass. Dry



a) Velocity mean = 0.33, standard deviation = 0.08

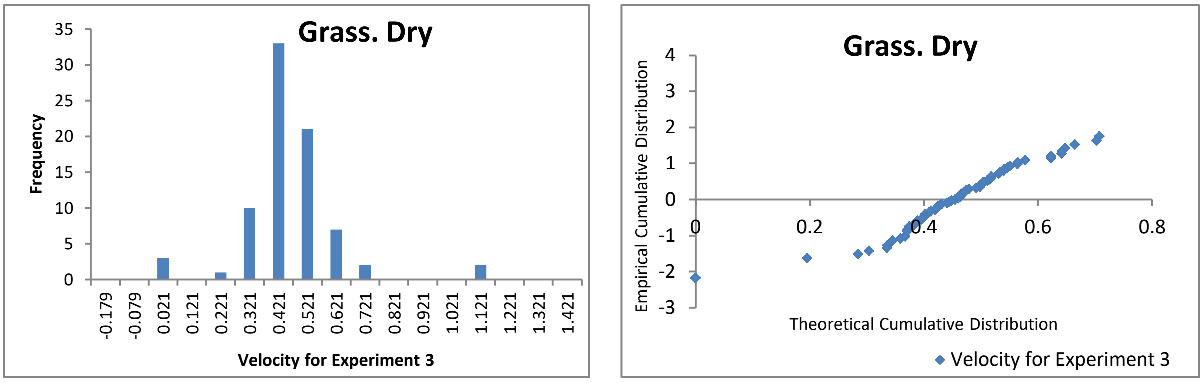


b) Power mean = 6.52, standard deviation = 0.79

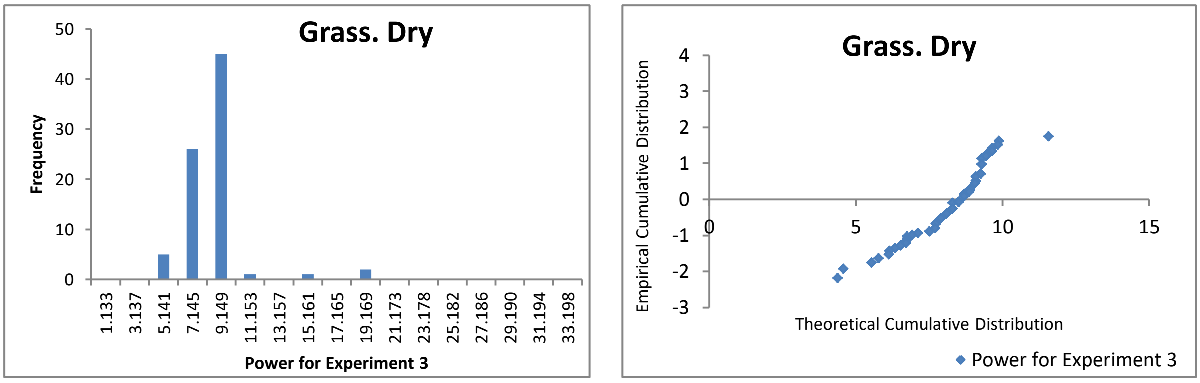


c) Slip mean = 3.79, standard deviation = 19.72

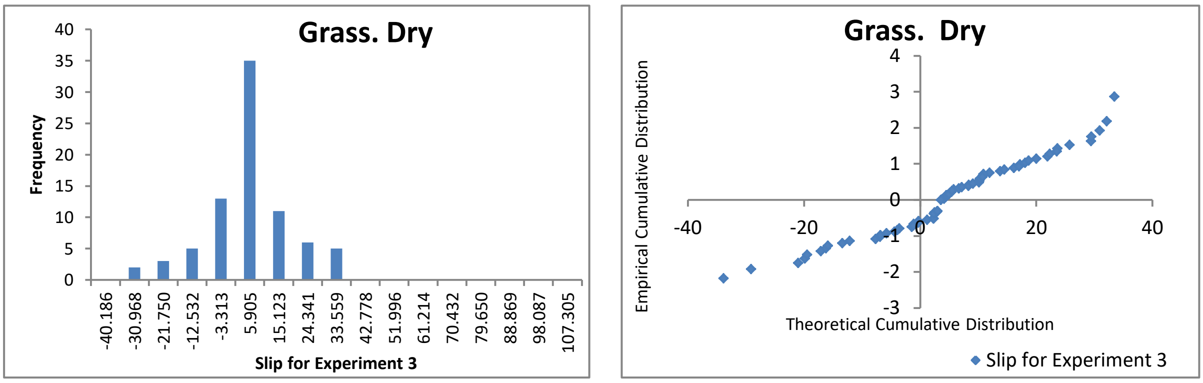
Figure A.34: Experiment 2. Grass. Dry



a) Velocity mean = 0.47, standard deviation = 0.20

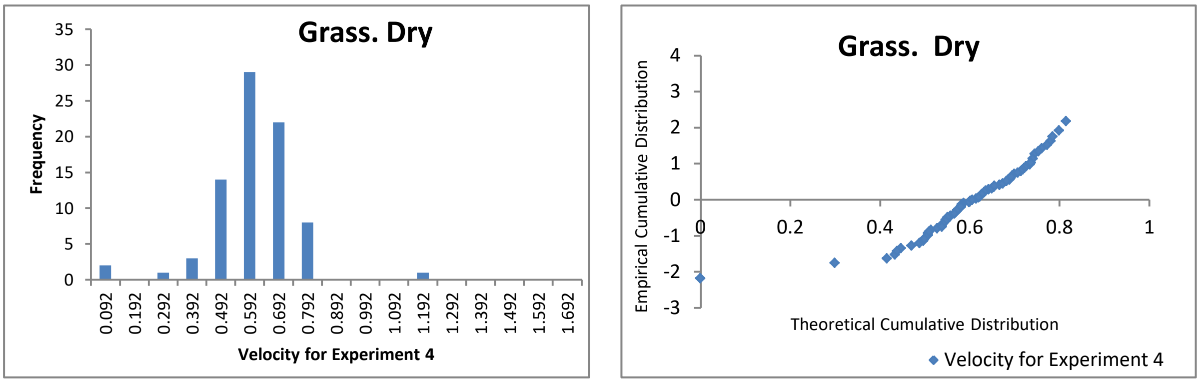


b) Power mean = 8.58, standard deviation = 2.15

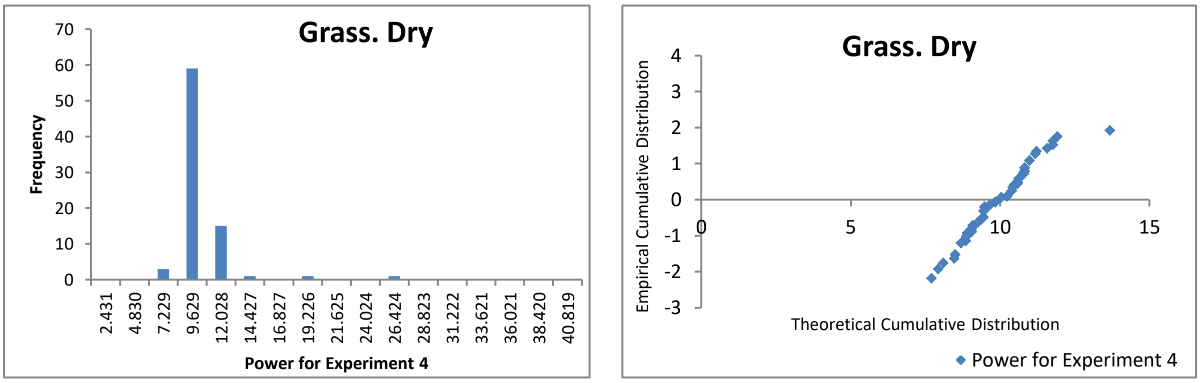


c) Slip mean = 4.85, standard deviation = 13.48

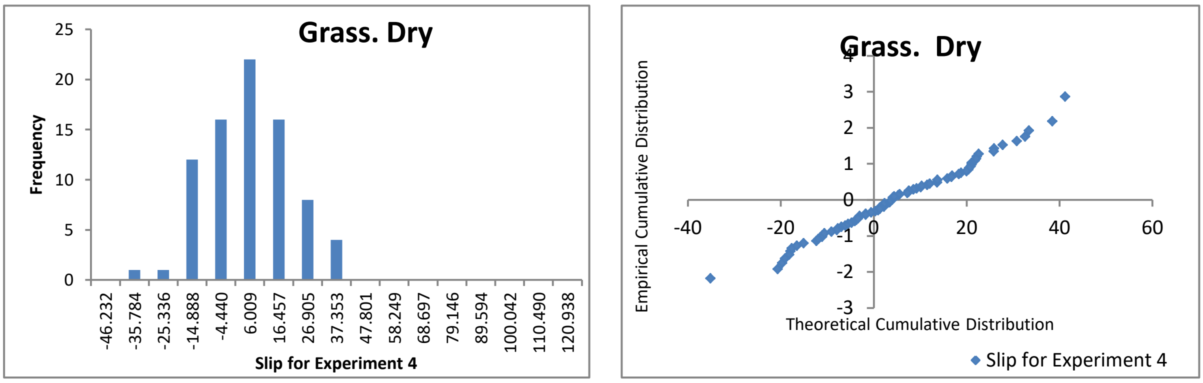
Figure A.35: Experiment 3. Grass. Dry



a) Velocity mean = 0.61, standard deviation = 0.10

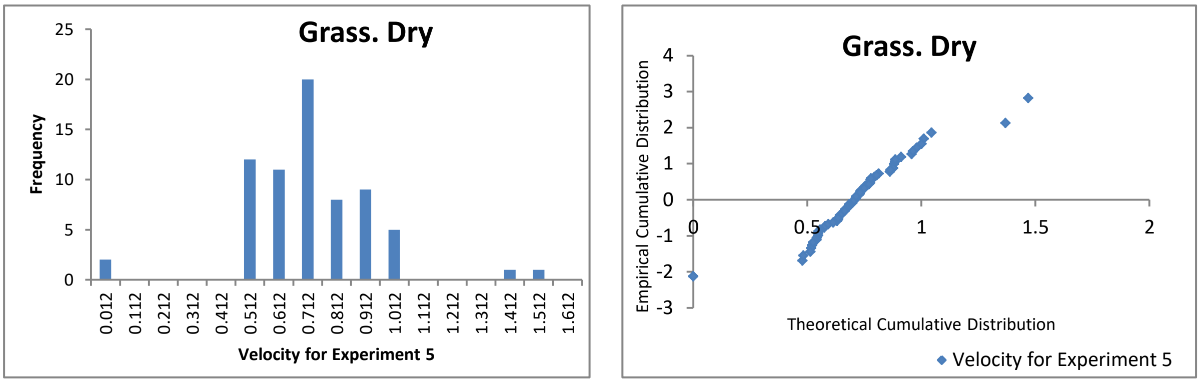


b) Power mean = 10.23, standard deviation = 2.20

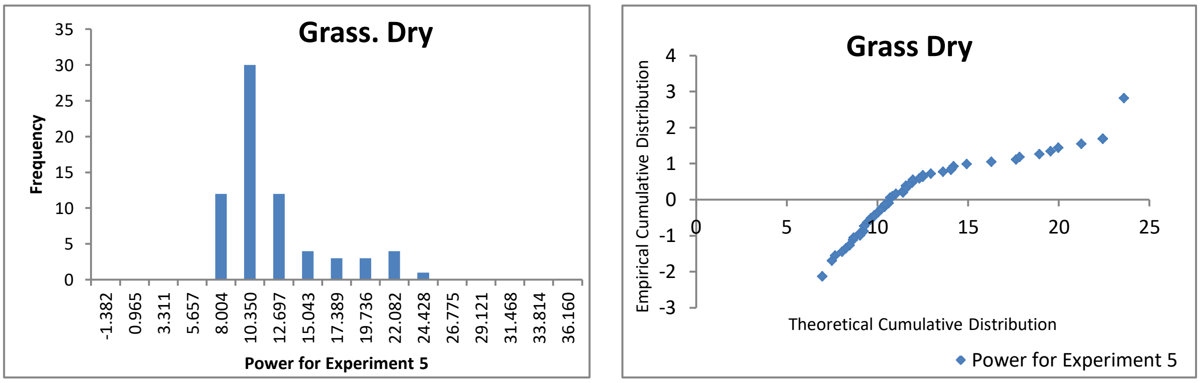


c) Slip mean = 5.39, standard deviation = 15.46

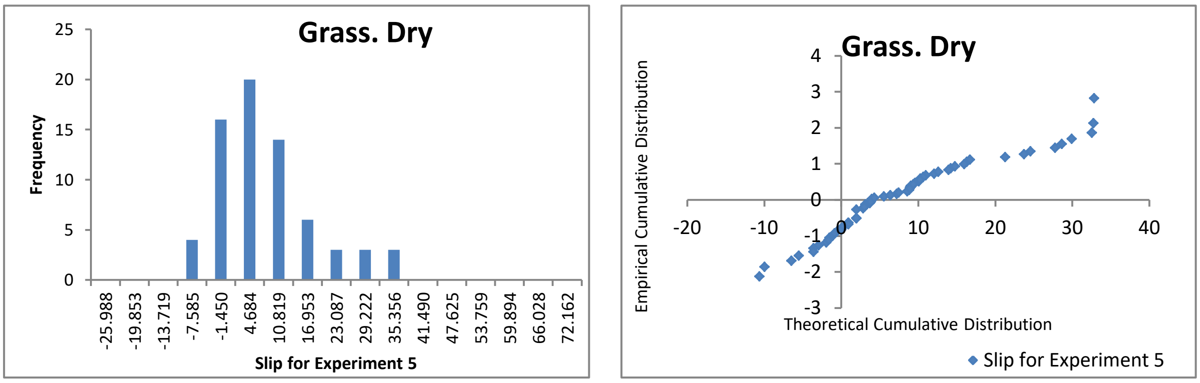
Figure A.36: Experiment 4. Grass. Dry



a) Velocity mean = 0.71, standard deviation = 0.14

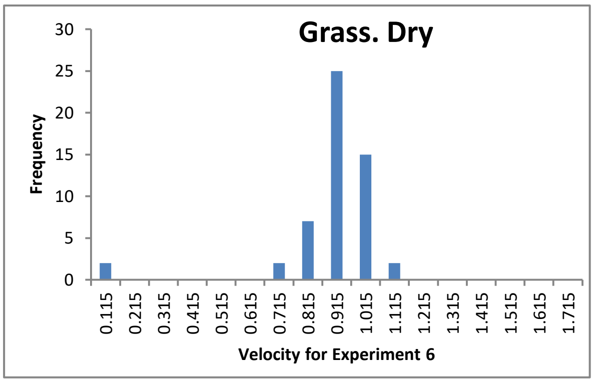


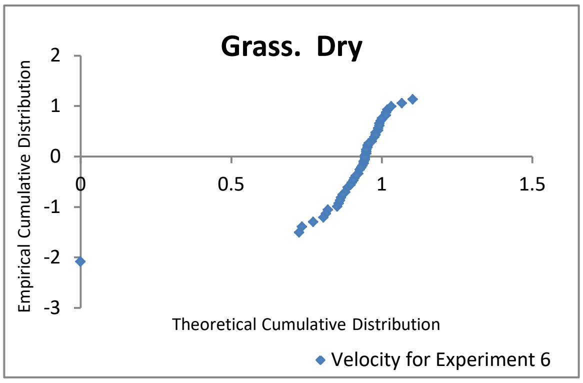
b) Power mean = 12.03, standard deviation = 4.08



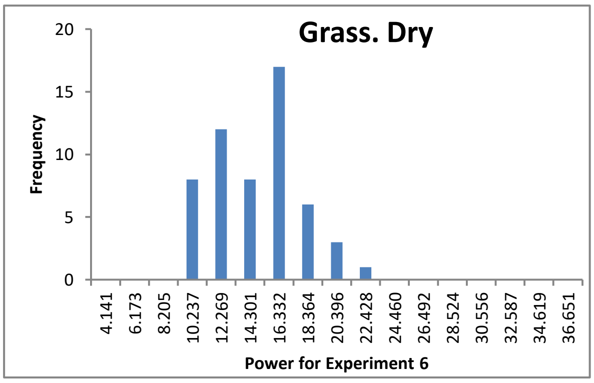
c) Slip mean = 6.44, standard deviation = 10.13

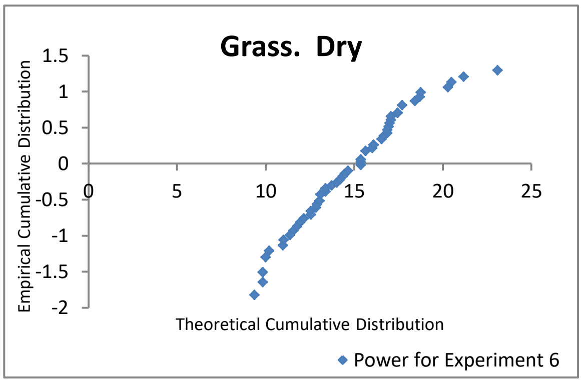
Figure A.37: Experiment 5. Grass. Dry



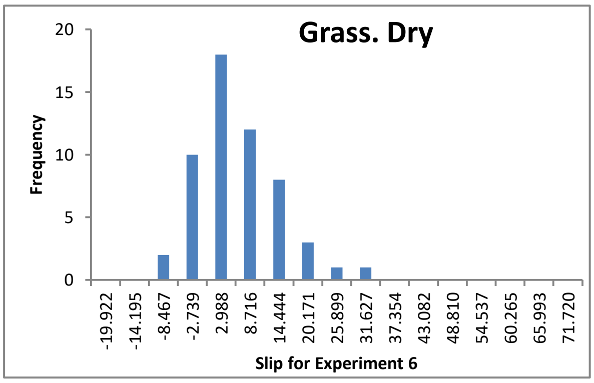


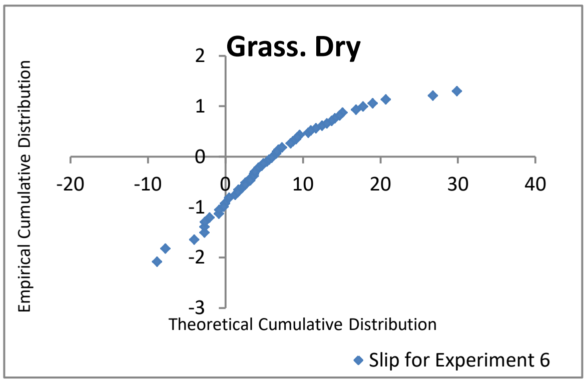
a) Velocity mean = 0.92, standard deviation = 0.08





b) Power mean = 14.76, standard deviation = 3.20

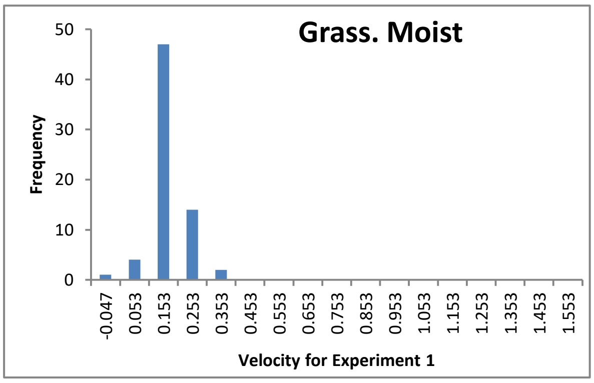


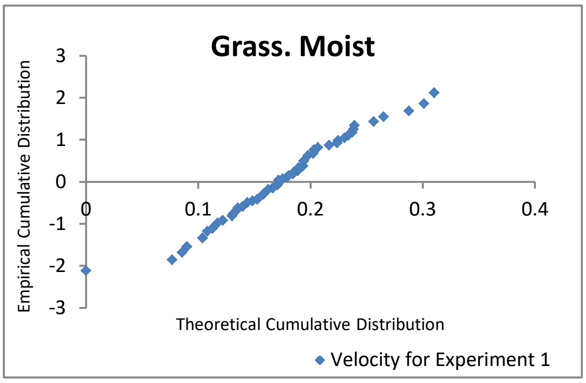


c) Slip mean = 6.45, standard deviation = 7.84

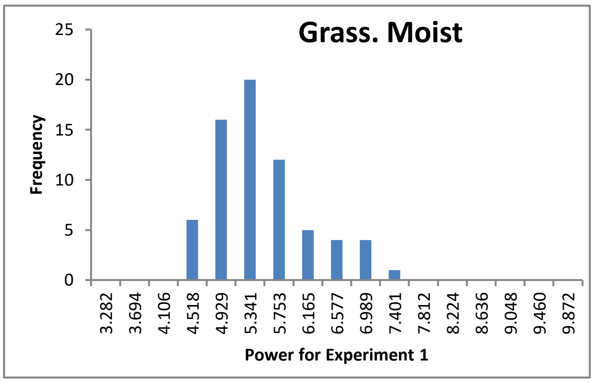
Figure A.38: Experiment 6. Grass. Dry

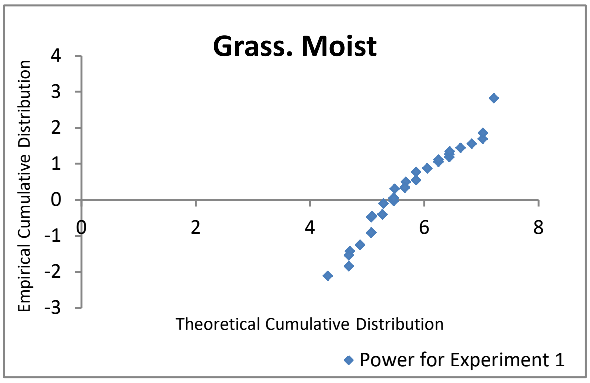
A.3.2. Grass - Moist condition



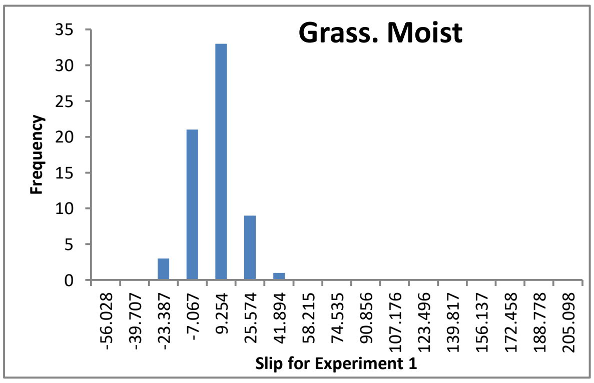


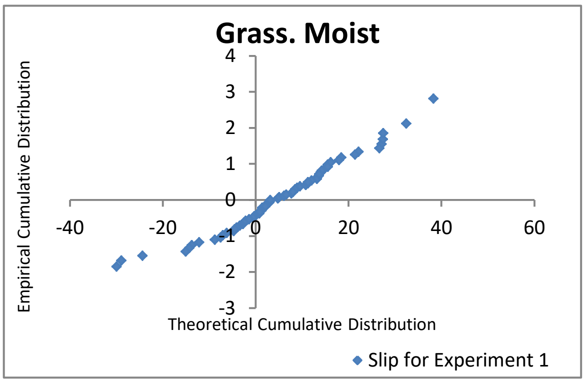
a) Velocity mean = 0.17, standard deviation = 0.05





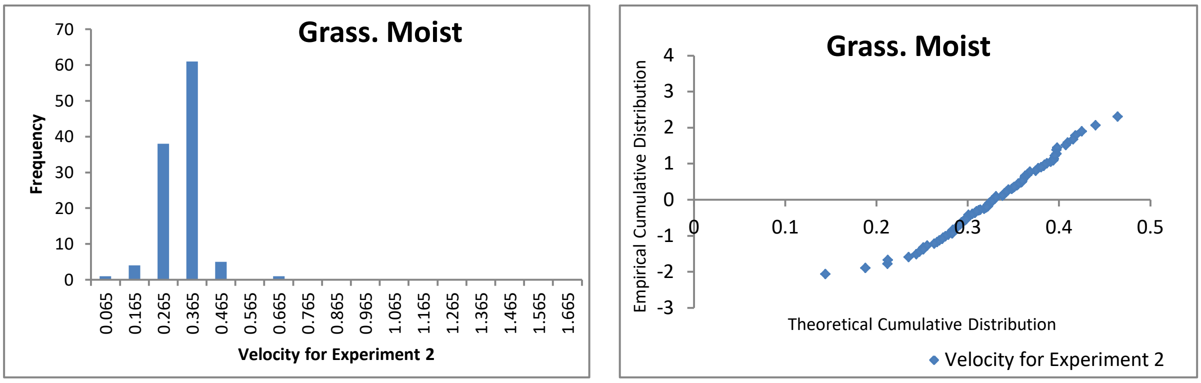
b) Power mean = 5.54, standard deviation = 0.68



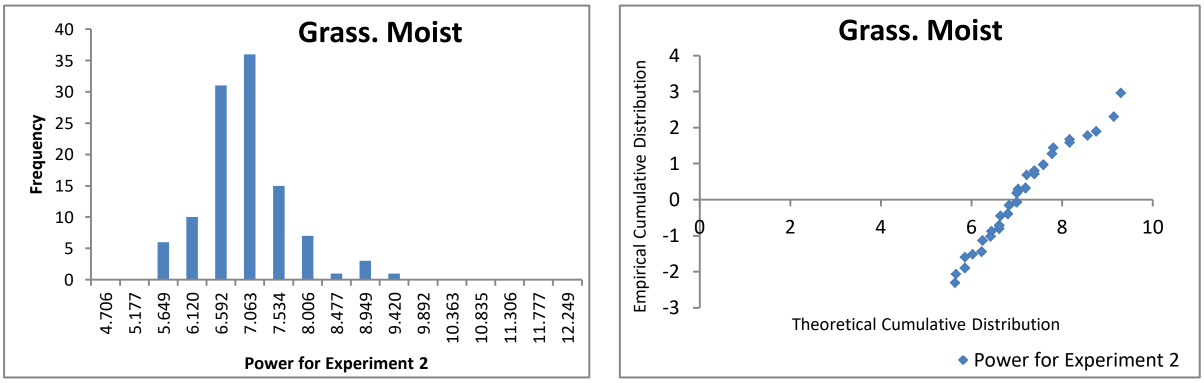


c) Slip mean = 4.44, standard deviation = 17.31

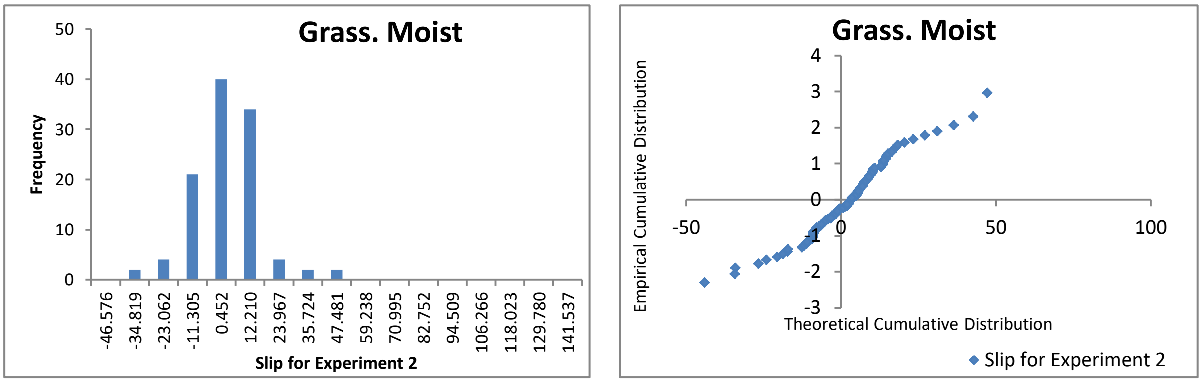
Figure A.39: Experiment 1 Grass.Moist



a) Velocity mean = 0.33, standard deviation = 0.05

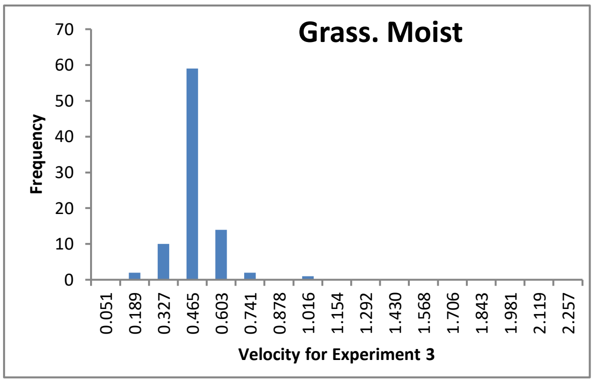


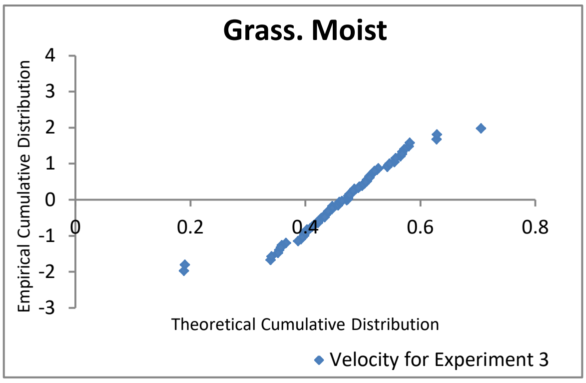
b) Power mean = 7.00, standard deviation = 0.69



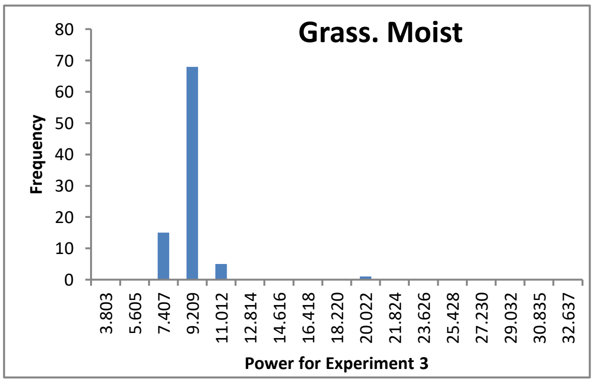
c) Slip mean = 4.76, standard deviation = 14.14

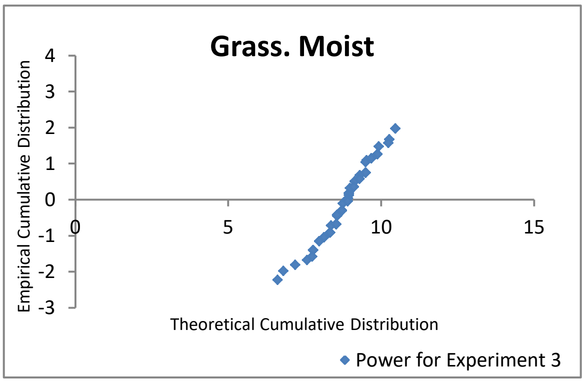
Figure A.40: Experiment 2. Grass.Moist



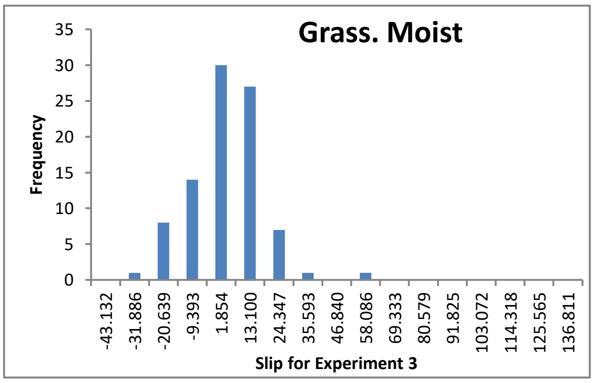


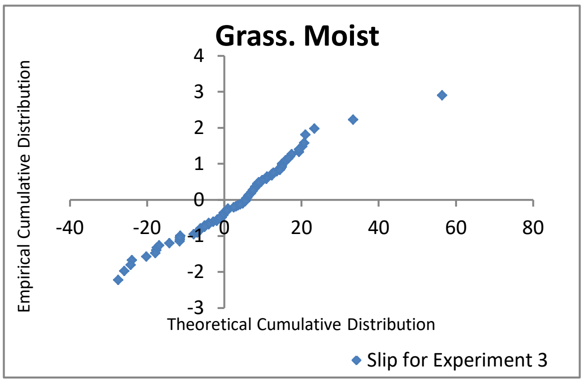
a) Velocity mean = 0.47, standard deviation = 0.09





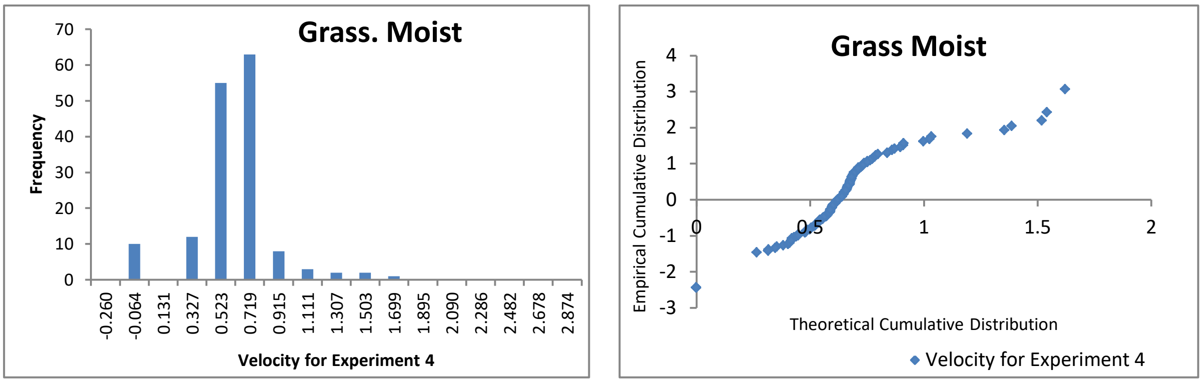
b) Power mean = 8.97, standard deviation = 1.42



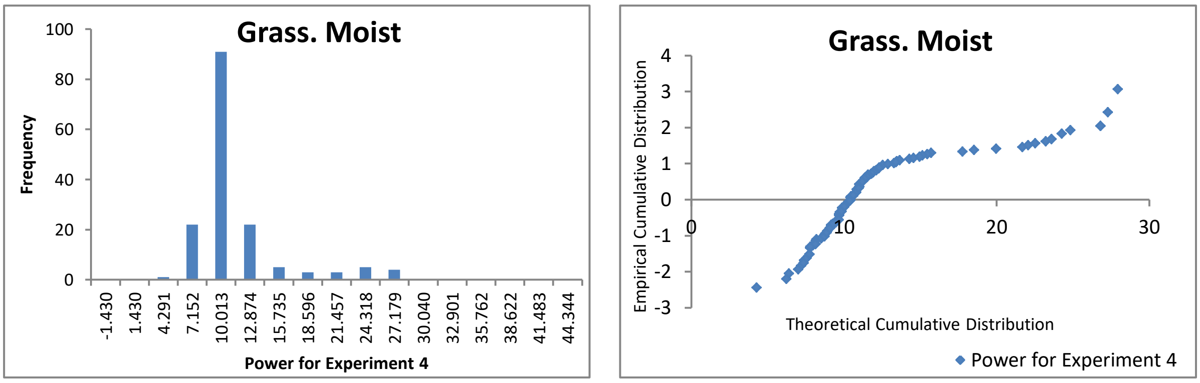


c) Slip mean = 6.02, standard deviation = 13.81

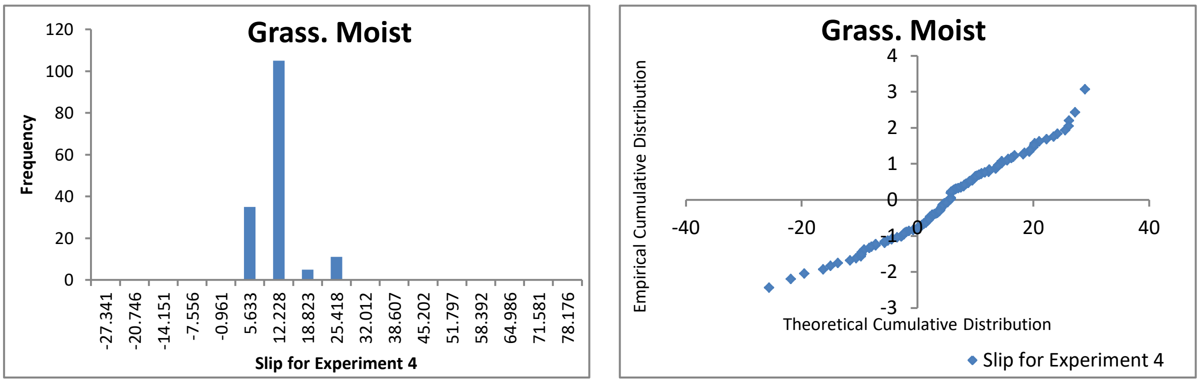
Figure A.41: Experiment 3. Grass. Moist



a) Velocity mean = 0.60, standard deviation = 0.14

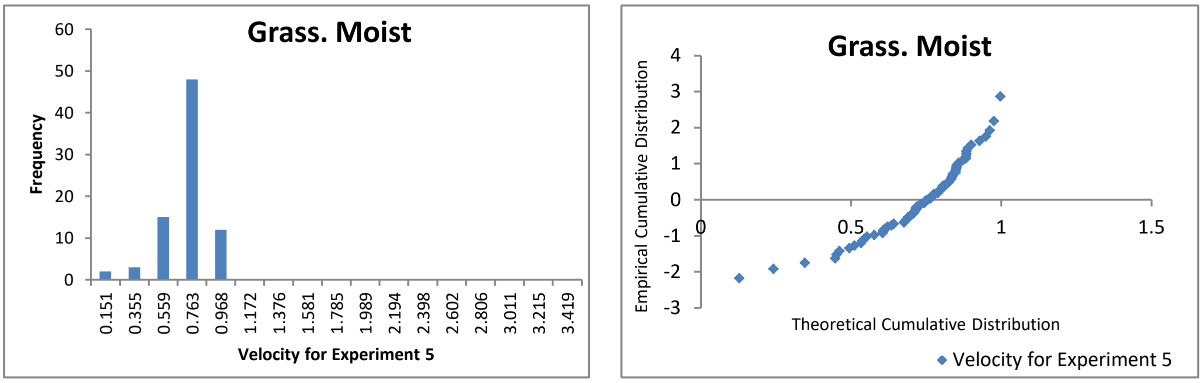


b) Power mean = 11.49, standard deviation = 4.40

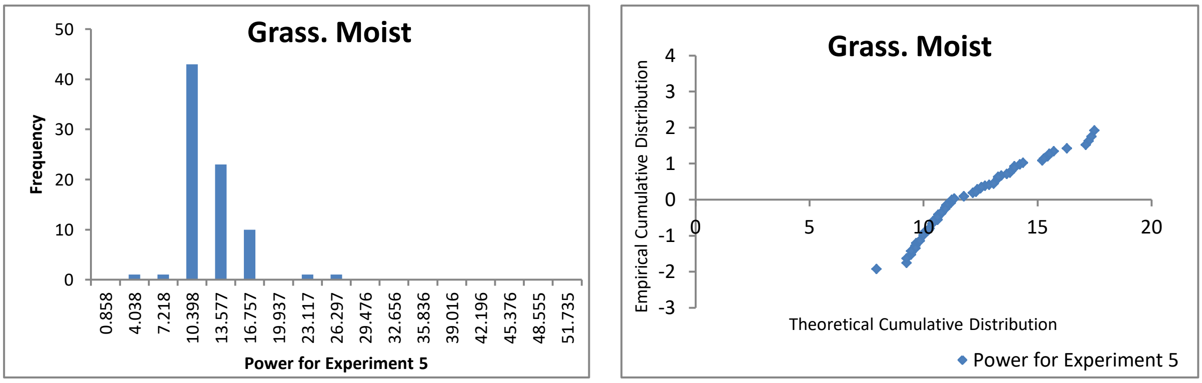


c) Slip mean = 6.75, standard deviation = 9.85

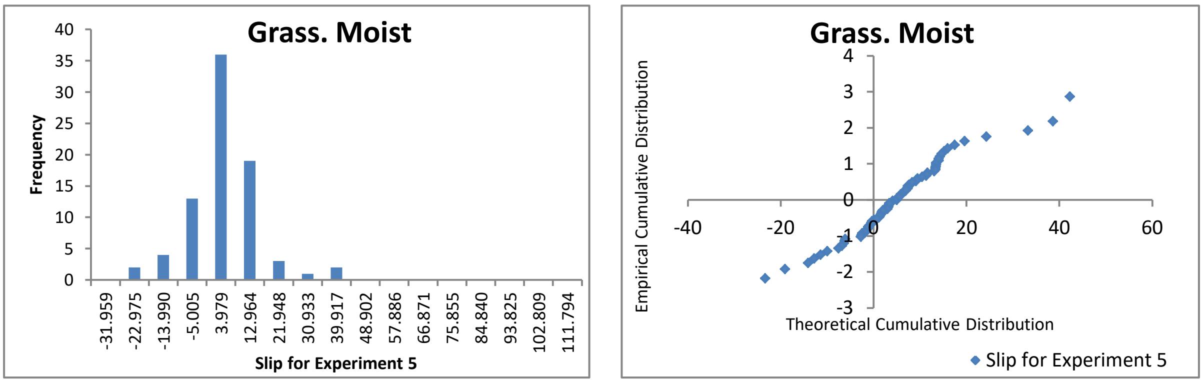
Figure A.42: Experiment 4. Grass. Moist



a) Velocity mean = 0.73, standard deviation = 0.16

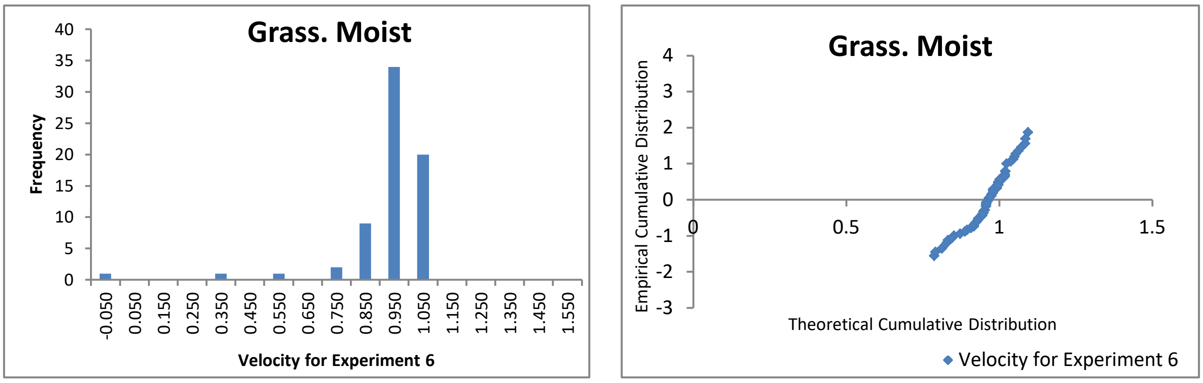


b) Power mean = 12.28, standard deviation = 3.28

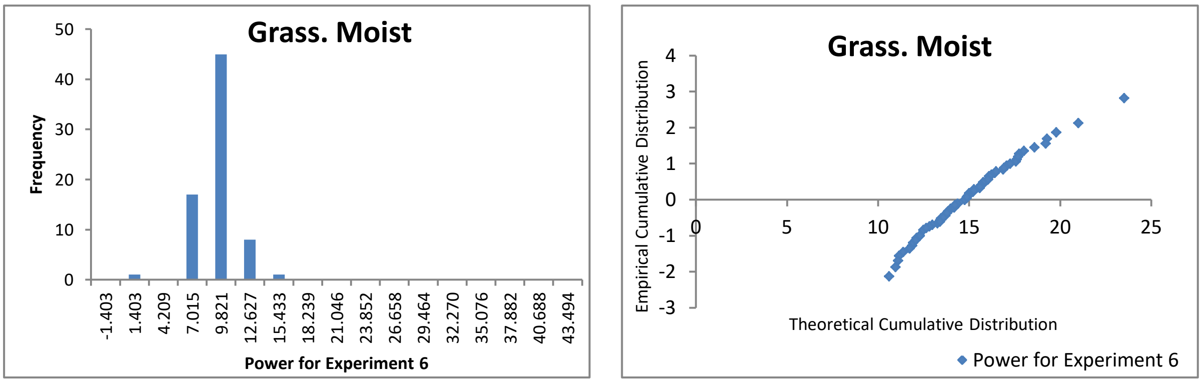


c) Slip mean = 6.98, standard deviation = 10.93

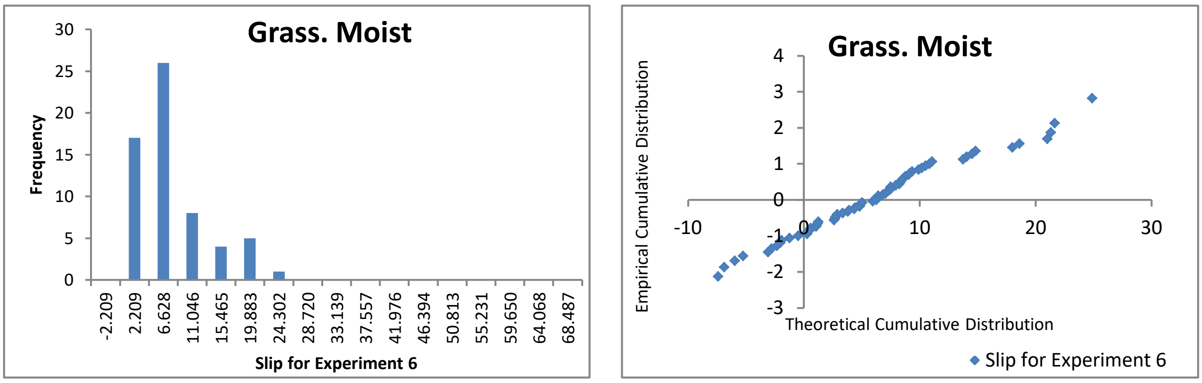
Figure A.43: Experiment 5. Grass. Moist



a) Velocity mean = 0.98, standard deviation = 0.25



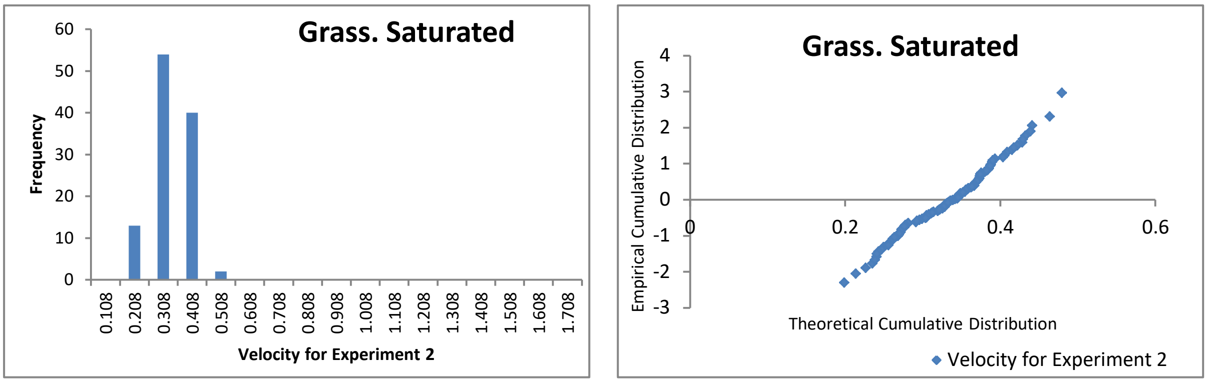
b) Power mean = 14.92, standard deviation = 3.03



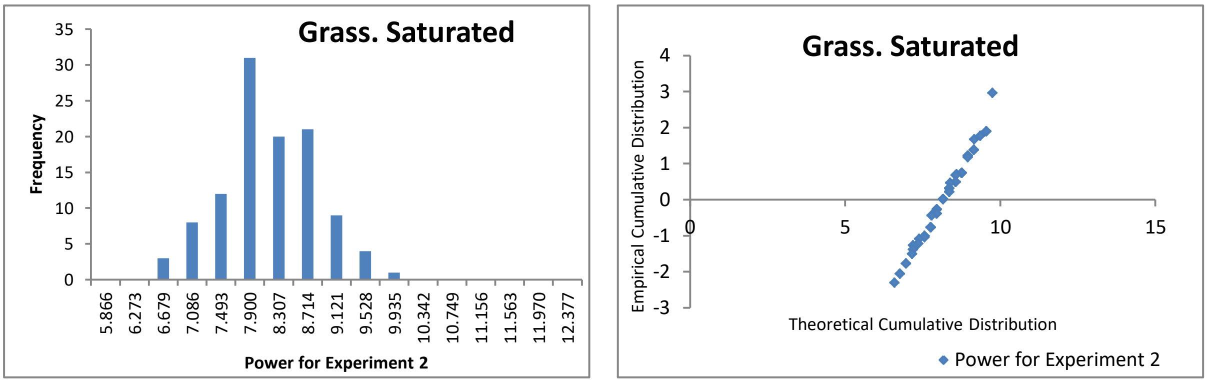
c) Slip mean = 7.52, standard deviation = 7.32

Figure A.44: Experiment 6. Grass. Moist

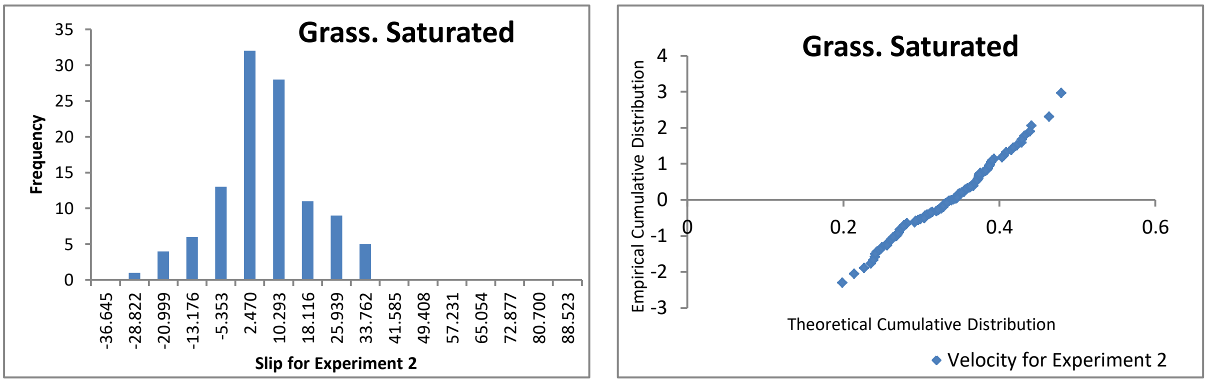
A.3.3. Grass - Saturated condition



a) Velocity mean = 0.33, standard deviation = 0.06

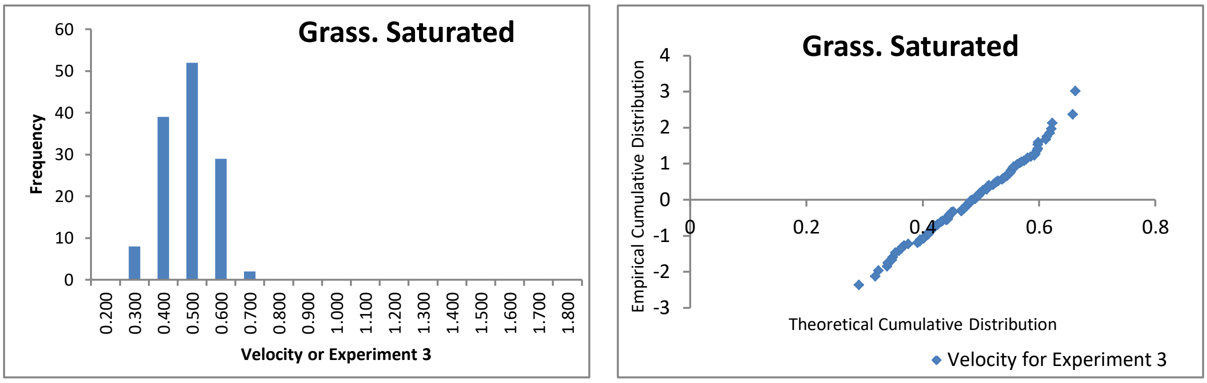


b) Power mean = 8.14, standard deviation = 0.69

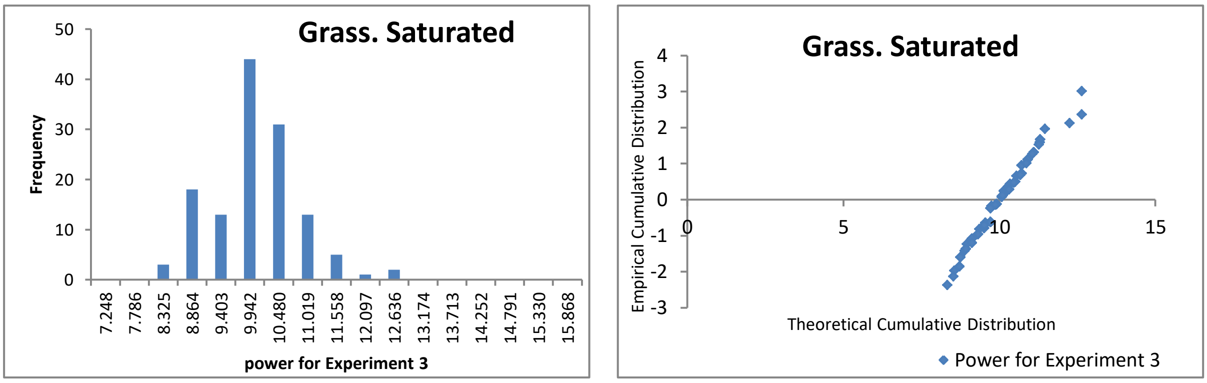


c) Slip mean = 6.28, standard deviation = 13.00

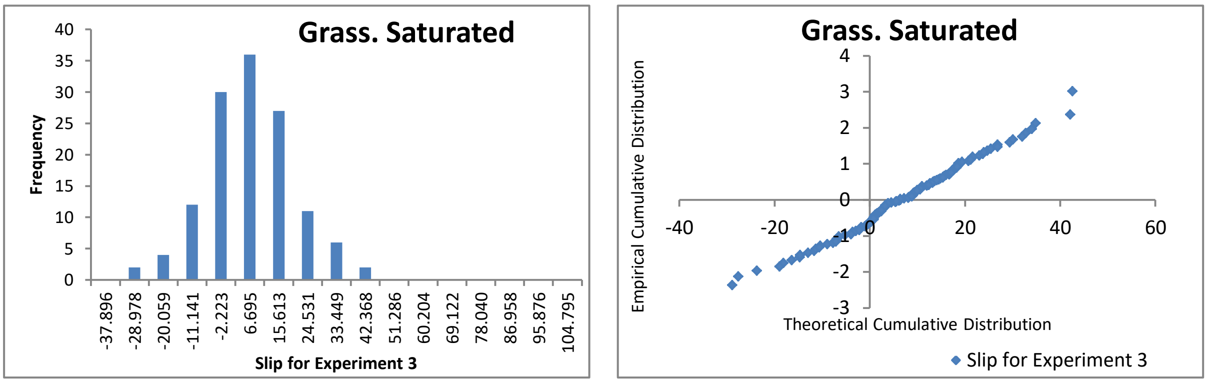
Figure A.45: Experiment 2. Grass. Saturated



a) Velocity mean = 0.49, standard deviation = 0.08

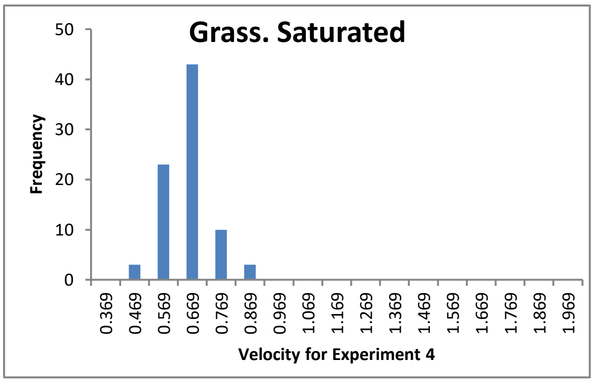


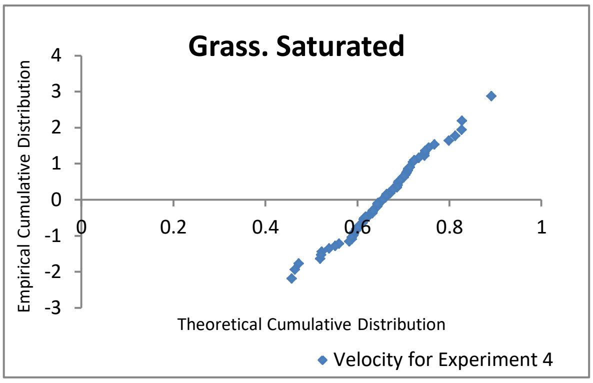
b) Power mean = 10.05, standard deviation = 0.84



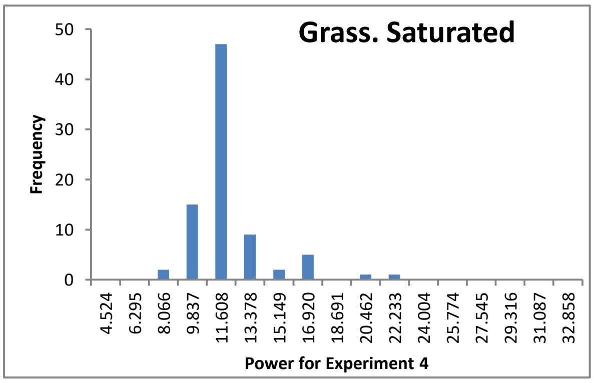
c) Slip mean = 7.09, standard deviation = 13.51

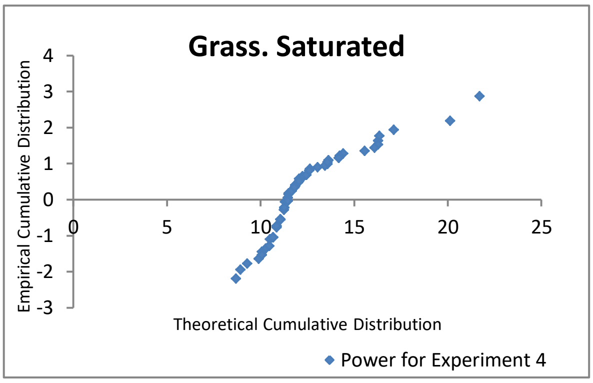
Figure A.46: Experiment 3. Grass. Saturated



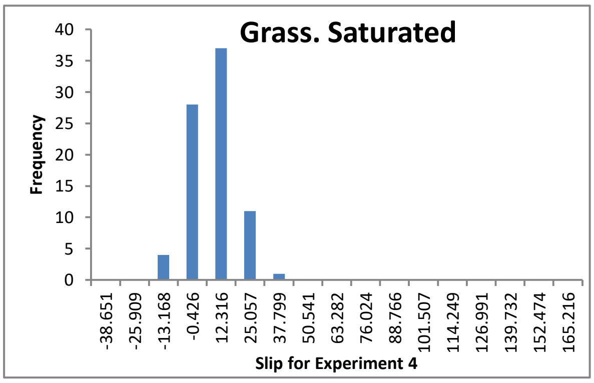


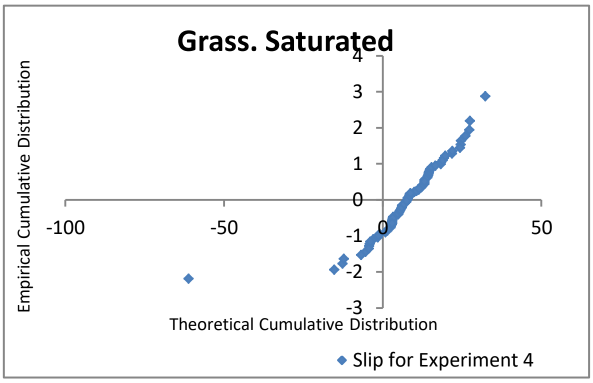
a) Velocity mean = 0.66, standard deviation = 0.08





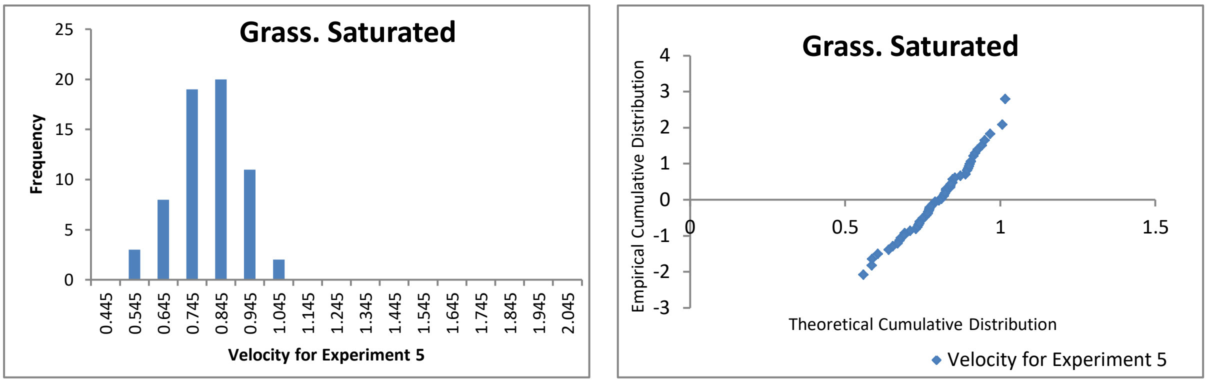
b) Power mean = 12.04, standard deviation = 2.21



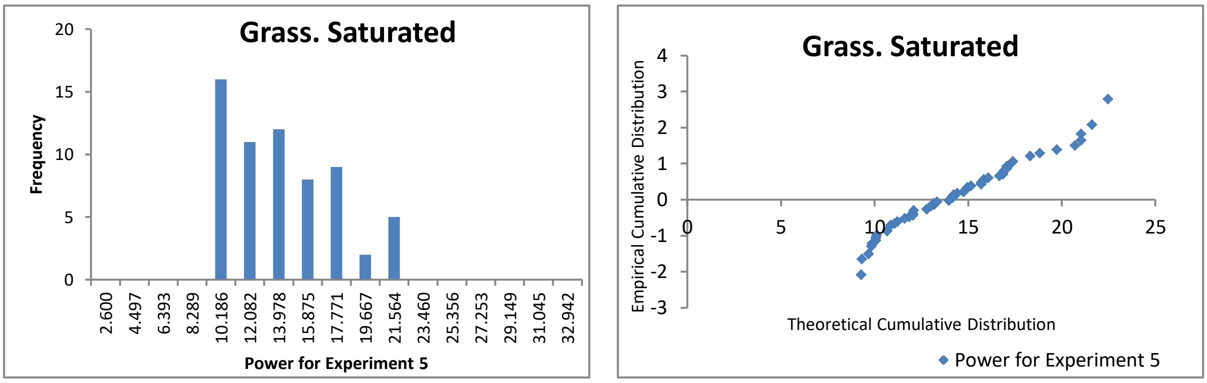


c) Slip mean = 7.82, standard deviation = 13.37

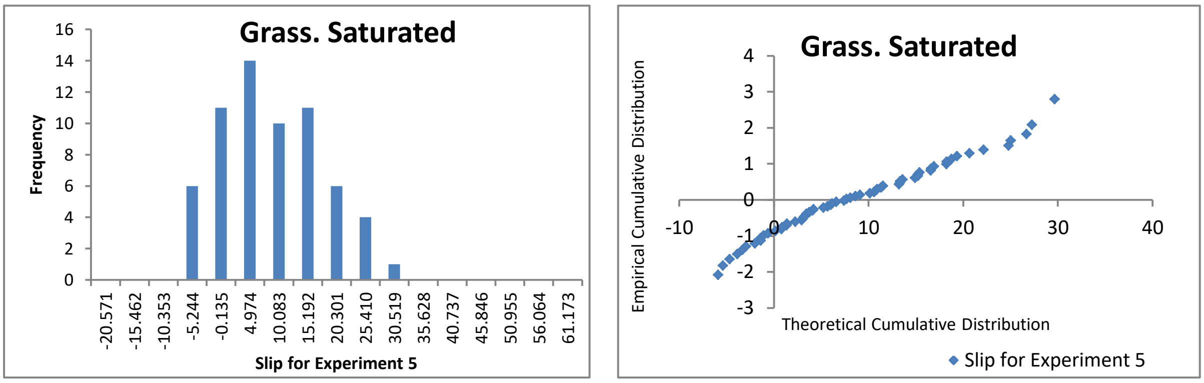
Figure A.47: Experiment 4. Grass. Saturated



a) Velocity mean = 0.78, standard deviation = 0.10

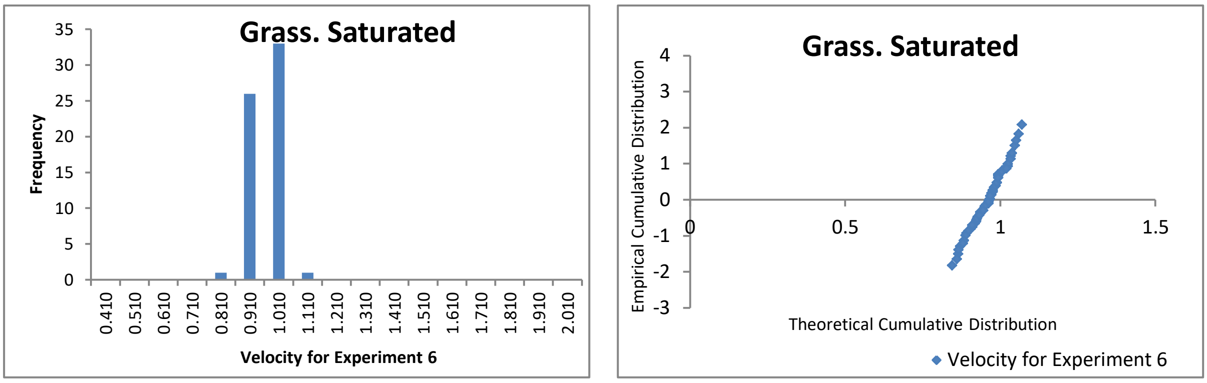


b) Power mean = 14.12, standard deviation = 3.52

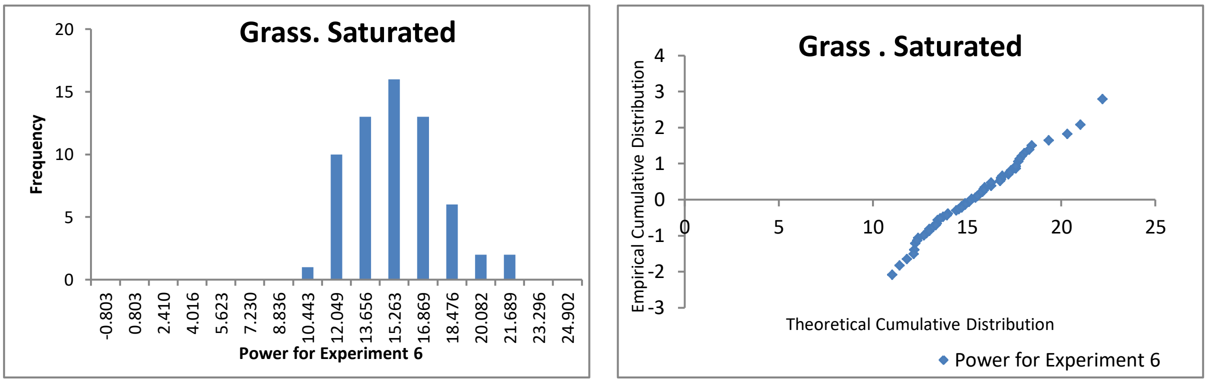


c) Slip mean = 8.79, standard deviation = 8.93

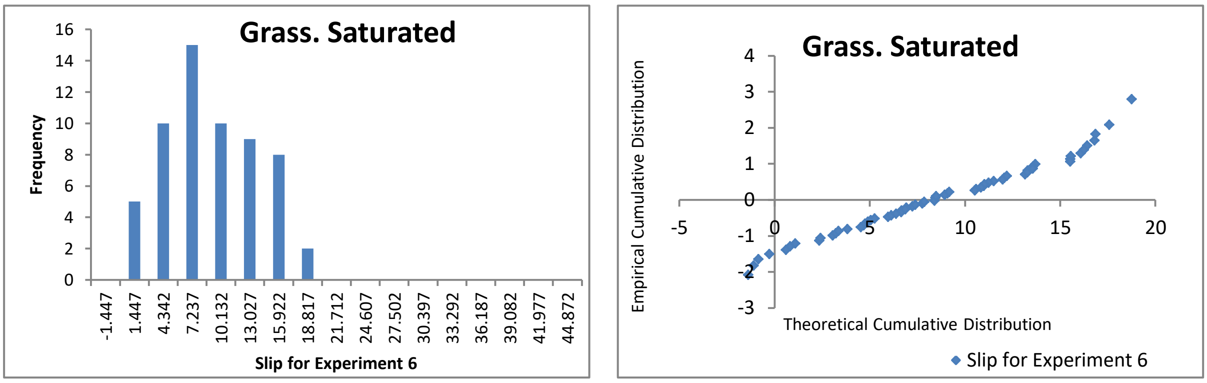
Figure A.48: Experiment 5. Grass. Saturated



a) Velocity mean = 0.96, standard deviation = 0.06



b) Power mean = 15.34, standard deviation = 3.52



c) Slip mean = 8.60, standard deviation = 5.28

Figure A.49: Experiment 6. Grass. Saturated