

Viasat AMEND - Machine Learning Team

ECE4871 Senior Design Project

Viasat AMEND – Machine Learning Team

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Table of Contents

Executive Summary	iii
1. Introduction	1
2. Project Description and Goals	2
3. Technical Specification	4
4. Design Approach and Details	
4.1 Design Approach	4
4.2 Codes and Standards	6
4.3 Constraints, Alternatives, and Tradeoffs.....	7
4.4 Codes and Standards	8
5. Schedule, Tasks, and Milestones	8
6. Project Demonstration	8
7. Marketing and Cost Analysis	
7.1 Marketing Analysis	9
7.2 Cost Analysis	9
8. Current Status	11
9. Leadership Roles	11
10. References	12
Appendix A	13

Executive Summary

Tracking satellite trajectories is a critical step for ensuring stable global communication and accurate data transfer between ground and low orbit satellites. One of the primary purposes of highly accurate tracking is to ensure ground dishes are pointed in the exact direction necessary to maximize Gain-to-Noise Temperature. Thus, a predictive tracking system is needed to steer ground dishes with a minimum accuracy of one tenth of a degree. This project specifically focuses on taking various inputs from a wide range of scenarios and training a machine learning algorithm to predict PID parameters based on previous orbit trajectories.

This project is the continuation of a previous team's work. This specific team will utilize machine learning (ML) techniques to efficiently produce control system parameters of an improved RF simulation model that can be used with Viasat systems. There is also a hardware team, that will aim to improve upon existing models. Both teams will work in close conjunction with one another.

The project involves using the existing Simulink model, which was left behind by the previous team. As the project progresses, the hardware team will focus on increasing the fidelity of the model, and the ML team will be consumers of the improved model. The ML team will then develop and utilize scenarios representative of the ground station functionality to generate data with the Simulink model. This data will be used to automatically populate a database that serves as an input to an advanced ML algorithm.

The ML model will analyze the data being fed into it and will predict necessary corrective actions from the parabolic dish's position. Ideally, this analysis will allow the team to effectively produce accurate PID parameters for the dish-satellite system and reduce angular position and tracking errors.

Viasat AMEND Machine Learning

1. Introduction

The Viasat AMEND Machine Learning team will not require any funding to complete its project of creating a machine learning algorithm that will generate reliable PID controller parameters. The end goal of the project is to generate reliable PID parameters that allow Viasat ground stations to reestablish communication with lost satellites, minimizing the time spent not communicating with the satellite. The existing model will produce some representative data of current scenarios, and the ML team will analyze this data using machine learning techniques to create more accurate inputs for the PID controllers. The main tasks for this project will be to create a populated database with representative scenarios and utilizing machine learning techniques to correctly parse the data to calculate improved input parameters. Future opportunities include implementing the remainder of this paper will be laid out as followed: section 2 – background, section 3 - technical specifications, section 4 - design approach, section 5 - schedule, section 6 - demonstration details, section 7 – market strategy, section 8 – current status, section 9 – leadership roles.

2. Project Description, Customer Requirements, and Goals

The AMEND ML Team will design and implement a ML algorithm capable of accepting a wide range of RF inputs and generating PID parameters that are used to take predictive actions. These actions will correct for errors in the relative position between the actively tracked low-Earth orbit satellite and the grounded parabolic dish. Since the algorithm implements machine learning techniques, the goal is to create increasingly accurate PID parameters that produce improved corrective actions for the tracking system.

The team will also create a Matlab database that will hold data points generated from the existing RF model. This database will be used to feed input data into the ML algorithm. Primary tools that need to be developed include a method of extracting data from the RF model, and a way to automatically populate the allocated database [1]. Lastly, we will need to implement a way to transfer this data into the ML algorithm.

This project's only stakeholder is Viasat, as they are the corporate sponsor who intend to use this technology for themselves. Some customer needs include the desire to create an ML solution that works with the existing Simulink model. Implementing a solution within Simulink will allow the team to create a tool with fewer moving parts than if the ML was done outside of the Matlab/Simulink toolbox.

There are several design constraints that we will have to keep in mind while developing our solution. Primarily, we will focus on keeping the algorithm latency to a manageable value. Having too high a latency will mean that the parameters will not be generated at the desired update rate [2]. We will also need to ensure that the results that we generate will be within the desired root mean squared error that will be specified by the consumer.

		Engineering Requirements					Competitor Benchmarks	
		Intelligent Tracking System	Satellite Damping System		Power Consumption	Factor in non-idealities in system model	AT&T	Dish
Customer Requirements	Simulink tool emulating satellite signals with noise and error models (for system trades)	x	x			x		
	Simulink model implementing a stepped track system (monopulse currently implemented)						x	x
	Model to back out system parameters from "measured" data	x				x	x	x
	Report showing Machine Learning applied to backing out system parameters from data	x		x		x		
	Robust algorithm to correct after satellites are displaced	x	x				x	x
Units								
		Correct dish trajectory to recover satellite position when displaced by external forces.	During refocusing, ensure that the dish will not physically overshoot or undershoot.	Timing accurate model, as opposed to functionally correct.	Enable high fidelity system while keeping low power draw.	EM Wave propagation power losses, maximizing finite response times (wave propagation speed), parasitic components in RF circuits - in relation to ML aspects		
		Engineering Targets						

Figure 1. Quality Function Diagram based on Customer Needs (Column 1) and Engineering Requirements (Row 1)

3. Technical Specifications

The following design specifications were mandated for last year's Viasat AMEND team and will be utilized for the development and implementation of the ML algorithm.

Minimum RF Input Bandwidth	200 MHz
Desired RF Input Bandwidth	3 GHz
I/Q Signal Bandwidth	10 MHz
Minimum SNR on Main Horn After Processing	7dB
Maximum Latency	0.5s
Control System Update Rate	50 Hz – 1kHz
Maximum Trackable Satellite Speed (Azimuth)	15°/s
Maximum Trackable Satellite Speed (Elevation)	3°/s
Maximum Mean Squared Tracking Error	0.01°RMS

Table 1. Technical specifications as requested by Viasat

4. Design Approach and Details

4.1 Design Concept Ideation, Constraints, Alternatives, and Tradeoffs

Our solution will be implemented within MATLAB/Simulink. It will utilize the Matlab Statistics and Machine Learning toolbox in order to stay within the existing model's environment [3]. Our project will exist as a separate entity from the existing model, but it will take inputs from and feed outputs back into the existing model.

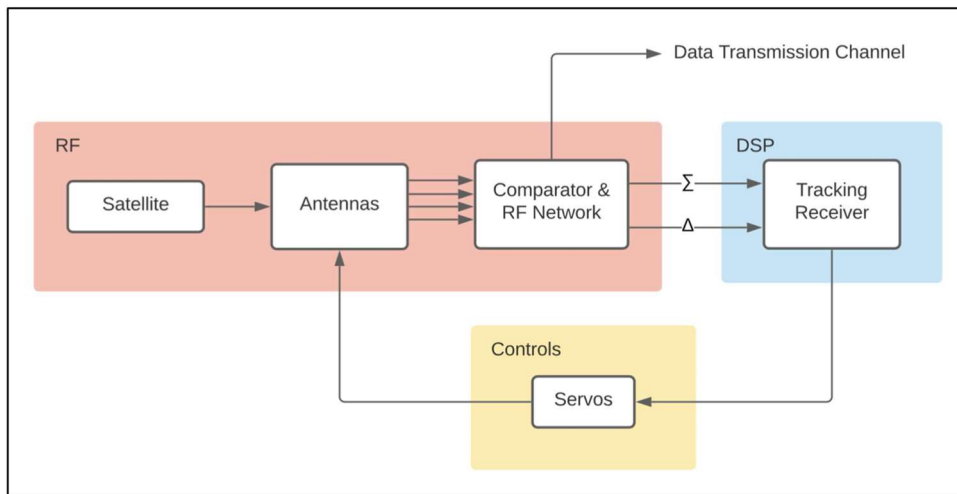


Figure 2. The block diagram for the existing RF Model

Within our project, there will exist two primary blocks. The first block will be a database that is populated by outputs from the existing RF model. We will have to create “scenarios” that can be used to generate model data. In other words, we will select certain input parameters, and get some outputs from the RF models using these input parameters. These outputs will then be placed within the database.

The second block will be where the machine learning techniques are utilized. The second block will take as input, the data points that were generated and stored within the database. Using these initial values, the ML algorithm implemented within the second block will generate improved PID parameters. The improved PID parameters will be fed back into the algorithm so that the more the model is utilized, the better results it will yield.

A key tradeoff that exists is the fact that we are sacrificing speed for simplicity in the model. Since the ML will be implemented using the Matlab ML toolbox, it will be easier to synchronize it with the data that is being generated from the RF model. However, there is computational overhead that comes with being within the Matlab/Simulink environment. The algorithm will not be as quick as it could be if implemented in a different language, but it will allow engineers to navigate through the tool more easily, allowing for future opportunity for improvement.

Another tradeoff lies in the fact that there is only a certain point up to which DSP systems can be added to the model before computational limits and latency start becoming a major issue. Thus, while higher signal processing power gives us more accurate computation for angle correction from angle error in signals, we will be limiting the DSP system power to make up for the lost speed in using MATLAB over other programming languages. This will leave room for improving the efficiency of the machine learning algorithm by increasing signal processing power in the future.

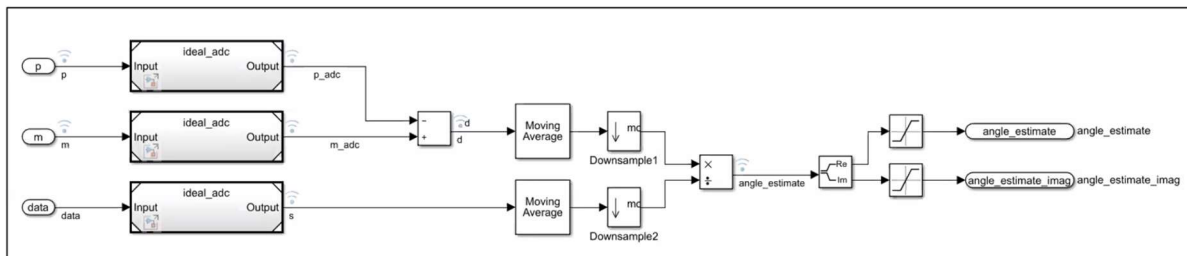


Figure 3. The DSP Subsystem

4.2 Preliminary Concept Selection and Justification

We selected our current path based mainly on what existing resources we had access to. The previous Viasat AMEND team, who had worked on this project during the 2020-2021 academic year, had created a Matlab/Simulink model that would simulate the dynamic response of the antenna tracking system in the time domain.

This existing model is the main tool that Viasat has provided us with to assist with our project. By utilizing it, we know that we can reliably yield data that can be used to train an ML algorithm. Not only does the RF model exist, but there is also another Viasat team, the Viasat AMEND – Analog team, that will be continuously improving this model as our project progresses. We have been provided with both a tool that will yield us measurements that would be too difficult to acquire otherwise, and a team that will work to improve the measurements given to us by the existing tool.

The design system for the database will rely heavily on receiving data from the existing RF model. We will need to carefully select realistic input parameters that will create good data points to be stored within the database. The more representative of the real world the scenarios, the more accurate the output we will receive from the model. With the analog team working to make improvements to the model, we can be confident that our base data set will be strong. If we did not have access to this tool, we would need to acquire Viasat’s historical data of how the reestablished communication between ground stations and satellites.

4.3 Engineering Analyses and Experiment

Since the equipment that we will be working with are expensive ground stations, it will not be viable to test our outputs on the ground stations themselves. If our results are not correct, they could potentially cost Viasat a large amount of money. The way we will test the results of our ML algorithm is by comparing our updated PID parameters to actual PID parameters that Viasat had historically created, through their existing tracking technology. For example, we will have some test case of a scenario that Viasat had actually run into before. We would then run the input parameters for that scenario through the RF model, generate an output, and run that through the ML model to yield some updated PID parameters. We would then need to compare these parameters to the data that Viasat

provided. If our updated parameters would yield more accurate (lower root mean squared error) results than the test cases, it would be safe to assume that the task is being done correctly.

4.4 Codes and Standards

FCC standard 15.209 regulates intentional emissions of RF energy. Although the auto tracking system will ideally not radiate any emissions, there is a chance that some RF energy is unintentionally emitted. Unintentional emissions are exempt from the standard, so it is unlikely that this standard will significantly affect the design [5].

The team will also need to comply with the FCC part 25 standard which contains regulations on carrier frequency tolerance, power radiation, frequencies used, as well as the angle of antenna elevation.

5. Project Demonstration

Our project will be demonstrated by running the Simulink model without errors in MATLAB. We will also ensure that the model can also run on the RF SoC board. To ensure that the model validates the project specifications, the outputs will be analyzed to see if they match the expected simulated outputs.

6. Schedule, Tasks, and Milestones

A detailed GANTT chart and PERT analysis has been included in **Appendix A**.

The analysis contains both the tasks that were completed in the current semester as well as for the next semester. The current semester's tasks include documentation and logistical assignments, while the next semester's tasks will include tasks like software development, testing, and analysis. With each team member doing their tasks, we anticipate completing the project on time.

7. Marketing and Cost Analysis

7.1 Marketing Analysis

A competitor's product is not available for this project since it is internal to Viasat, and is thus specific to their ground stations. However, simulink models have been created by the previous team for the control system and tracking receiver. Our project will extend the model to better examine system performance trades and will add scenario modeling to support Machine Learning.

7.2 Cost Analysis

The Viasat AMEND Machine Learning team will be creating a software solution to generate improved motor calibration parameters for satellite ground stations. The effort will involve minimal physical hardware and materials. Any physical material necessary will be equipment inherited from industry partner Viasat. The nature of the project means that this will not be a product for sale, but an internal tool that Viasat can use to save costs during their normal operations.

The estimated labor cost will be calculated as follows:

Estimated Hourly Pay Rate (via Payscale.com)

Entry Level Software Engineering salary = \$91,000 per year

Hourly Rate = 91,000 / 2080 hours = \$44 per hour

First Semester - 12 weeks	Total Number of Hours	Cost
Assignment Completion	24	\$1056
Industry Sponsor Meetings	6	\$264
Faculty Advisor Meetings	6	\$264
Second Semester - 15 weeks		
Coding/Engineering	90	\$3960
Industry Sponsor Meetings	7.5	\$330
Faculty Advisor Meetings	7.5	\$330
	Total Labor Cost per Engineer	\$6204

	Total Labor Cost for 5 Engineers on Team	\$31020
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As can be seen from the above calculations, the total labor cost for our group working on this project is forecasted to be around **\$31,020**. Our industry project partners, Viasat, provided us with a financial principle used to estimate the development cost of a program depending on the number of labor hours put in. The principle is called the “Rule of Three,” and it takes the following factors into account:

- 1. Overhead** – Accounts for costs like software, licenses, stationary, power, etc. (120% - 150% Labor Cost) Fringe Benefits – (30% Labor cost)
- 2. Fees** – Covers unallowable costs (expenses acquired by contractor that do not meet the criteria to be billed) and overruns (5% - 10% Labor cost)
- 3. Profits** – bonuses & shareholder dividends, cost necessary for program to turn a profit (10% - 20% Labor Cost)

Accounting for the above factors together yields a 200% increase from just the labor cost. As a result, our final cost calculation is as follows.

Estimated Program Cost = \$31,020 * 3 = \$93,060

Our estimated program cost utilizes the “Rule of Three” that we were given, which accounts for all costs supplementary to our labor cost.

The nature of our partnership with Viasat means that if this project was being completed in industry, rather than as a senior design project, Viasat would foot the bill for any related costs and expenses.

8. Current Status

As of now, the team has spent time in meetings with both our faculty advisor as well as our external partners to understand the project's background. After the proposal is completed and accepted, we will have a few more meetings with our external partners and faculty advisor before we commence our work at the beginning of next semester.

9. Leadership Roles

We have split our team roles into technical interests and expertise. Although all people will spend time developing our product next semester, certain people will insight into their respective fields

Our team roles have been divided in the following manner:

1. Webmaster/ Git Coordinator – Tyler Cole
2. RF Insider – Mikias Balkew
3. Documentation/Viasat Coordinator - Shreyas Mhasawade
4. DSP insider - Adrija Bhattacharya
5. Expo Coordinator - Chris Rothmann

10. References

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Appendix A: GANTT Chart & PERT Analysis



Paths

- 1-2-4-5-8-9-10-12-13-14-15-16-17
- 1-2-4-6-8-9-10-12-13-14-15-16-17
- 1-2-4-5-8-9-11-12-13-14-15-16-17
- 1-2-4-6-8-9-11-12-13-14-15-16-17
- 1-3-4-5-8-9-10-12-13-14-15-16-17
- 1-3-4-6-8-9-10-12-13-14-15-16-17
- 1-3-4-5-8-9-11-12-13-14-15-16-17
- 1-3-4-6-8-9-11-12-13-14-15-16-17

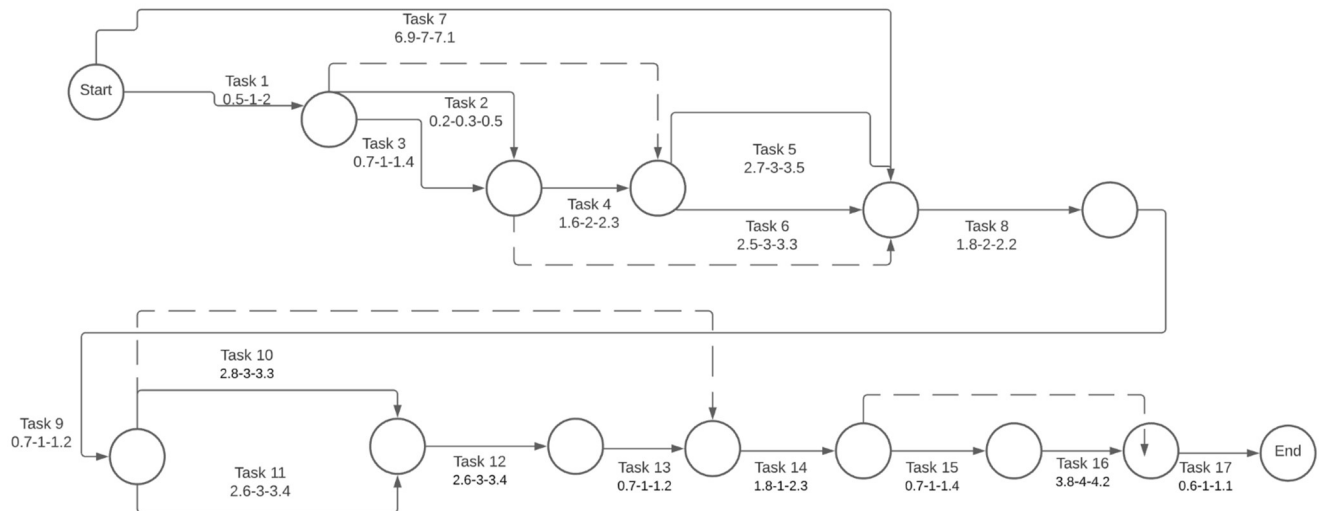
Critical Path:

- 1-3-4-5-8-9-10-12-13-14-15-16-17

Time calculations for the critical path:

Critical Path							
Task	Optimistic time	Most likely time	Pessimistic time	Expected Time	Dependencies	Std Dev	Variance
1	0.5	1	2	1.08		0.25	0.0625
3	0.7	1	1.4	1.016666667	3	0.116667	0.013611
4	1.6	2	2.3	1.983333333	4	0.116667	0.013611
5	2.7	3	3.5	3.033333333	4	0.133333	0.017778
8	1.8	2	2.2	2		0.066667	0.004444
9	0.7	1	1.2	0.983333333	8	0.083333	0.006944
10	2.8	3	3.3	3.016666667	9	0.083333	0.006944
12	0.8	1	1.3	1.016666667	10,11	0.083333	0.006944
13	0.7	1	1.2	0.983333333	12	0.083333	0.006944
14	1.8	2	2.3	2.016666667	13	0.083333	0.006944
15	0.7	1	1.4	1.016666667	14	0.116667	0.013611
16	3.8	4	4.2	4	15	0.066667	0.004444
17	0.6	1	1.1	0.95	17	0.083333	0.006944
Sums			27.4	23.09666667		1.366667	0.171667
							0.414327

PERT CHART from GANTT CHART:



From PERT analysis, the critical path did not change.

1. Expected duration of the project: **23.09 weeks**
2. Expected standard deviation for the critical path: **.414**
3. Probability of finishing project one week prior to design expo: **99.9999999987202 %**
- a. Mathematics below

$P(T_{\text{project}} < T_{\text{left-before-1-week-before-expo}})$ = probability of completing the project 1 week before the design expo.

$$\sigma_T = (\sigma_A + \sigma_B + \sigma_C + \sigma_D + \sigma_E + \sigma_F + \sigma_G + \sigma_H + \sigma_I + \sigma_J + \sigma_H + \sigma_K + \sigma_L + \sigma_M + \sigma_N + \sigma_O + \sigma_P)^{(1/2)}$$

$$z_S = (T_s - T_e) / \sigma_T$$

where:

$T_s = 26$ weeks = time before 1 week before design expo

$T_e = 23.09$ weeks = sum of expected times from each task (expected duration, critical path)

$\sigma_T = 0.414327$ = total standard deviation of completion time (expected)

$$z_S = (T_s - T_e) / \sigma_T = 7.0234$$

using a standard z table:

$$P(T_{\text{project}} < T_{\text{left-before-1-week-before-expo}}) = 1 - P(T_{\text{project}} > T_{\text{left-before-1-week-before-expo}}) = 1 - 0.0000000000127981 = \mathbf{99.9999999987202 \%}$$