Study on Parametric Estimation of Ship Maneuvering Models by Support Vector Machine

by

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ABSTRACT

In maritime World, finding hydrodynamic values is crucial importance for analysing various forces acting on the ship hull. In parallel, Learning from data is new trend. As we studied in our guidance and control course, Non-linear hydrodynamic coefficients also take part in maneuvering motion.In order to find the parameters associated with ship maneuvering motion, we try to implement linear regression for this highly non-linear model. Multi Co-linearity plays as inevitable hindrance, while predicting the desired dependency. We made simulation data for Mariner's ship in

1. ZigZag test
2. Turning Circle Test and
3. Spiral Test

We use sophisticated Machine Learning algorithm called Support Vector machine**(SVM)** for predicting the hydrodynamic derivatives values and trajectories.

We used python programming for this study and used **"Sci-kit Learn"** library for constructing the support vector machine and made study on the effect of regularization parameters.

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NOMENCLATURE

code file x	python code file number x
u	Surge speed
v	Sway speed
r	Yaw rate
U	Total velocity
δ	Rudder angle
ψ	Heading angle
ϵ	Sensitivity loss in SVM
C	Condition number
HDV	Hydrodynamic Derivative Values

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Assessments

Literature Survey :

https://github.com/sramarjunan/Parameter-Estimation-SVM

Code Files :

https://github.com/sivaramansOE19S012/Codes

Image Files :

https://github.com/sivaramansOE19S012/Images

Introduction

On considering JSR 2009 paper titled *"Parametric Identification of Ship Maneuvering Models by Using Support Vector Machines"* as reference to our research, We have main focus on regression by various machine learning algorithm. In this paper, they used first order method for formulating governing equation of surge, sway and yaw. In order to avoid uncertainty in six degree of freedom model, we use 3 degree of freedom model for our work.

$$\begin{aligned}(m - X_{\dot{u}})\dot{u} &= f_1(u, v, r, \delta)\\ (m - Y_{\dot{v}})\dot{v} + (mx_G - Y_{\dot{r}})\dot{r} &= f_2(u, v, r, \delta)\\ (mx_G - N_{\dot{v}})\dot{v} + (I_z - N_{\dot{r}})\dot{r} &= f_3(u, v, r, \delta)\end{aligned}$$

In above governing equation, right hand side would be expanded by Taylor series as mentioned in reference paper. At presence, there are many algorithm like Maximum Likelihood, Particle Swarm Optimization, Genetic Algorithm, etc., are available for Linear Regression. But, These algorithms like ML, PSO are only works for pattern recognition, density estimation and classification. When it comes to Non-Linear model, SVM only has hope for parameter estimation. For example, We could see how "*Genetic Algorithm*" works for different model.

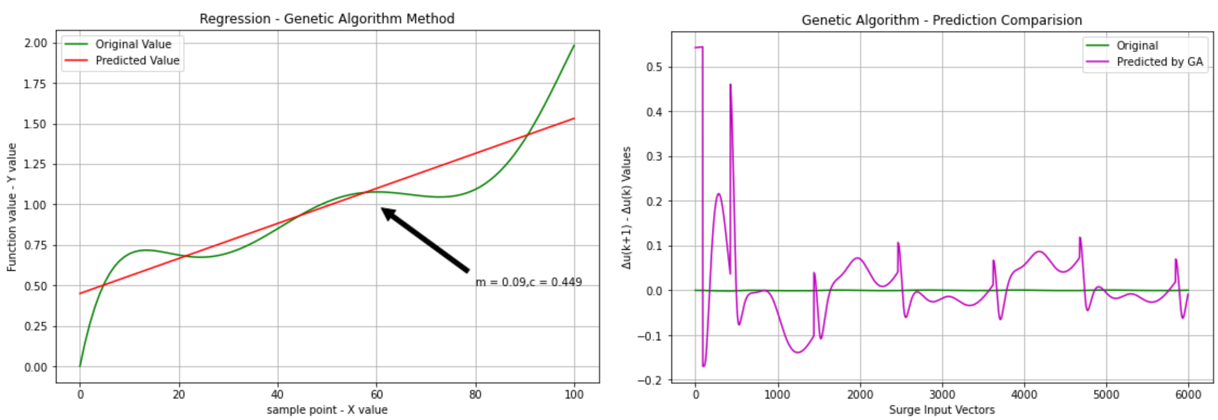

Figure 1 . Genetic Algorithm Comparison on Linear and Non-linear Model
Source : *code file* 1

To the extent to first order method, we have tried second order method at here.

<u>Second Order Method Formation:</u>

$$\delta u_k = \Delta u(k+1) \text{ - } \Delta u(k) = \frac{h}{L(m' - X'_{\dot{u}})} \; [\; X'_u \Delta u(k) U(k) + X'_{uu} \Delta^2 u(k) + \cdots \; \cdots \;] \tag{1}$$

$$\delta u_{k+1} = \Delta u(k+2) \text{ - } \Delta u(k+1) = \frac{h}{L(m' - X'_{\dot{u}})} \; [\; X'_u \Delta u(k+1) U(k+1) + X'_{uu} \Delta^2 u(k+1) + \cdots \; \cdots \;] \tag{2}$$

Subtracting equation (2) from (1),
δu_{k+1} - $\delta u_k = \Delta u(k+2)$ - 2 $*\Delta u(k+1)$ - $\Delta u(k) =$

$$\frac{h}{L(m' - X'_{\dot{u}})} \; [\; X'_u \; (\Delta u(k+1)U(k+1) \text{ -} \Delta u(k)U(k)\;) + X'_{uu} \; (\Delta^2 u(k+1) \text{ - } \Delta^2 u(k)) + \cdots \; \cdots \;] \tag{3}$$

This third equation should replace the equation (18) in JSR 2009 for having second order method.We can follow this for sway and yaw governing equations as well.

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Why Support Vector machine ?

In current world, parameter estimation for Non linear model is challenging one, because of *Multi Co-linearity.* however, we have seen how genetic algorithm performed in the case of Non linear regression. We can perform Non-linear Regression for prediction. But, for parameter identification, Linear SVM is the only optimal option.

Linear SVM - kernel function takes L_2 norm .So, we can have separable coefficients in Ax form. Where A is regression coefficient column matrix.

Data Simulation

We use Numerical Simulation instead of experimental data. As mentioned in JSR 2009 paper, we use **mariner's ship** for various trajectory tests such as Zigzag, turning circle and spiral test.

ZigZag Test:

Ship : Mariner
Simulation Time : 600 seconds - 0.1 second interval

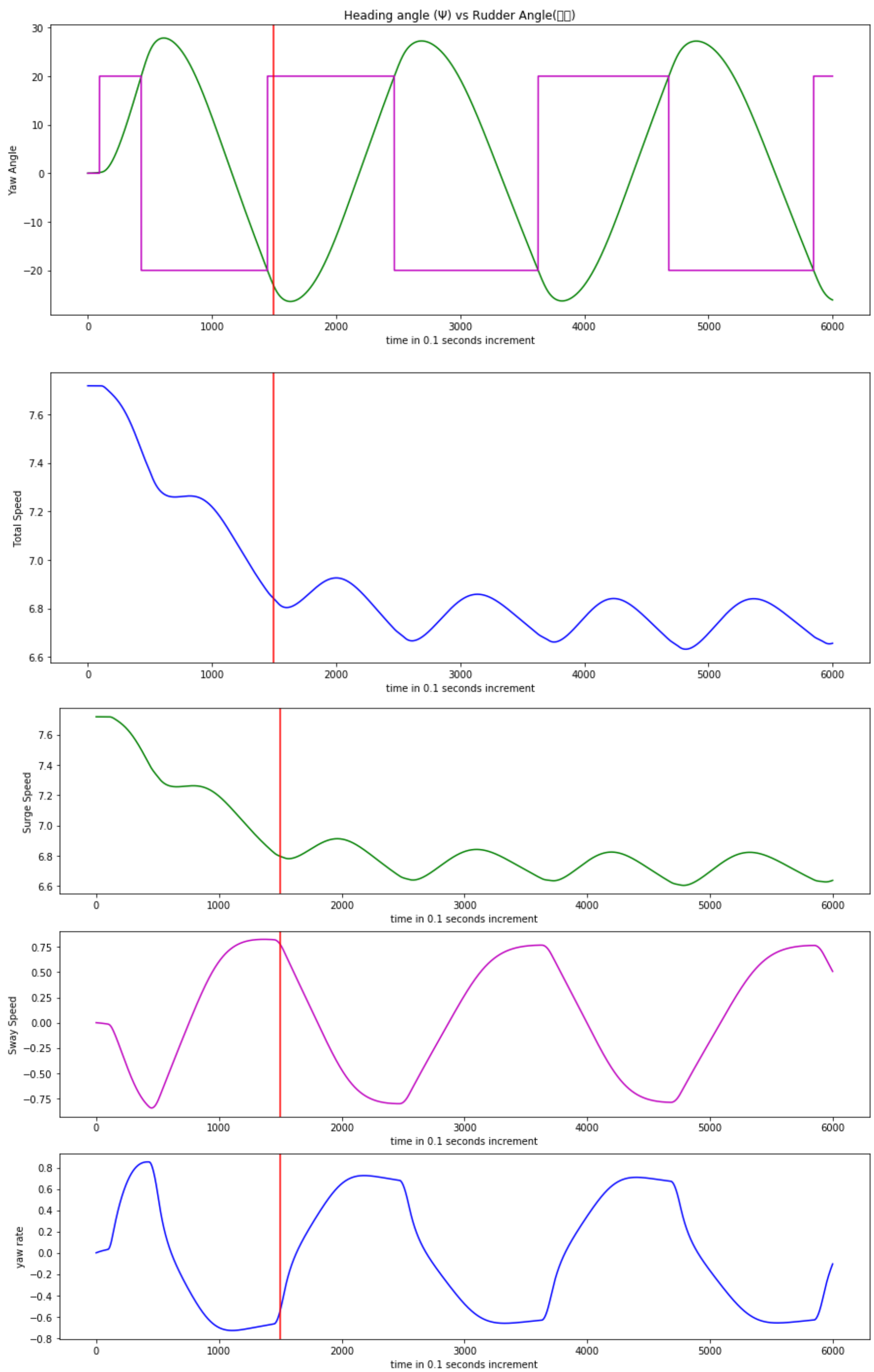

Figure 2. ZigZag Test Simulation Plots
Source : *code file* 2

. **ZigZag Test for Different Combination:**

Ship : Mariner
Simulation Time : 4000 seconds - 0.1 second interval

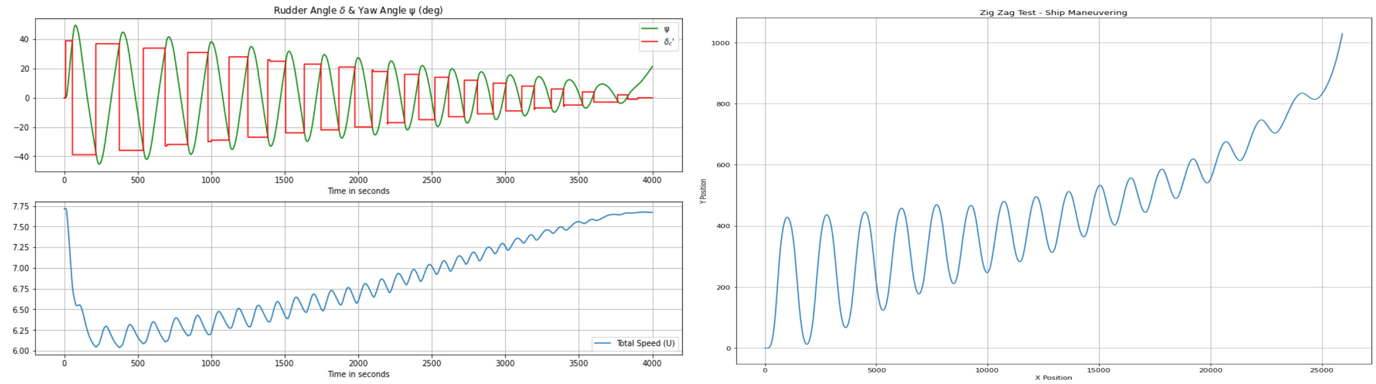

Figure 3. ZigZag Test 40 degree to 1 degree Simulation Plots
Source : *code file* 3

Ship : Mariner
Simulation Time : 2000 seconds - 0.1 second interval

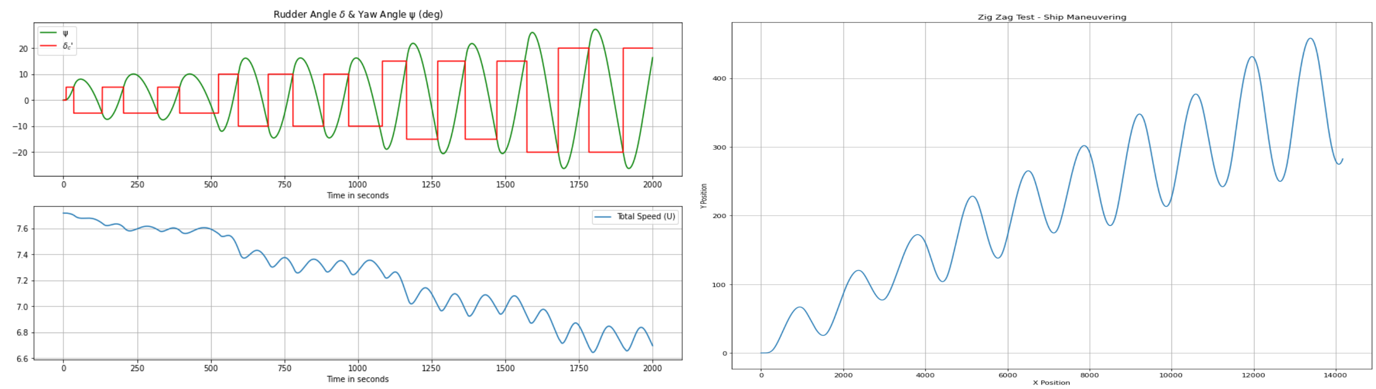

Figure 4. ZigZag Test 5 degree to 40 degree Simulation Plots
Source : *code file* 4

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Turn Circle Test:

Ship : Mariner
Simulation Time : 400 seconds - 0.1 second interval

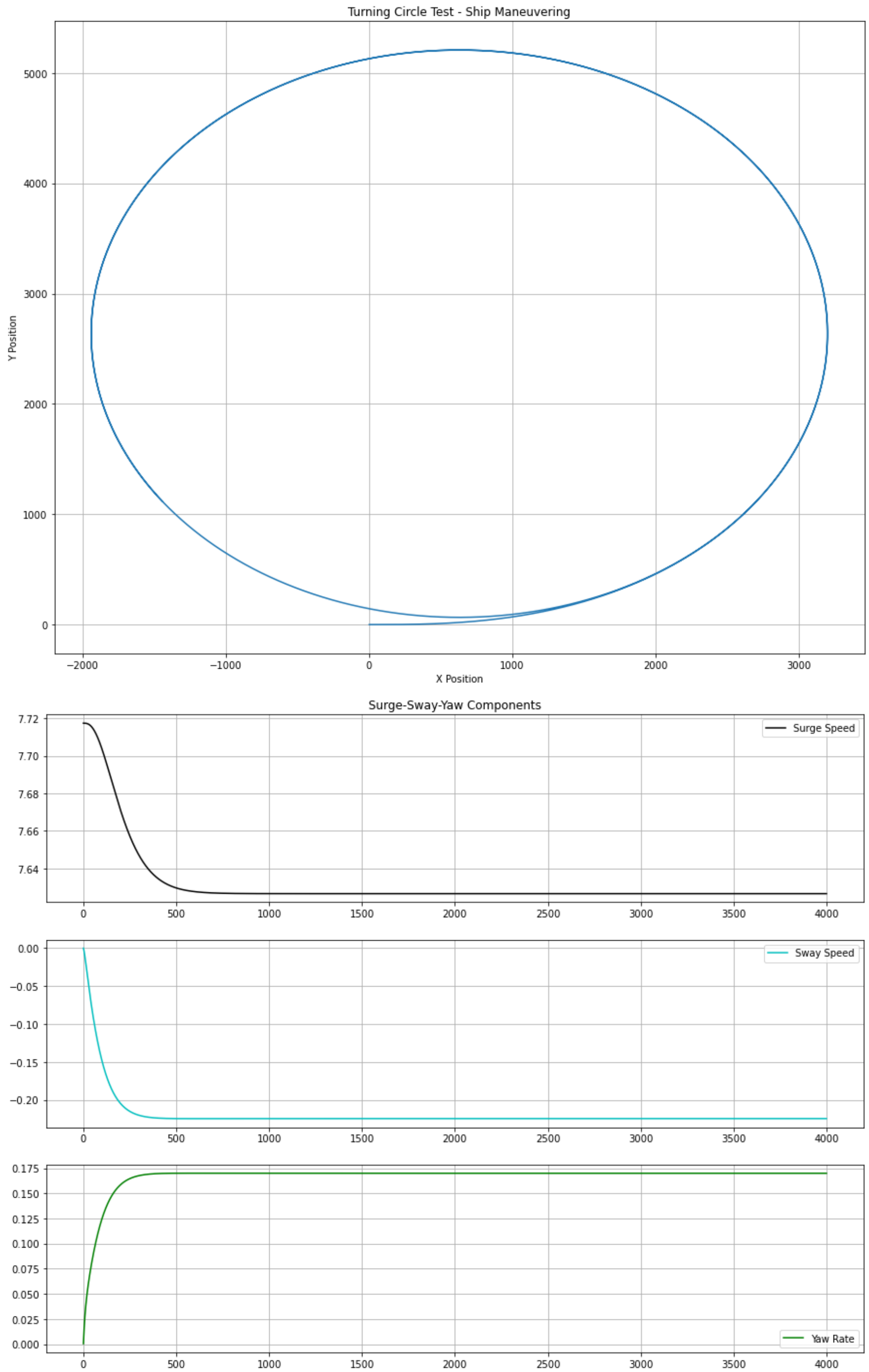

Figure 5. Turning Circle Test Simulation Plots
Source : *code file* 5

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Spiral Test:

Ship : Mariner's ship
Simulation time : 6000 seconds

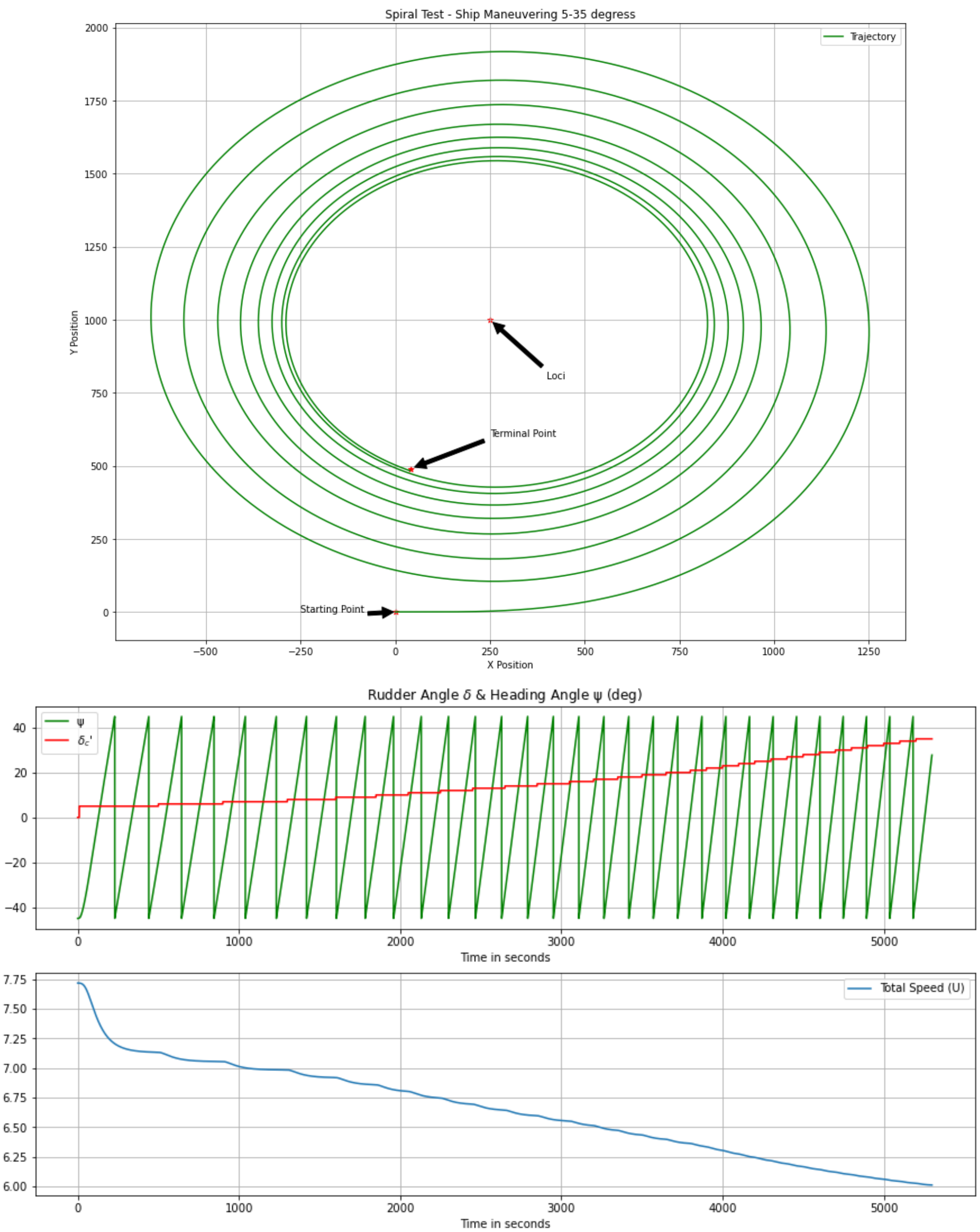

Figure 6. Spiral Test Simulation Plots
Source : *code file* 6

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Spiral Test with equal yaw time:

Ship : Mariner's ship
Simulation time : 9600 seconds

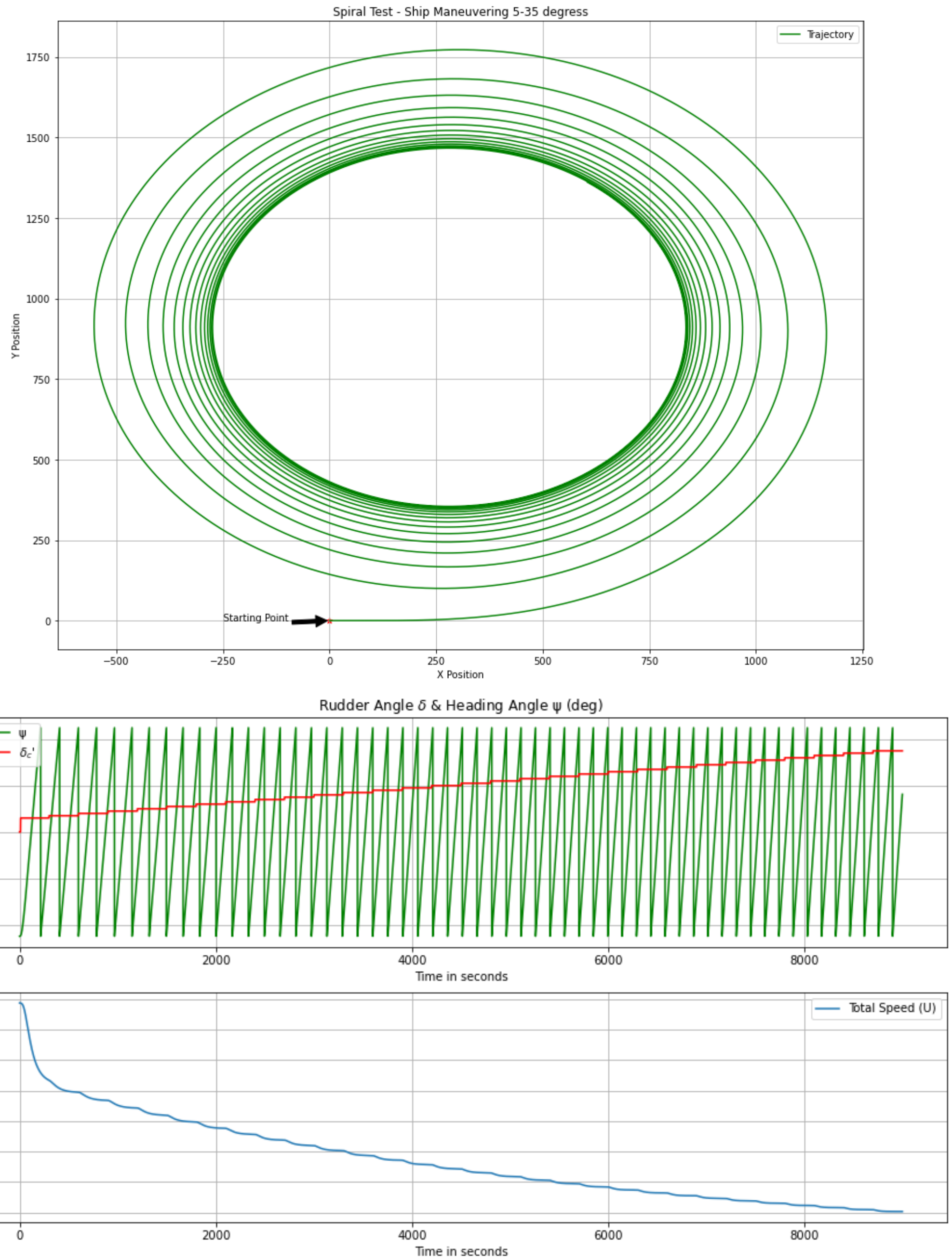

Figure 7. Spiral Test with Constant yaw rate Simulation Plots
Source : *code file* 6 (we have only change yaw time in code file 6)

Literature Survey

Year	*Title of Paper*	*Objective and Methodology*	*Author details*
2015	**1.**Introduction of MMG standard method for ship maneuvering predictions	Journal of Marine Science and Technology maneuvering predictions **Simulation**	H. Yasukawa Graduate School of Engineering, Hiroshima University, **japan** J Mar Sci Technol (2015) 20:37–52 DOI 10.1007/s00773-014-0293-y
2009	**2.**Parametric Identification of Ship Maneuvering Models by Using Support Vector Machines	Journal of Ship Research Parametric Identification **SVM**	W. L. Luo , Z. J. Zou School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai, **China** Journal of Ship Research, Vol. 53, No. 1, March 2009, pp. 19–30
2016	**3.**Parameter Identification of Ship Maneuvering Model Based on Support Vector Machines and Particle Swarm Optimization	Journal of Offshore Mechanics and Arctic Engineering Parametric Identification **SVM & PSO**	Weilin Luo , C. Guedes Soares CENTEC, **Lisbon** J. Offshore Mech. Arct. Eng. Jun 2016, 138(3): 031101
2010	**4.**Parameters identification for ship motion model based on particle swarm optimization	The international journal of cybernetics, systems and management sciences Parametric Identification **PSO**	Yongbing Chen Huazhong University of Science and Technology, Wuhan, **China** ISSN: 0368-492X
2016	**5.**Vector field path following for surface marine vessel and parameter identification based on LS-SVM	Journal of Ocean Engineering Parametric Identification **LS-SVM**	Haitong Xu, C. Guedes Soares CENTEC, **Lisbon** Ocean Engineering 113(2016) 151-161
2017	**6.**Identification-based simplified model of large container ships using support vector machines and artificial bee colony algorithm	Journal of Applied Ocean Research Parametric Identification **SVM - artificial bee colony algorithm**	Man Zhu, , Axel Hahn University of Oldenburg, Oldenburg, **Germany** Applied Ocean Research 68(2017) 249-261

2019	**7.**Identification of Abkowitz model for ship manoeuvring motion using ε –Support Vector Machine	Journal of Hydrodynamics Parametric Identification **ε -SVM**	ZHANG Xin-guang Shanghai Jiao Tong University, Shanghai, **China** 2011,23(3):353-360 DOI: 10.1016/S1001-6058(10)60123-0
2017	**8.**Parameter Identification of Ship Maneuvering Models Using Recursive Least Square Method Based on Support Vector Machines	the International Journal on Marine Navigation and Safety of Sea Transportation Parametric Identification Recursive - **LS-SVM**	M. Zhu & A. Hahn Carl-von-Ossietzky University of Oldenburg, Oldenburg, **Germany** DOI: 10.12716/1001.11.01.01
2016	**9.**Parameter Identiability of Ship Manoeuvring Modeling Using System Identication	Mathematical Problems in Engineering Parametric Identification **System Identication**	Weilin Luo Fuzhou University, Fuzhou, **China** Mathematical Problems in Engineering Volume 2016, Article ID 8909170,
2017	**10.**System-based investigation on 4-DOF ship maneuvering with hydrodynamic derivatives determined by RANS simulation of captive model tests	Journal of Applied Ocean Research Parametric Identification **RANS simulation** of captive model tests	Hai-peng Guo Shanghai Jiao Tong University, Shanghai**, China.** Applied Ocean Research 68(2017) 11-25
2015	**11.**Method for estimating parameters of practical ship manoeuvring models based on the combination of RANSE computations and System Identification	Journal of Applied Ocean Research Parametric Identification **RANSE computations and System Identification**	M. Bonci , M. Viviani University of Genoa, Genova, **Italy** Applied Ocean Research 52(2015) 274-294
2015	**12.**Parametric estimation of ship maneuvering motion with integral sample structure for identification	Journal of Applied Ocean Research Parametric Identification **LS-SVM**	Cao Jiana & Zhuang Jiayuana Harbin Engineering University, **China** Applied Ocean Research 52(2015) 212-221
2018	**13.**Estimation of hydrodynamic derivatives of a container ship using PMM simulation in OpenFOAM	Journal of Ocean Engineering Parametric Identification **RANS solver & OpenFOAM**	Hafizul Islam, C. Guedes Soares CENTEC, **Lisbon** Ocean Engineering 164(2018) 414-425

2017	**14.** Measures to diminish the parameter drift in the modeling of ship manoeuvring using system identification	Journal of Applied Ocean Research parameter drift **System identification**	Weilin Luoa, Xinyu Li Fuzhou University, Fuzhou, **China** Applied Ocean Research 67(2017) 9-20
2018	**15.** Nonparametric identification of nonlinear ship roll motion by using the motion response in irregular waves	Journal of Applied Ocean Research Non-Parametric Identification **RDT and SVR**	Xian-Rui Houa, Zao-Jian Zou Shanghai Maritime University, Shanghai **,China** Applied Ocean Research 73(2018) 88-99
2015	**16.**Parameter identification of nonlinear roll motion equation for floating structures in irregular waves	Journal of Applied Ocean Research Parametric Identification **random decrement technique and SVR**	Xian-Rui Houa, Zao-Jian Zoua Shanghai Jiao Tong University, Shanghai**, China.** Applied Ocean Research 55(2016) 66-75
1982	**17.**Cancellation effect and parameter identifiability of ship steering dynamics	Journal of International Shipbuilding Progress Parametric Identification **Slender-body theory**	Hwang, Wei-Yuan National Taiwan University, Taipei, **Taiwan** DOI: 10.3233/ISP-1982-2933201
2016	**18.**Modeling of Ship Maneuvering Motion Using Neural Networks	Journal of Marine Science and Technology Parametric Identification (acceleration derivatives) **Neural Network**	Weilin Luo School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou, **China.** DOI: 10.1007/s11804-016-1380-8
2014	**19.** An algorithm for offline identification of ship manoeuvring mathematical models from free-running tests	Ocean Engineering offline identification of ship manoeuvring model **classic genetic algorithm-from free-running tests**	Serge Sutulo, C. Guedes Soares (CENTEC), Instituto Superior Técnico, University of Lisbon, Av. Rovisco Pais, 1049-001 Lisbon, **Portugal.** Ocean Engineering 79(2014) 10-25
2019	**20.** On the application of empiric methods for prediction of ship manoeuvring properties and associated uncertainties	Ocean Engineering Parametric Identification (acceleration derivatives) **Empirical Methods**	Serge Sutulo, C. Guedes Soares (CENTEC), Lisbon, **Portugal.** Ocean Engineering 186(2014) 106111

Support Vector Machine and Results

With reference to *JSR* 2009 Paper, we followed the mathematical model(first order method) and encoded in python programming(*code file* 7) accordingly. For surge 10 hydrodynamic derivative components, for sway and yaw 14 hydrodynamic derivative components were taken.
In order to understand the dependence of each components, first we tend to plot the Δu, Δv, Δr and $\Delta\delta$ values here and others following

Components Plots (Mariner's Ship Data - ZigZag Test - 600 seconds):

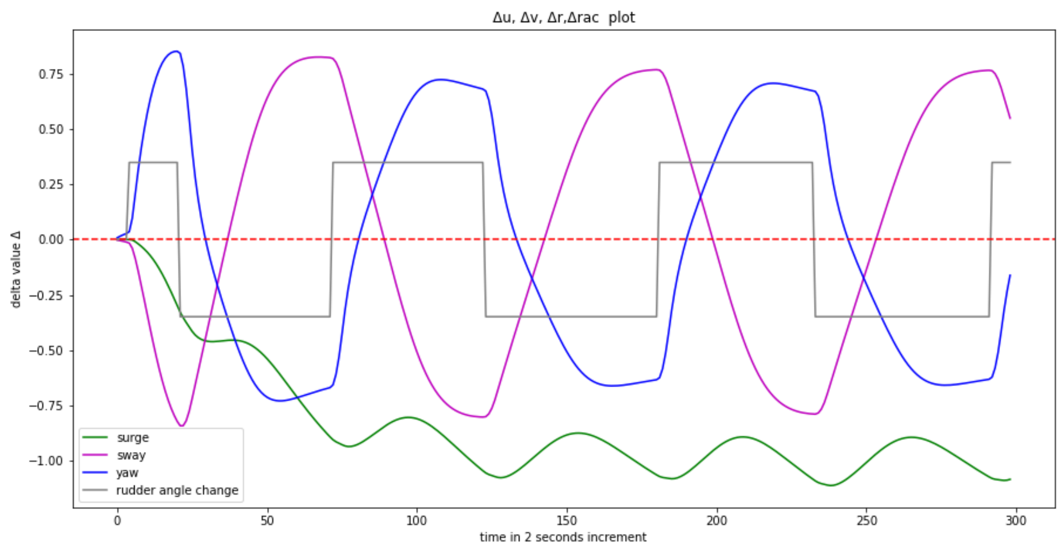

Figure 7. Basic five independent components

As we took (10,14,14) hydrodynamic derivative values for surge, sway and yaw, *SVM*'s input vector for training needs (10,14,14) components. So, we plotted this as well for understanding the numerical dependency.

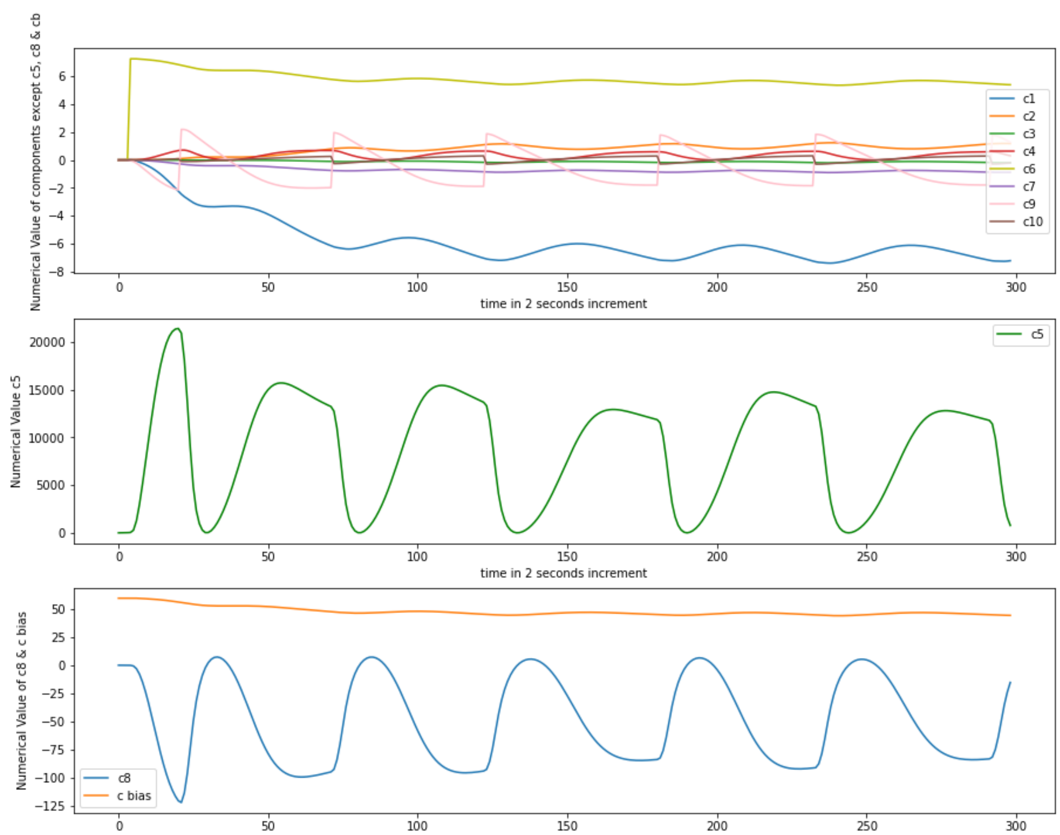

Figure 8. Surge Input components

While expanding right hand side force term in governing equation by Taylor's series 3rd order, Sway and Yaw input vectors shares same input, only first term in 2^{nd} and 3^{rd} governing equations are different.

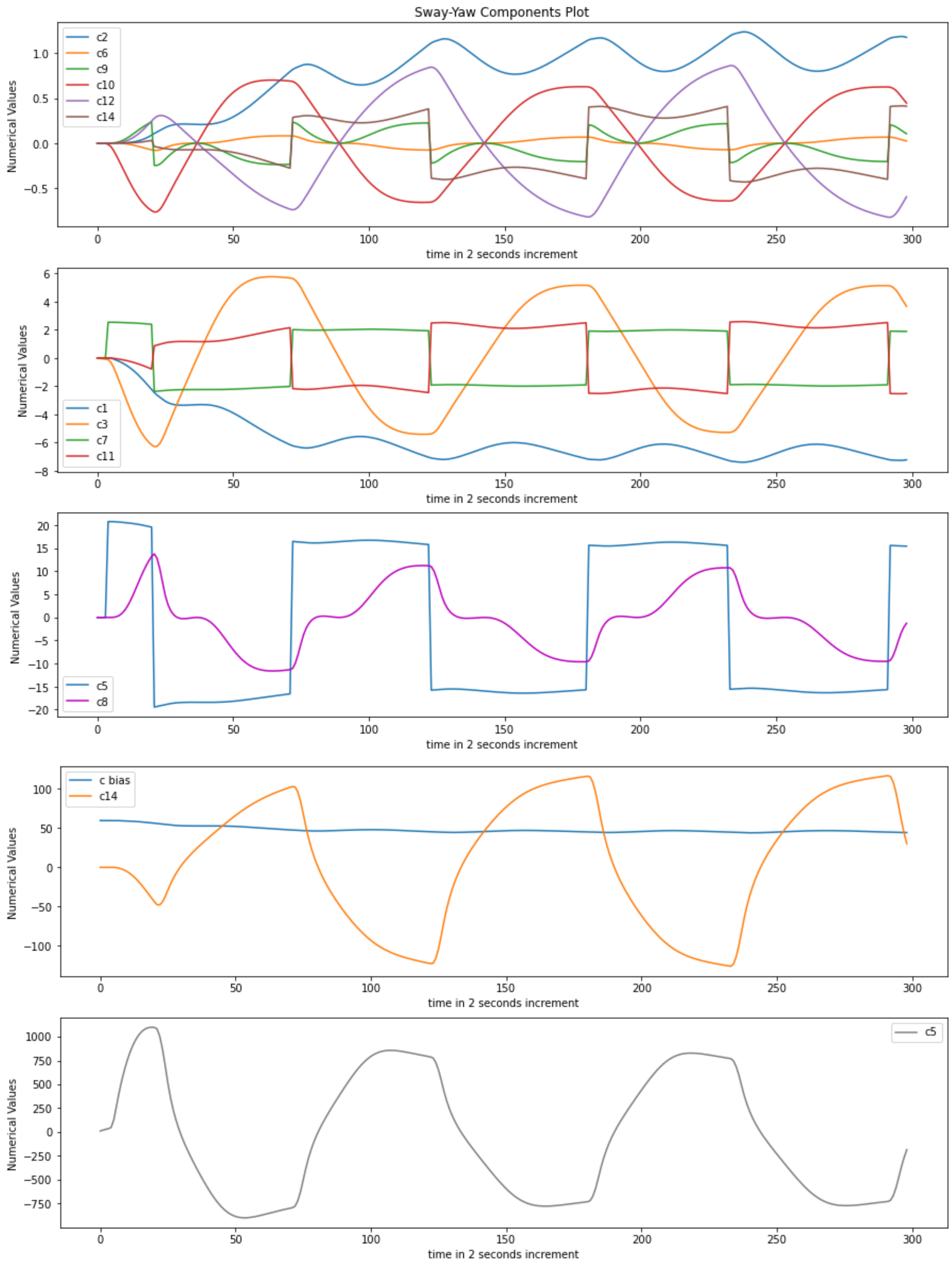

Figure 9. Sway-Yaw component

As we mentioned earlier, We tend to find the Hydrodynamic Derivatives values in Non-dimensional and we calculate the Train set accuracy as well.

Train set accuracy of Surge on LinearSVR method: 1.00
Train set accuracy of Sway on LinearSVR method: 1.00
Train set accuracy of Yaw on LinearSVR method: 1.00

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	10142	10117
2	X`uu	-110	-2182	-2163
3	X`uuu	-215	390	384
4	X`vv	-899	-21	-26
5	X`rr	18	0	0
6	X`δδ	-95	215	223
7	X`δδu	-190	1235	1232
8	X`vr	798	18	13
9	X`vδ	93	-192	-209
10	X`vδu	93	204	205

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	2056	2055
2	Y`ou	-8	-249	-231
3	Y`ouu	-4	-217	-251
4	Y`v	-1160	-258	-213
5	Y`r	-499	13735	13739
6	Y`δ	278	-115	-94
7	Y`vvv	-8078	-591	-590
8	Y`δδδ	-90	20	20
9	Y`vvr	15356	-72	-72
10	Y`vvδ	1190	-10	2
11	Y`vδδ	-4	-393	-390
12	Y`δu	556	1681	1677
13	Y`vu	-1160	-4839	-4813
14	Y`ru	-499	-1979	-1971
15	Y`δuu	278	186	174

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	-26	-26
2	N`ouu	6	2284	2133
3	N`v	3	1286	1229
4	N`r	-264	2284	2132
5	N`δ	-166	3268	3266
6	N`vvv	-139	931	896
7	N`δδδ	1636	3895	3920
8	N`vvr	45	83	81
9	N`vvδ	-5483	474	477
10	N`vδδ	-489	-2544	-2611
11	N`δu	13	663	639
12	N`vu	-278	446	485
13	N`ru	-264	7117	7131
14	N`δuu	0	2037	2013

Source : *code file* 7

while Constructing SVM, regularization parameters such as epsilon(ϵ) and Condition Number(CN) played vital role. minimum value of sensitivity loss tends to better prediction. but, for the case of CN, things are are different. We have to optimize it, In order to find best Condition Number only, there many journals encountered many optimization algorithms like PSO, (ABC) - Artificial Bee Colony Algorithm.

We take Condition Number which is ranging from { 1 to 1×10^{16} } and monitored, how the HDV are close is real one.

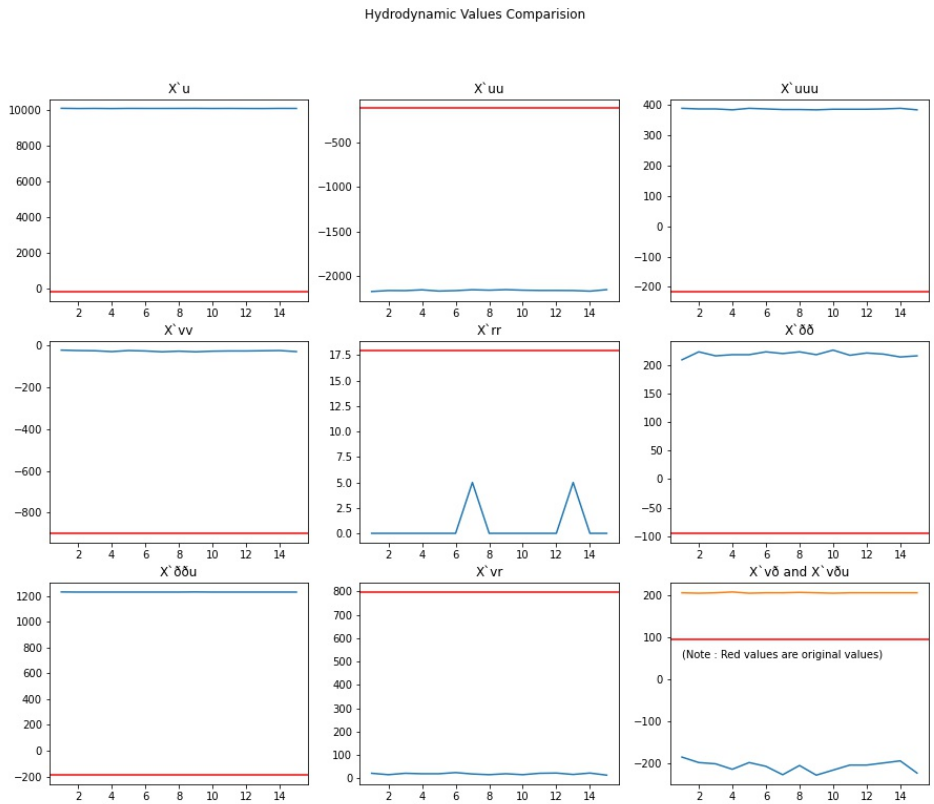

Figure 10. Condition Number Effect on Surge HDV
Source : *code file* 7

Condition Number Effect on Sway Hydrodynamic Derivative Values:

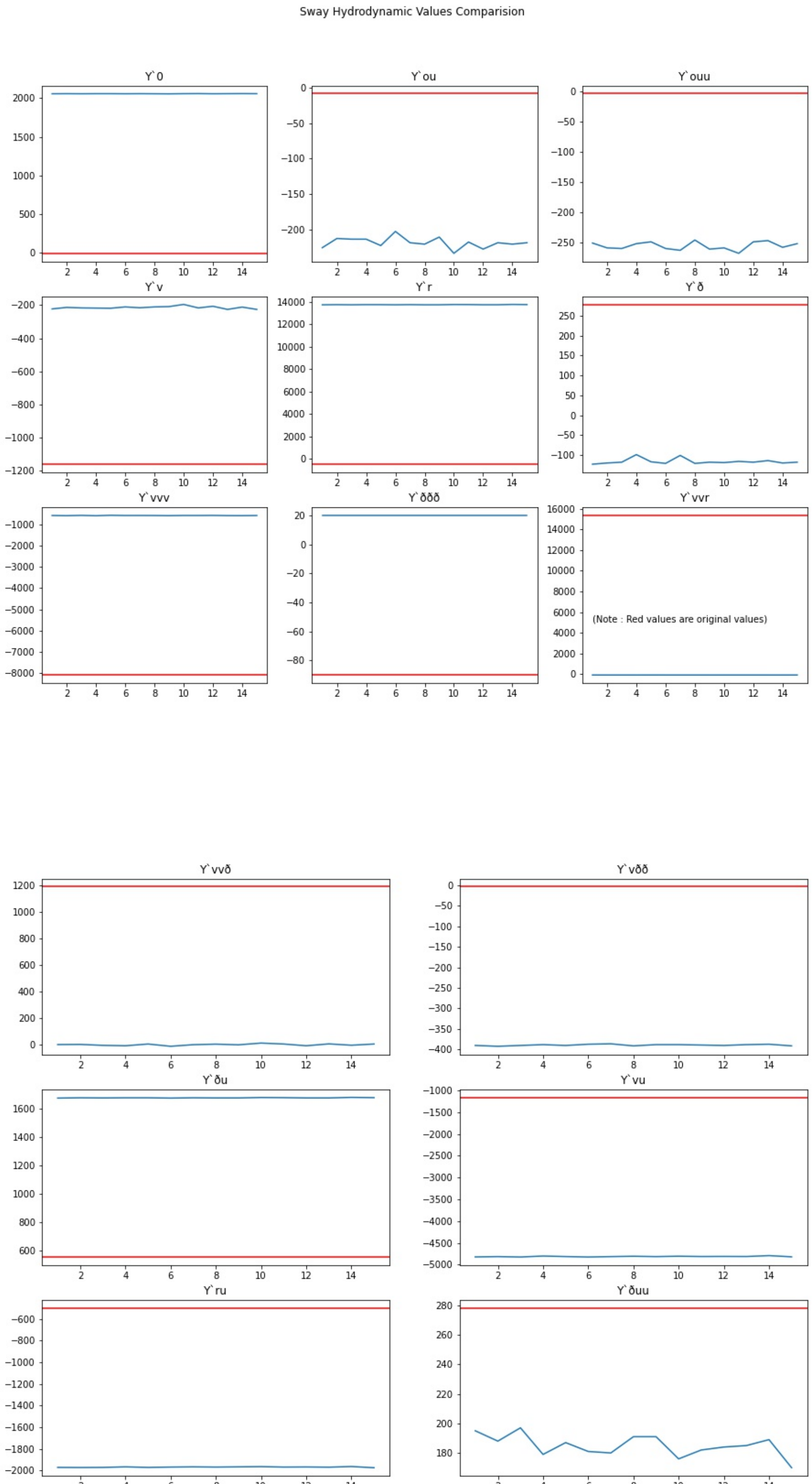

Figure 11. Condition Number Effect on Sway HDV
Source : *code file* 7

Condition Number Effect on Yaw Hydrodynamic Derivative Values:

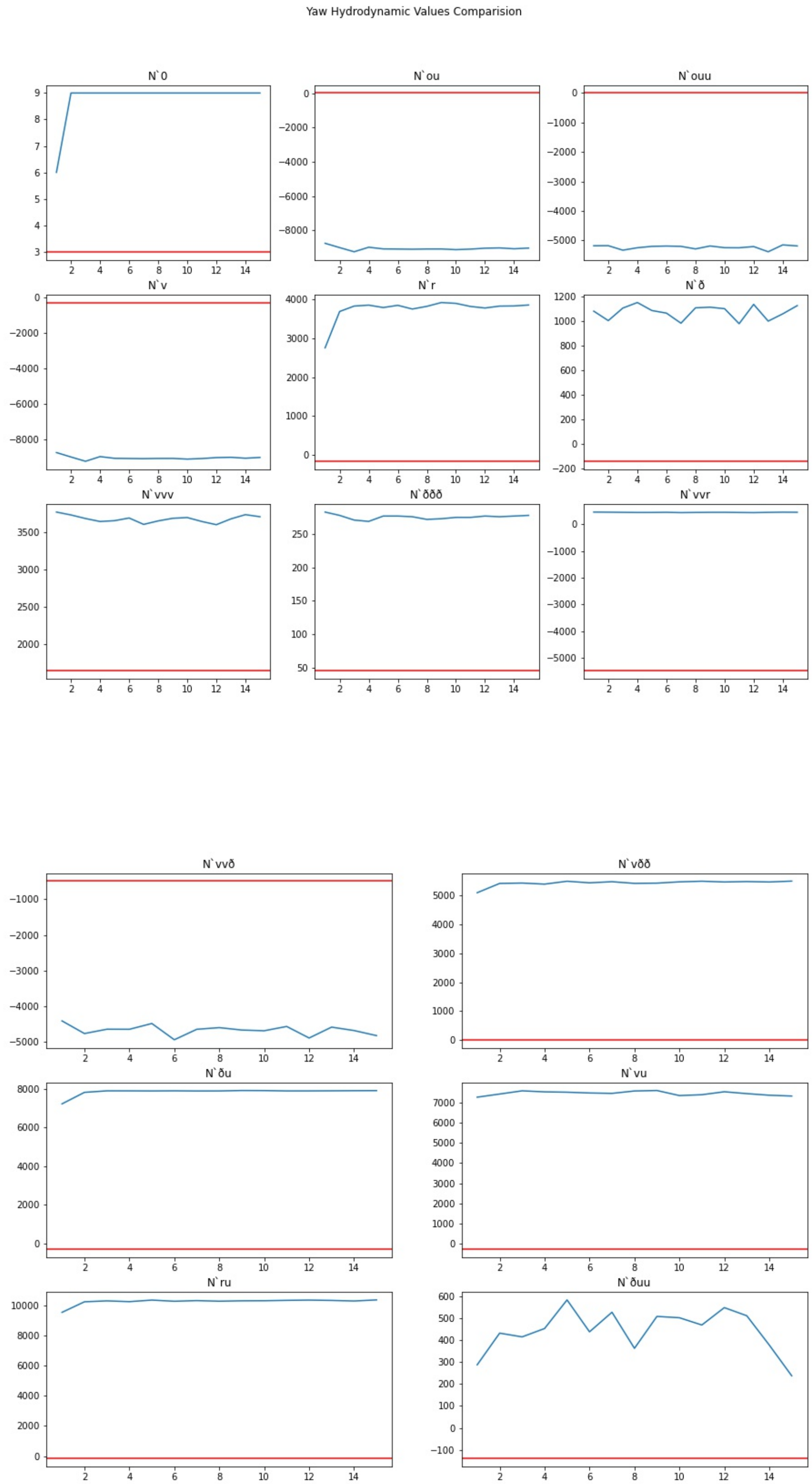

Figure 12. Condition Number Effect on Yaw HDV
Source : *code file* 7

SVM Prediction on Trajectories:

Even though there is no coincide in predicted Hydrodynamic Derivatives Values(regression coefficients), SVM shows good accuracy in function estimation of all three governing equation. from plot, we can understand it.

Train Data : sample at odd number(1,3,5,.....,599 second)
Test Data : sample at even number(2,4,6,.....,600 second)

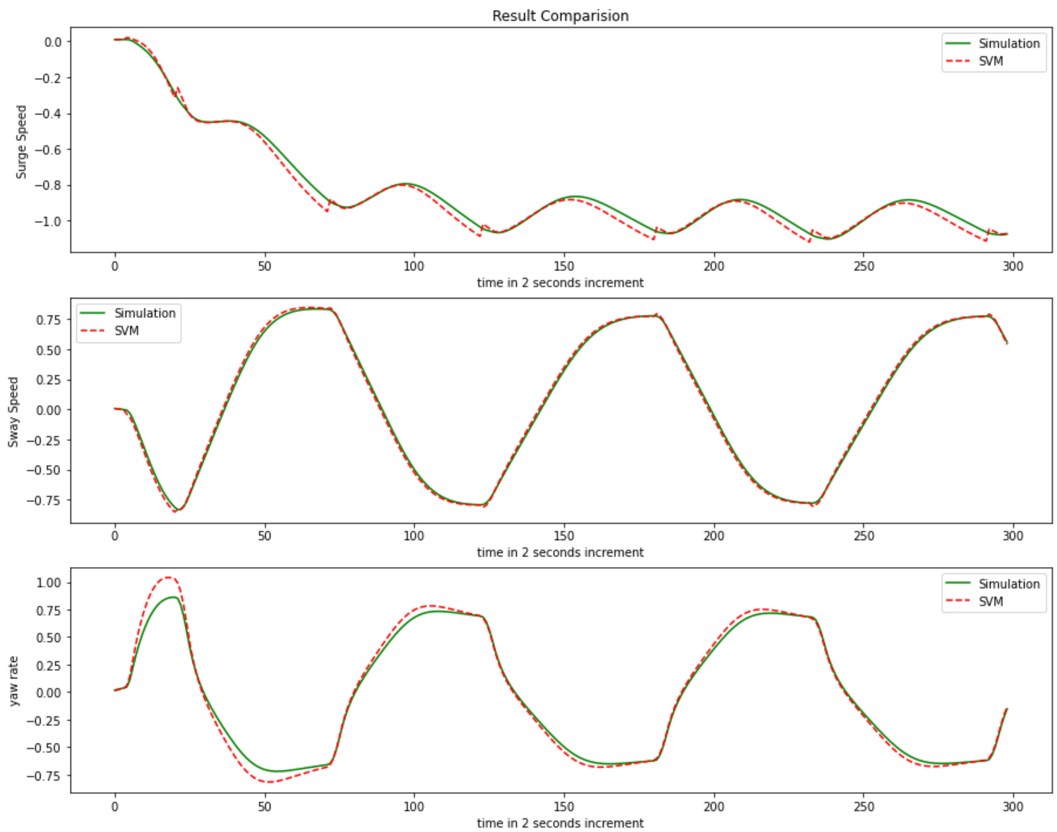

Figure 12. Function Estimation by SVM
Source : *code file* 7

Support Vector Machine by (y - x_1) method and Results

The problem with *jsr* 2009 paper is, we have to fix the first element's coefficient as numerical value 1. But, when we do regression in Support Vector Machine(by using **Sci-kit Learn** library), it's not possible to fix the value as 1 until we build our own kernel.However, building kernel is beyond our scope now. Instead we can do regression by (y - x_1).

```
Train set accuracy of Surge on LinearSVR method: 0.02
Train set accuracy of Sway on LinearSVR method: 0.96
Train set accuracy of Yaw on LinearSVR method: 0.42
```

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	-140	-164
2	X`uu	-110	70	75
3	X`uuu	-215	-14	-15
4	X`vv	-899	-15	-14
5	X`rr	18	0	0
6	X`ðð	-95	-61	-62
7	X`ððu	-190	-17	-20
8	X`vr	798	22	22
9	X`vð	93	-84	-84
10	X`vðu	93	-2	-2

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	-182	-182
2	Y`ou	-8	-244	-208
3	Y`ouu	-4	-142	-180
4	Y`v	-1160	-384	-357
5	Y`r	-499	-1758	-1748
6	Y`ð	278	-7	-12
7	Y`vvv	-8078	-602	-589
8	Y`ððð	-90	-14	-14
9	Y`vvr	15356	-73	-71
10	Y`vvð	1190	419	422
11	Y`vðð	-4	-61	-59
12	Y`ðu	556	-222	-225
13	Y`vu	-1160	-1008	-1002
14	Y`ru	-499	-186	-183
15	Y`ðuu	278	-34	-33

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	4	4
2	N`ouu	6	2278	2116
3	N`v	3	1309	1215
4	N`r	-264	2280	2118
5	N`ð	-166	3521	3436
6	N`vvv	-139	-50	5
7	N`ððð	1636	3923	3787
8	N`vvr	45	80	77
9	N`vvð	-5483	478	461
10	N`vðð	-489	-1869	-1892
11	N`ðu	13	664	647
12	N`vu	-278	476	506
13	N`ru	-264	7060	7055
14	N`ðuu	0	1999	1983

Source : *code file* 8

Condition Number effect in (y - x_1):

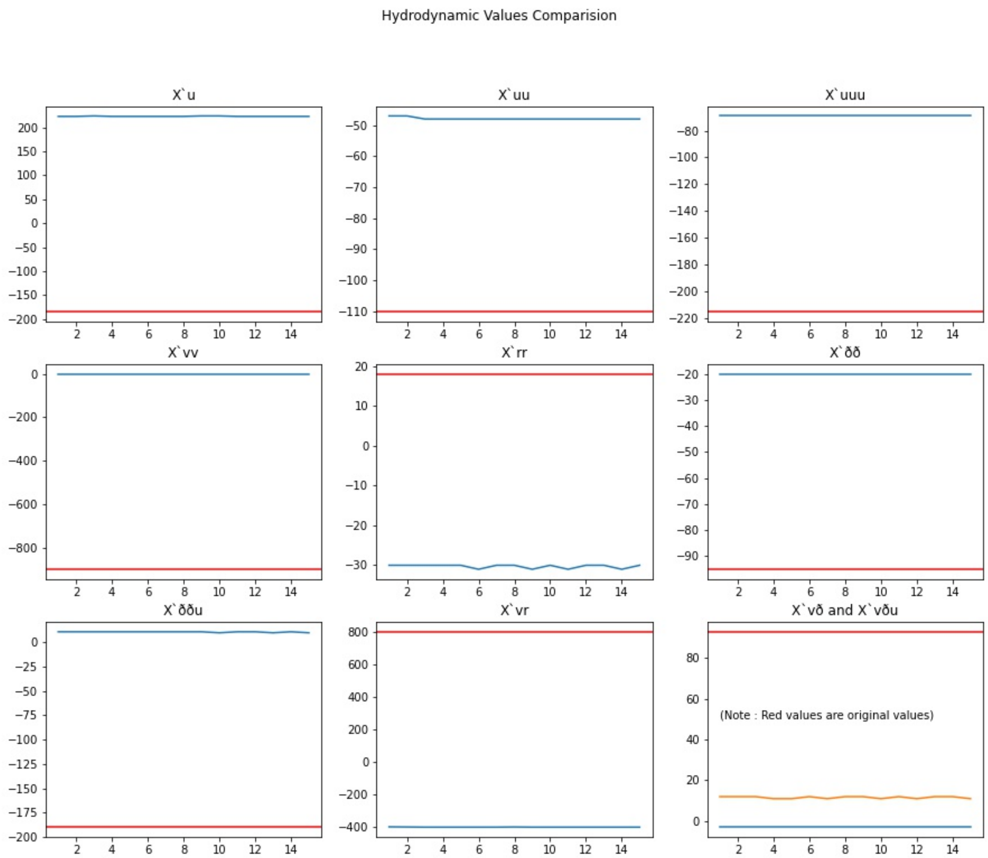

Figure 13. Condition Number Effect on Surge HDV by (y - x_1)

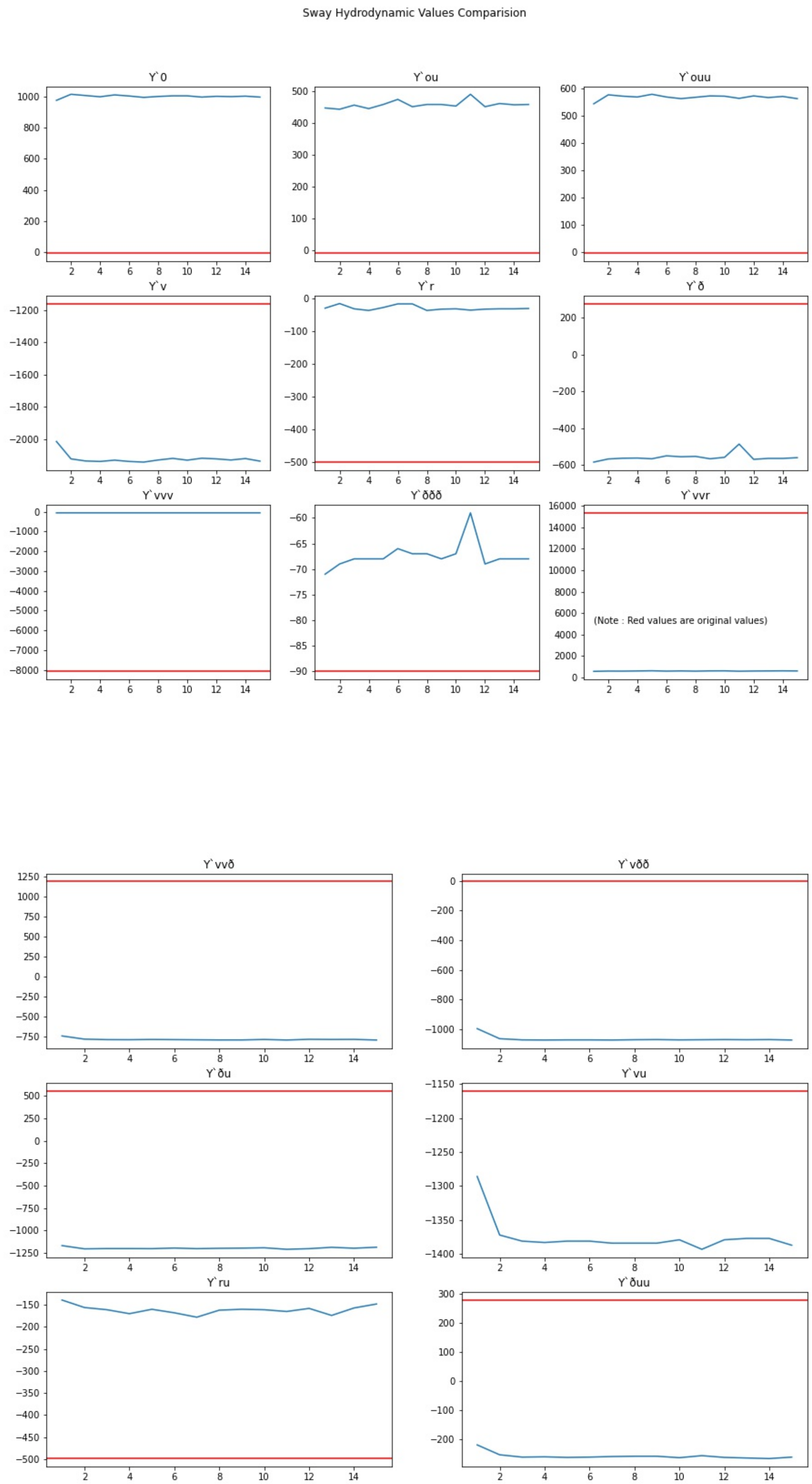

Figure 14. Condition Number Effect on Sway HDV by (y - x_1)
Source : *code file* 8

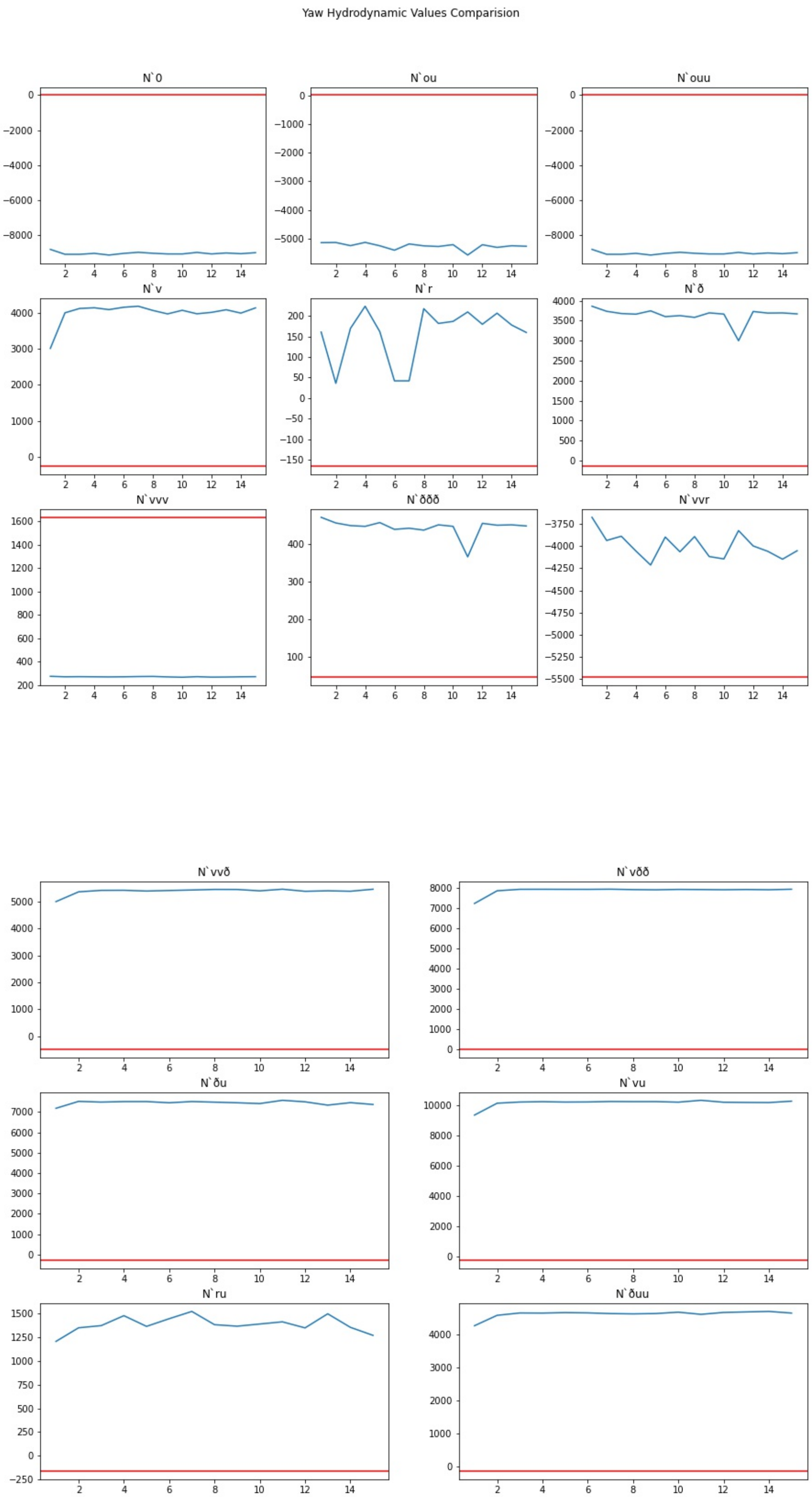

Figure 15. Condition Number Effect on Yaw HDV by (y - x_1)
Source : *code file* 8

SVM on Second Order Derivative Method (y - x_1)

We have tried this second order method(*code file* 9) to form governing equation as we mentioned on earlier. The same Mariner's ship $20-20$ ZigZag Test Data was used for study.In order to understand the dependence of each components, first we tend to plot the { $\Delta u(k+1) - \Delta u(k)$ }, $\Delta v(k+1) - \Delta u(k)$, $\Delta r(k+1) - \Delta r(k)$ and $\Delta\delta(k+1) - \Delta\delta(k)$ values here and others following

Observations:

Second Order Method not gives good result in neither function estimation nor parameter estimation.

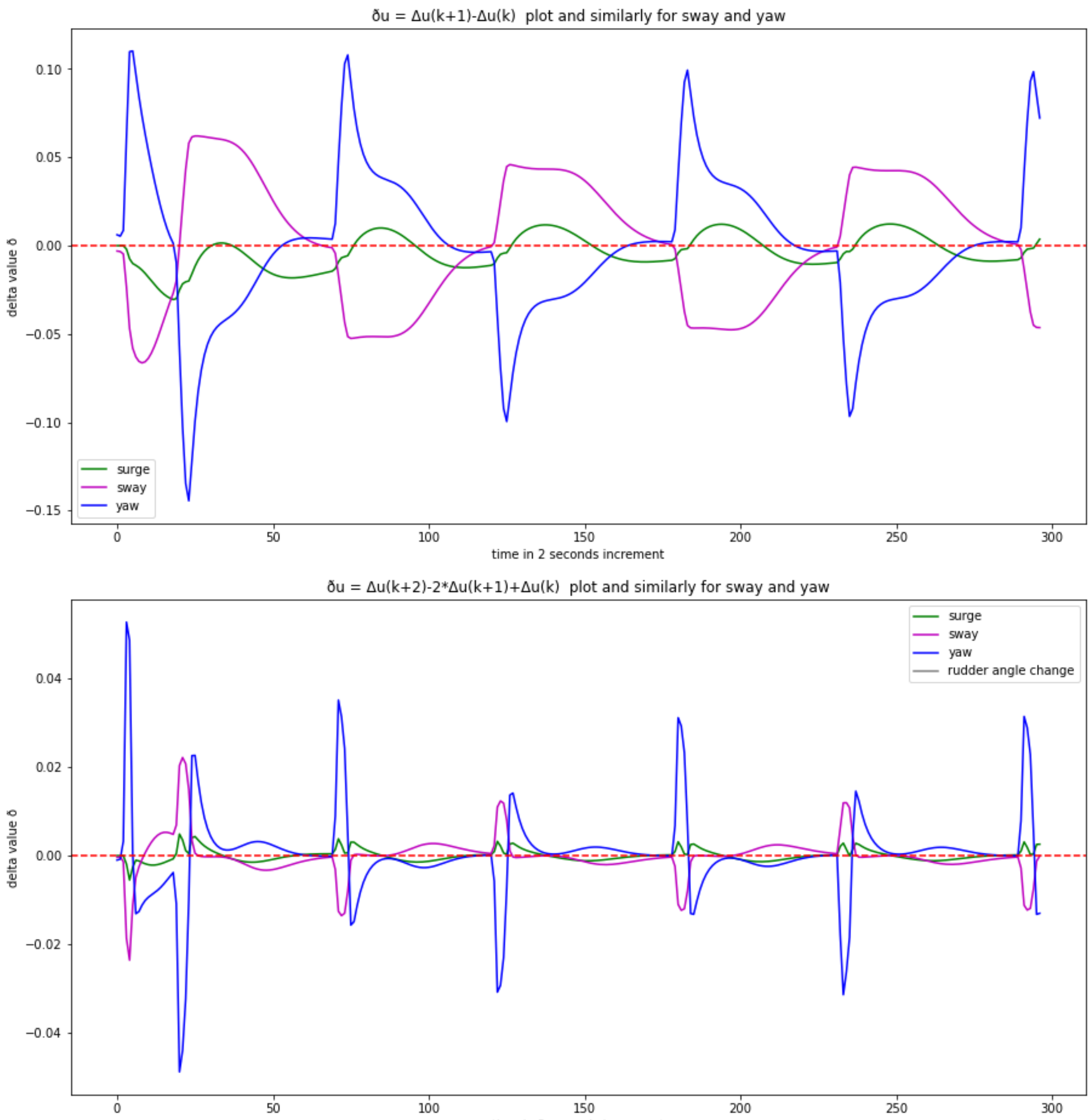

Figure 16. LHS Value in Governing Value
Source : *code file* 9

As we took (10,14,14) hydrodynamic derivative values for surge, sway and yaw,SVM's input vector for training needs (10,14,14)components. So, we plotted this as well for understanding the numerical dependency.

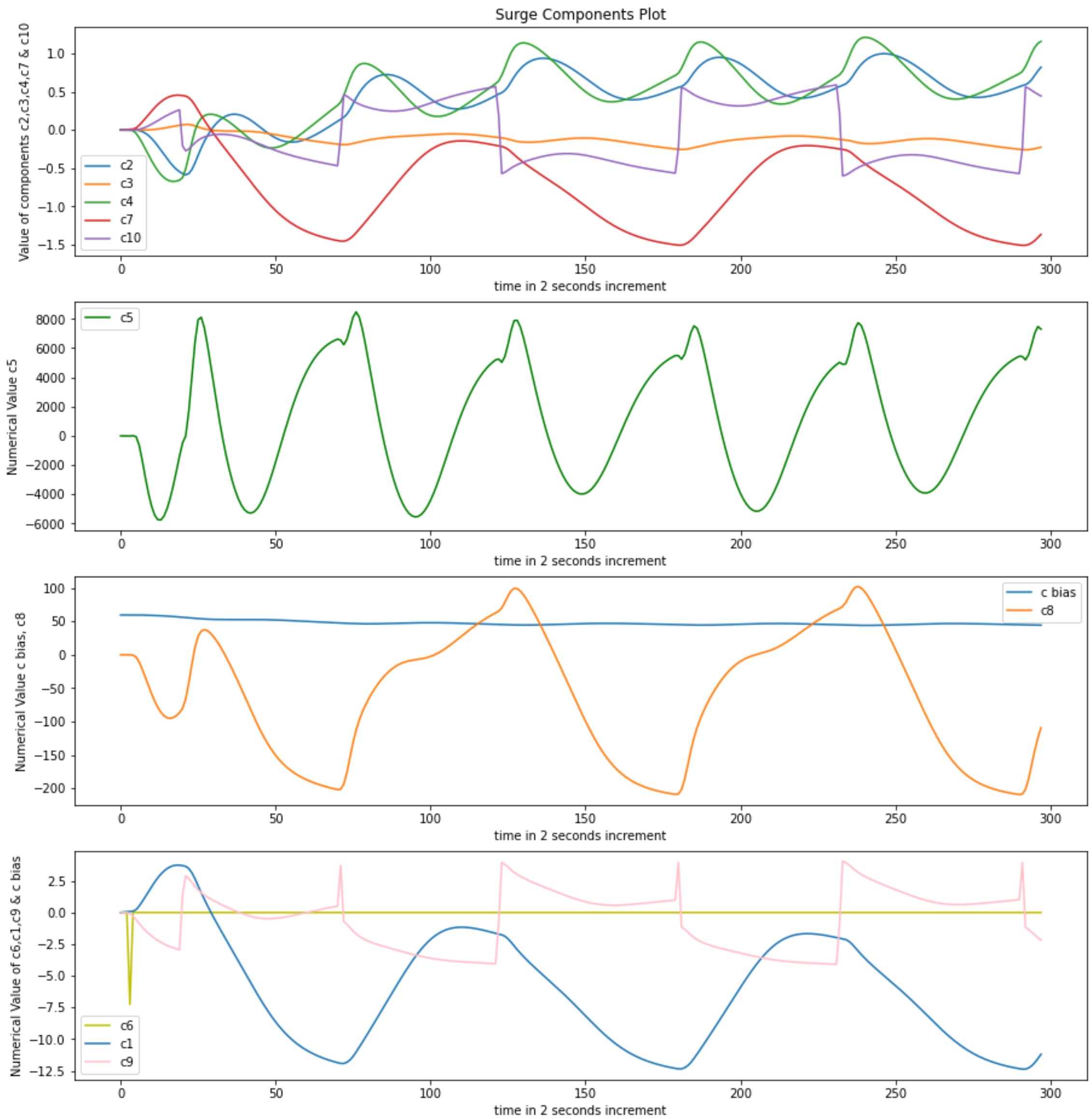

Figure 17. Surge Components - Second Order Method

While expanding right hand side force term in governing equation by Taylor's series 3^{rd} order, Sway and Yaw input vectors shares same input, only first term in 2^{nd} and 3^{rd} governing equations are different

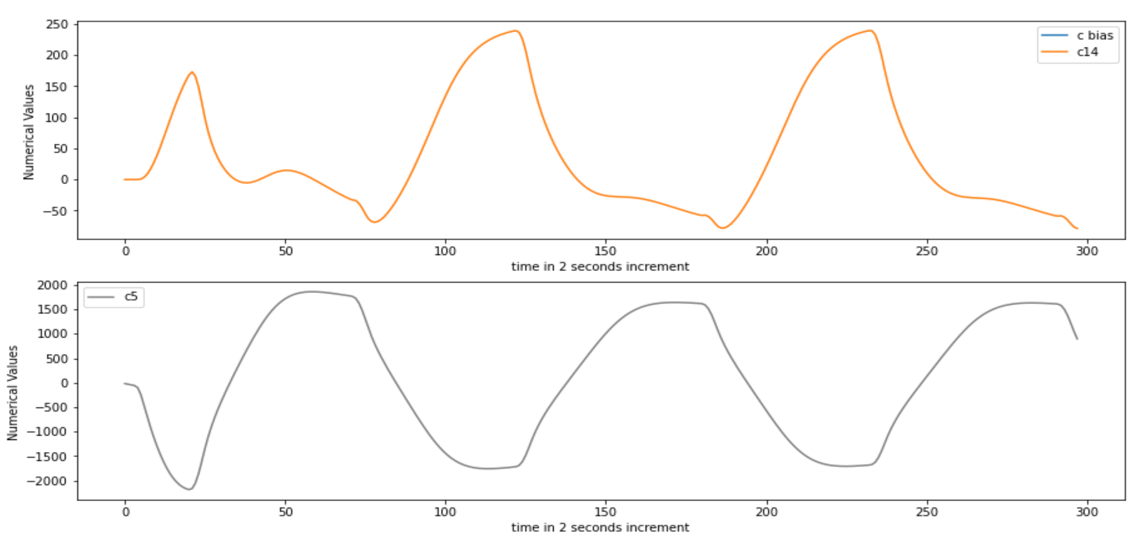

Figure 18a. Sway Yaw Components - Second Order Method

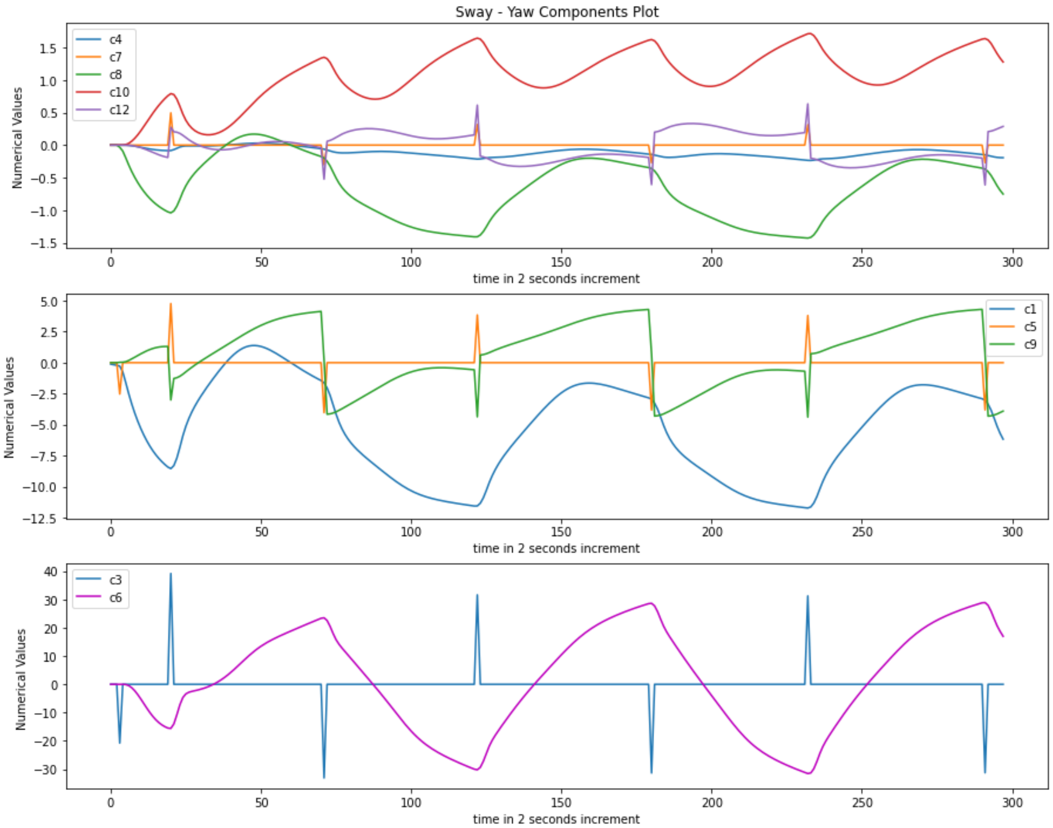

Figure 18b. Sway Yaw Components - Second Order Method

SVM Prediction on Trajectories:

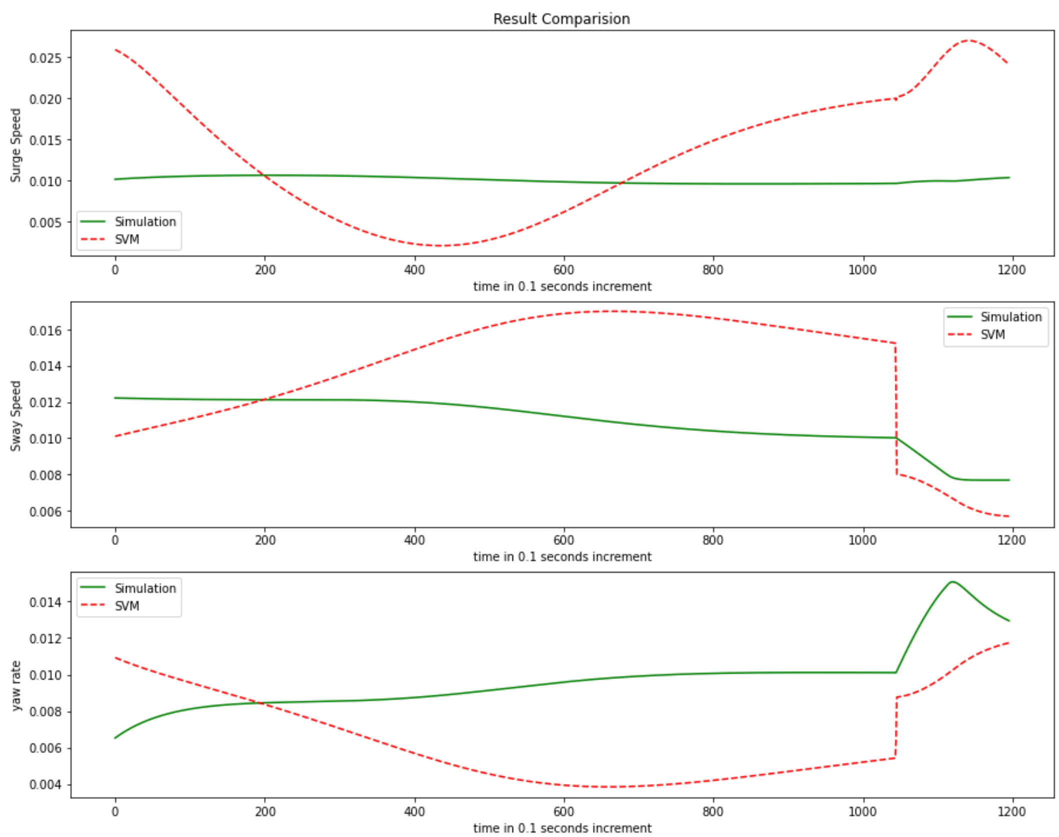

Figure 19. Function Estimation by SVM
Source : *code file* 9

Predicted Hydrodynamic Derivative Values by Second Order Method:

Train set accuracy of Surge on LinearSVR method: -0.16
Train set accuracy of Sway on LinearSVR method: 0.55
Train set accuracy of Yaw on LinearSVR method: 0.22

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	0	0
2	X`uu	-110	0	0
3	X`uuu	-215	-9	-14
4	X`vv	-899	1	4
5	X`rr	18	11	10
6	X`ðð	-95	-18	-4
7	X`ððu	-190	341	617
8	X`vr	798	18	-3
9	X`vð	93	0	0
10	X`vðu	93	-1	16

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	1445	9841
2	Y`ou	-8	-730	15736
3	Y`ouu	-4	1447	9818
4	Y`v	-1160	-4010	-5531
5	Y`r	-499	-19	-81
6	Y`ð	278	-459	-572
7	Y`vvv	-8078	-11	-11
8	Y`ððð	-90	785	997
9	Y`vvr	15356	560	940
10	Y`vvð	1190	-2	-4
11	Y`vðð	-4	-430	-1180
12	Y`ðu	556	797	1707
13	Y`vu	-1160	2716	1497
14	Y`ru	-499	-3708	-14205
15	Y`ðuu	278	-4	-9

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	-13309	-90527
2	N`ouu	6	4578	-141817
3	N`v	3	-13309	-90527
4	N`r	-264	12748	26500
5	N`ð	-166	11	536
6	N`vvv	-139	2988	3825
7	N`ððð	1636	100	103
8	N`vvr	45	-5367	-6883
9	N`vvð	-5483	-4540	-8013
10	N`vðð	-489	17	43
11	N`ðu	13	3414	10510
12	N`vu	-278	-6405	-15019
13	N`ru	-264	-24918	-13702
14	N`ðuu	0	31841	129393

Source : *code file* 9

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SVM Trained with One Data and Tested by Another Data

In order to understand the SVM's Function estimation and robustness, here, we tried to train the SVM with one and using another set of data for prediction. We took the ZigZag test in different combination.

Data Descriptions:(All samples are in 0.1 seconds interval)

. Data 1 : ZigZag Test 20-20 (600 seconds)

. Data 2 : ZigZag Test (20-15-10-5) (1600 seconds)

. Data 3 : ZigZag Test (20-17.5-15-12.5-....-5) (2800 seconds)

SVM Training Data Description:

- Number of input Vectors for training :4800 (from JSR 2009 data)first 80% Data 1
- **SVM:** Condition Number - 1×10^4, epsilon - 1×10^{-6}, ramp value - 0.01

Once we constructed the SVM with the above mentioned data, here, we are going to test with different data.

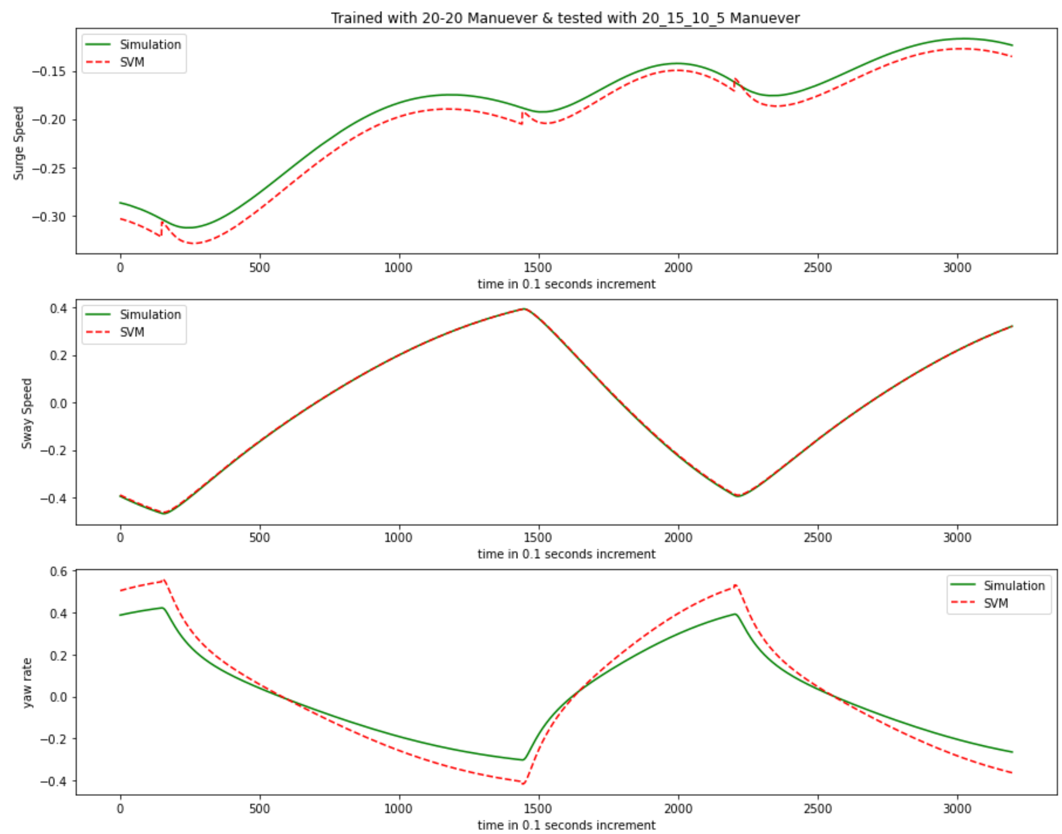

Figure 20. Tested on Data 2: 3200 vectors,interval between (1300-1600 seconds)
Source : *code file* 10*a*

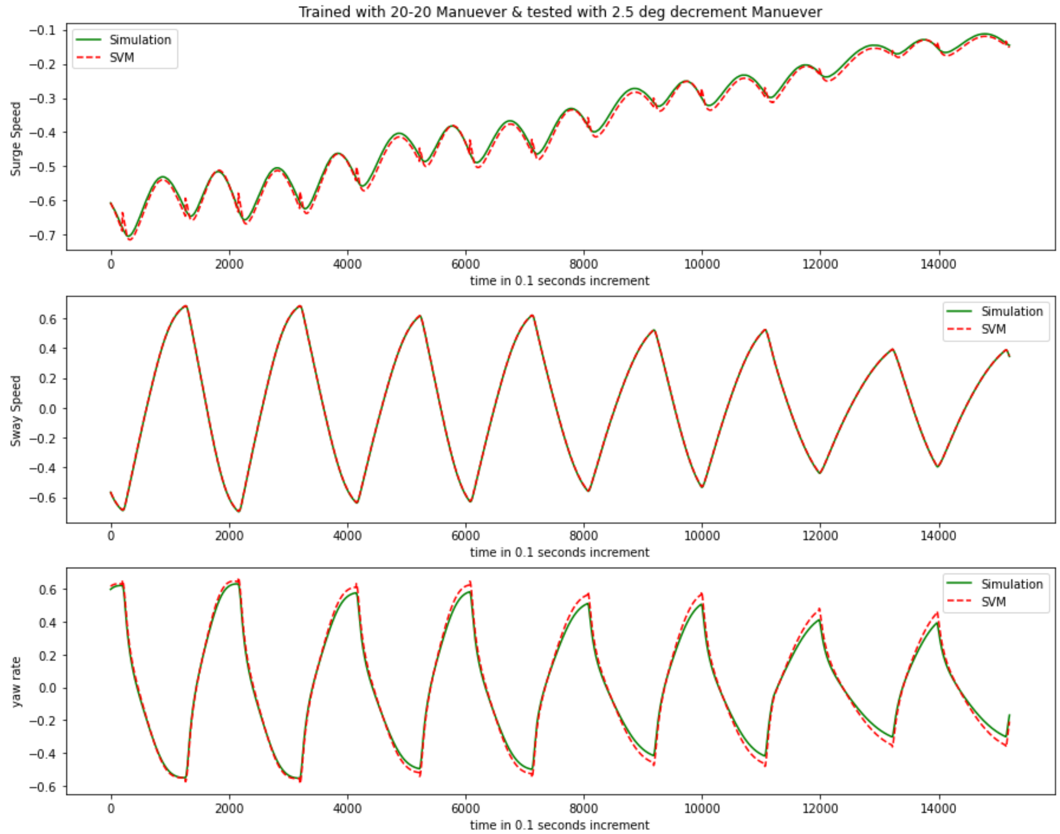

Figure 21. Tested on Data 3: 14000 vectors,interval between (1200-2800 seconds)
Source : *code file* 10*b*

Observations:
SVM's function estimation is good, when it tests with different ZigZag Manoeuvre. However, matching HDV values needs much attention.

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Limited Number of Hydrodynamic Derivative Values and Results

As we expand the force in Taylor series upto 3^{rd} order, we will get 23 elements.However, On considering certainty,in JSR 2009 paper, it will be reduced to (10-14-14) in (surge-sway-yaw) components. If we expand Taylor series up to 5^{th} order, still, we can predict every hydrodynamic derivative values. But, the term "**Multi co-linearity**" would be the key factor in deciding the number of elements. In our case, here, we tried different number of combination to understand the hydrodynamic values (*code file* 11).

SVM with First Order Linear coefficients:

Train set accuracy of Surge on LinearSVR method: 0.17
Train set accuracy of Sway on LinearSVR method: 0.93
Train set accuracy of Yaw on LinearSVR method: 0.90

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	-161	-161

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`v	-1160	-2214	-1190
2	Y`r	-499	-7	-6
3	Y`δ	278	-490	-567

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`v	-264	7074	-2377
2	N`r	-166	-16	-64
3	N`δ	-139	3142	4026

SVM with Linear coefficients:

Train set accuracy of Surge on LinearSVR method: 0.80
Train set accuracy of Sway on LinearSVR method: 0.91
Train set accuracy of Yaw on LinearSVR method: 0.52

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	-10	-10
2	X`uu	-110	776	775
3	X`uuu	-215	-162	-161
4	X`vv	-899	-504	-503
5	X`rr	18	0	0
6	X`δδ	-95	-33	-32

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`v	-1160	-1191	-1198
2	Y`r	-499	-3	2
3	Y`δ	278	-540	-571
4	Y`vvv	-8078	-343	-343
5	Y`δδδ	-90	-65	-69

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`v	-264	-2401	-2296
2	N`r	-166	-34	-93
3	N`δ	-139	3642	3893
4	N`vvv	1636	1973	1985
5	N`δδδ	45	443	474

SVM with Linear coefficients with Intercept:

```
Train set accuracy of Surge on LinearSVR method: 0.79
Train set accuracy of Sway on LinearSVR method: 0.94
Train set accuracy of Yaw on LinearSVR method: 0.79
```

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	-11	-11
2	X`uu	-110	776	775
3	X`uuu	-215	-162	-161
4	X`vv	-899	-504	-503
5	X`rr	18	0	0
6	X`δδ	-95	-32	-32

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	-994	-994
2	Y`ou	-8	-5792	-5787
3	Y`ouu	-4	-1289	-1286
4	Y`v	-1160	-1	-4
5	Y`r	-499	-537	-542
6	Y`δ	278	-334	-333
7	Y`vvv	-8078	-65	-66

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	5862	5942
2	N`ouu	6	33540	33442
3	N`v	3	-1711	-1764
4	N`r	-264	-54	-61
5	N`δ	-166	3624	3761
6	N`vvv	-139	1919	1924
7	N`δδδ	1636	441	458

SVM with Non Linear coefficients upto 2^{nd} order:

```
Train set accuracy of Surge on LinearSVR method: 0.56
Train set accuracy of Sway on LinearSVR method: 0.89
Train set accuracy of Yaw on LinearSVR method: 0.65
```

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	217	217
2	X`uu	-110	-60	-60
3	X`uuu	-215	0	0
4	X`vv	-899	-25	-25
5	X`rr	18	10	10
6	X`δδ	-95	-459	-459

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`v	-1160	-2633	-2671
2	Y`r	-499	-28	-21
3	Y`δ	278	-510	-498
4	Y`δu	556	-1502	-1562
5	Y`vu	-1160	-769	-742
6	Y`ru	-499	-116	-132

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`v	-264	6275	9913
2	N`r	-166	105	250
3	N`δ	-139	3421	2527
4	N`δu	-278	8773	14341
5	N`vu	-264	3315	-16055
6	N`ru	-166	816	1463

SVM with Non Linear coefficients:

```
Train set accuracy of Surge on LinearSVR method: 0.54
Train set accuracy of Sway on LinearSVR method: 0.98
Train set accuracy of Yaw on LinearSVR method: 0.90
```

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	71	77
2	X`uu	-110	-14	-15
3	X`uuu	-215	-15	-15
4	X`vv	-899	0	0
5	X`rr	18	-61	-61
6	X`δδ	-95	-17	-20
7	X`δδu	-190	22	21
8	X`vr	798	-86	-86
9	X`vδ	93	-2	-2
10	X`vδu	93	0	12

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`v	-1160	-1520	-1511
2	Y`r	-499	-10	-18
3	Y`δ	278	-648	-655
4	Y`vvv	-8078	-12	-12
5	Y`vvr	15356	-78	-79
6	Y`vvδ	1190	447	451
7	Y`vδδ	-4	-1012	-1017
8	Y`δu	556	-136	-136
9	Y`vu	-1160	-38	-37
10	Y`ru	-499	-5	-8

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`v	-264	558	1146
2	N`r	-166	-9	68
3	N`δ	-139	4309	4344
4	N`vvv	1536	53	59
5	N`vvr	-5483	525	529
6	N`vvδ	-489	-2189	-2062
7	N`vδδ	13	6682	7109
8	N`δu	-278	1464	1553
9	N`vu	-264	255	197
10	N`ru	-166	47	289

Source : *code file* 11

SVM on Turning Circle Test

With reference to *JSR* 2009 Paper, we followed the mathematical model(first order method) and encoded in python programming(*code file* 12) accordingly. For surge 10 hydrodynamic derivative components, for sway and yaw 14 hydrodynamic derivative components were taken.In order to understand the dependence of each components, first we tend to plot the Δu, Δv, Δr and $\Delta\delta$ values here and others following

Components Plots (Mariner's Ship Data - Turning Circle Test - 400 seconds):

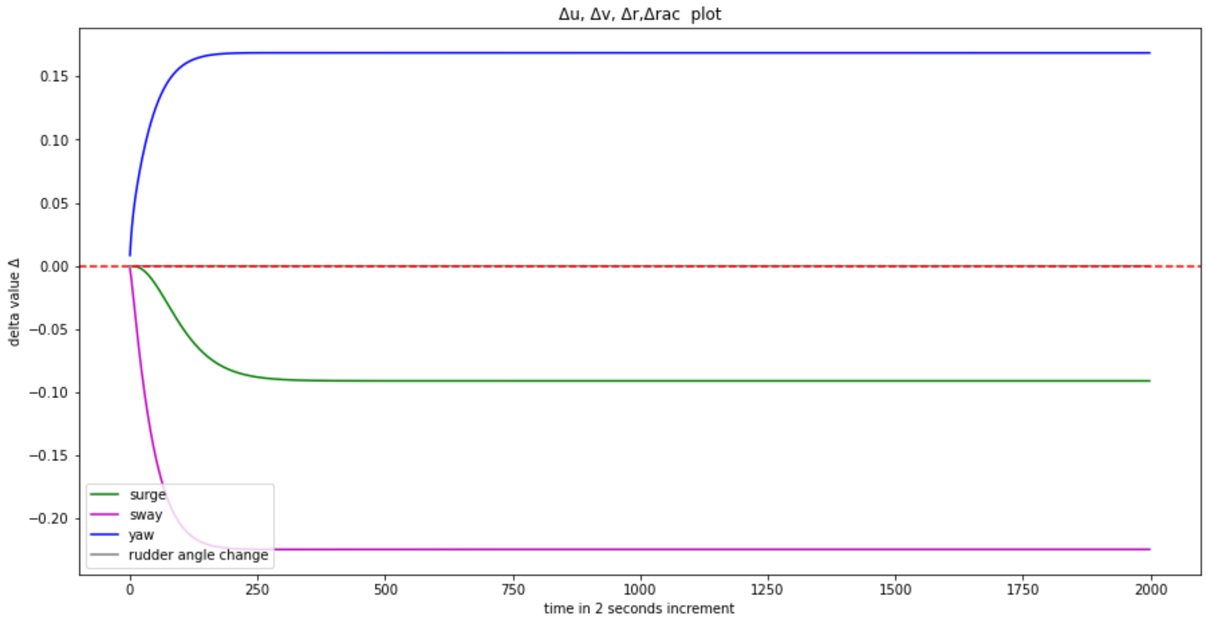

Figure 22. Basic Five Components

As we took (10,14,14) hydrodynamic derivative values for surge, sway and yaw,SV M's input vector for training needs (10,14,14)components. So, we plotted this as well for understanding the numerical dependency.

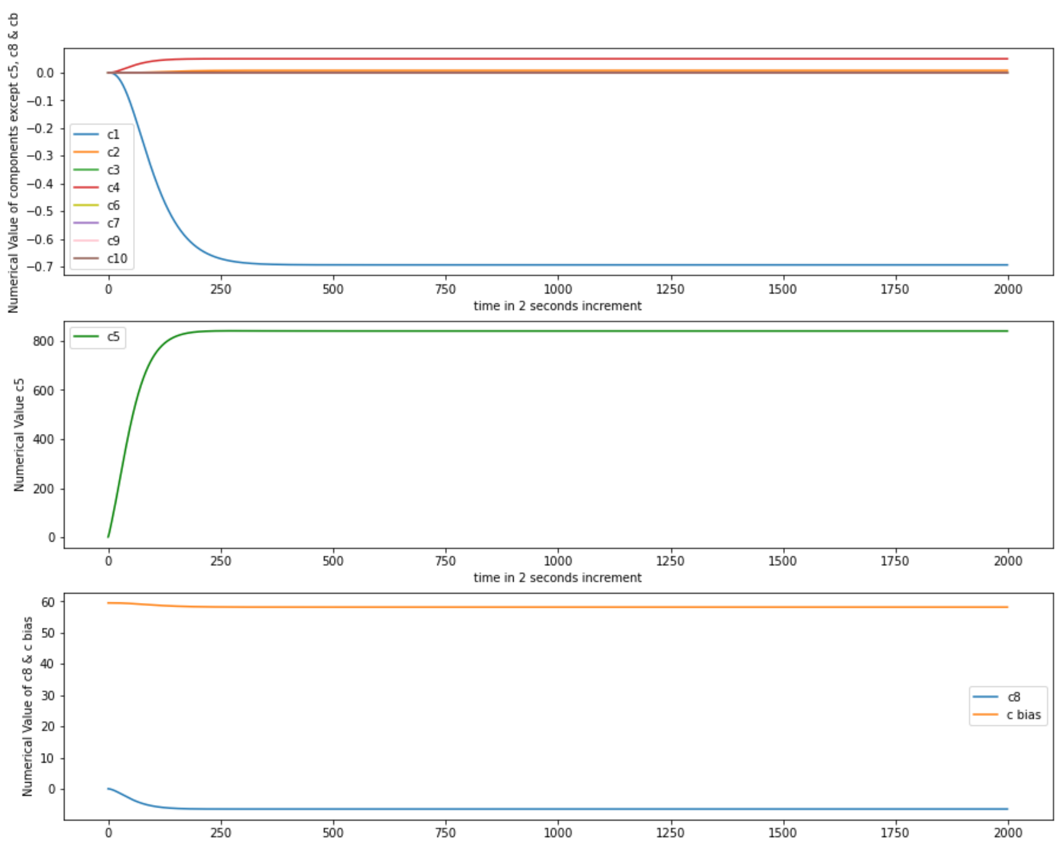

Figure 23. Surge Components Plots

While expanding right hand side force term in governing equation by Taylor's series 3^{rd} order, Sway and Yaw input vectors share same input, only first term in 2^{nd} and 3^{rd} governing equations are different.

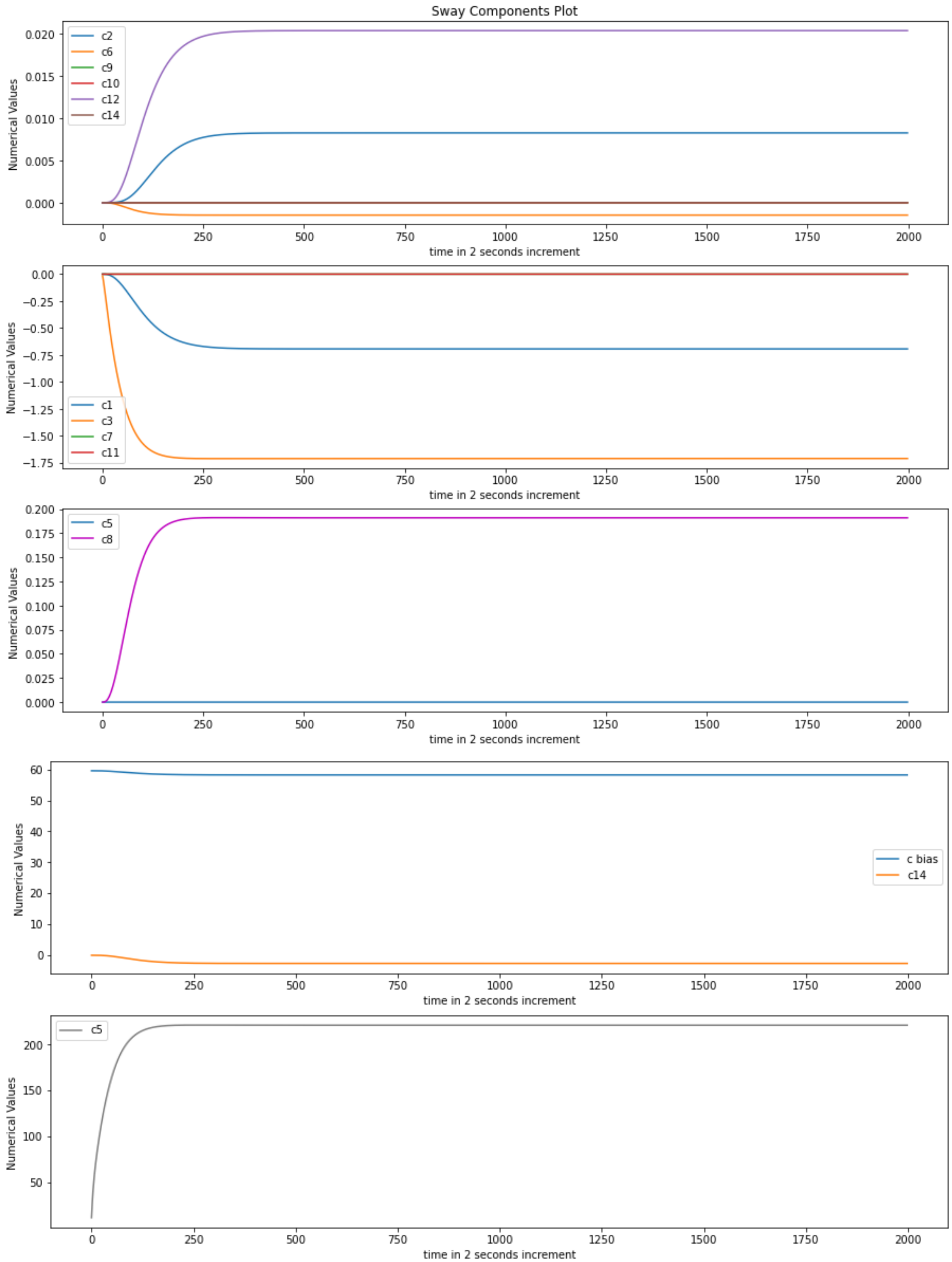

Figure 24. Sway & Yaw Components Plot

As we mentioned earlier, We tend to find the Hydrodynamic Derivatives values in Non-dimensional and we calculate the Train set accuracy as well.

```
Train set accuracy of Surge on LinearSVR method: 0.06
Train set accuracy of Sway on LinearSVR method: 0.96
Train set accuracy of Yaw on LinearSVR method: 0.70
```

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	0	0
2	X`uu	-110	0	0
3	X`uuu	-215	0	0
4	X`vv	-899	0	0
5	X`rr	18	0	0
6	X`ðð	-95	0	0
7	X`ððu	-190	-41	-48
8	X`vr	798	0	0
9	X`vð	93	0	0
10	X`vðu	93	0	119

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	-84	121
2	Y`ou	-8	116	67
3	Y`ouu	-4	0	-2
4	Y`v	-1160	-10	-1283
5	Y`r	-499	69	64
6	Y`ð	278	0	0
7	Y`vvv	-8078	0	0
8	Y`ððð	-90	0	0
9	Y`vvr	15356	-57	37
10	Y`vvð	1190	0	0
11	Y`vðð	-4	0	0
12	Y`ðu	556	0	0
13	Y`vu	-1160	-2	-3
14	Y`ru	-499	398	417
15	Y`ðuu	278	0	0

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	13	38
2	N`ouu	6	-2750	-2523
3	N`v	3	11	40
4	N`r	-264	-2124	9581
5	N`ð	-166	-535	-450
6	N`vvv	-139	0	0
7	N`ððð	1636	-9	-3
8	N`vvr	45	0	0
9	N`vvð	-5483	1219	375
10	N`vðð	-489	0	0
11	N`ðu	13	0	0
12	N`vu	-278	0	0
13	N`ru	-264	74	86
14	N`ðuu	0	-9801	-10903

Source : *code file* 12

SVM on Spiral Test

With reference to JSR 2009 Paper, we followed the mathematical model(first order method) and encoded in python programming(*code file* 13) accordingly. For surge 10 hydrodynamic derivative components, for sway and yaw 14 hydrodynamic derivative components were taken.In order to understand the dependence of each components, first we tend to plot the Δu, Δv, Δr and $\Delta\delta$ values here and others following

Components Plots (Mariner's Ship Data - Spiral Test - 6000 seconds):

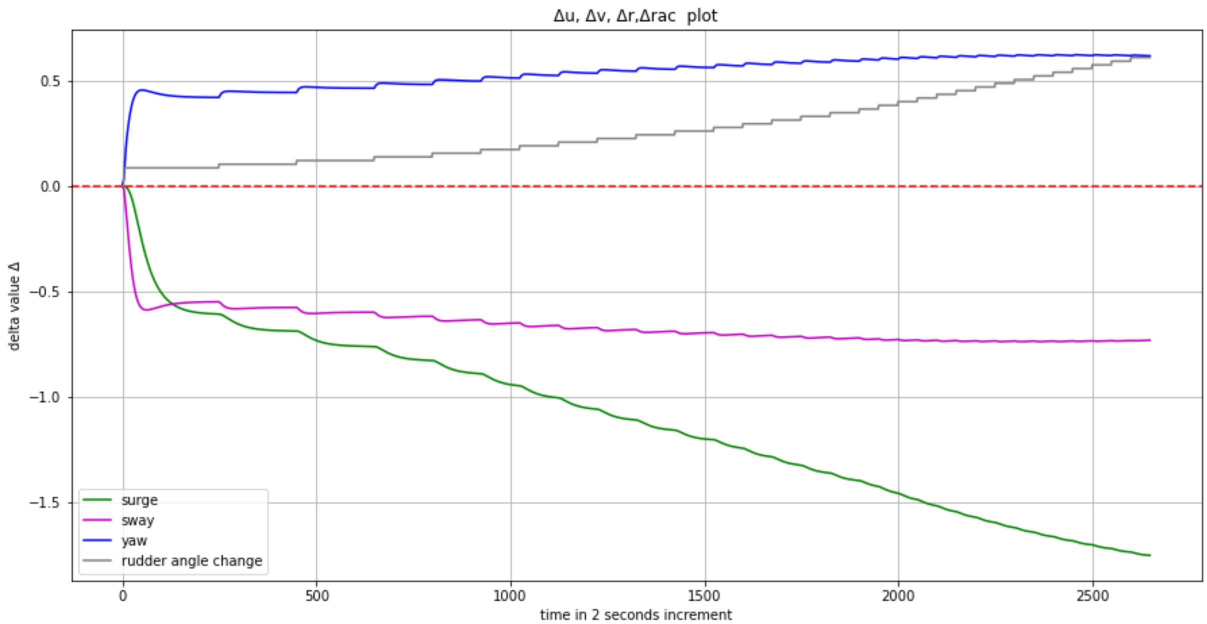

Figure 25. Basic Five Components

As we took (10,14,14) hydrodynamic derivative values for surge, sway and yaw,SV M's input vector for training needs (10,14,14)components. So, we plotted this as well for understanding the numerical dependency.

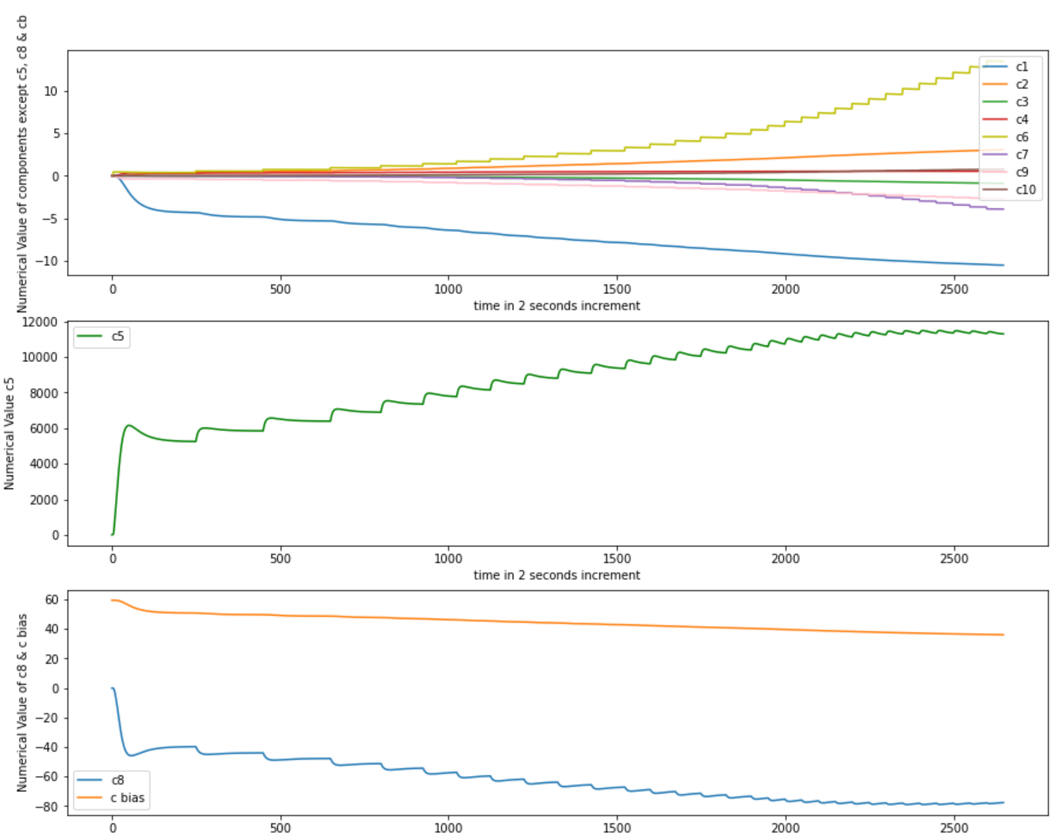

Figure 26. Surge Components Plots

While expanding right hand side force term in governing equation by Taylor's series 3^{rd} order, Sway and Yaw input vectors share same input, only first term in 2^{nd} and 3^{rd} governing equations are different.

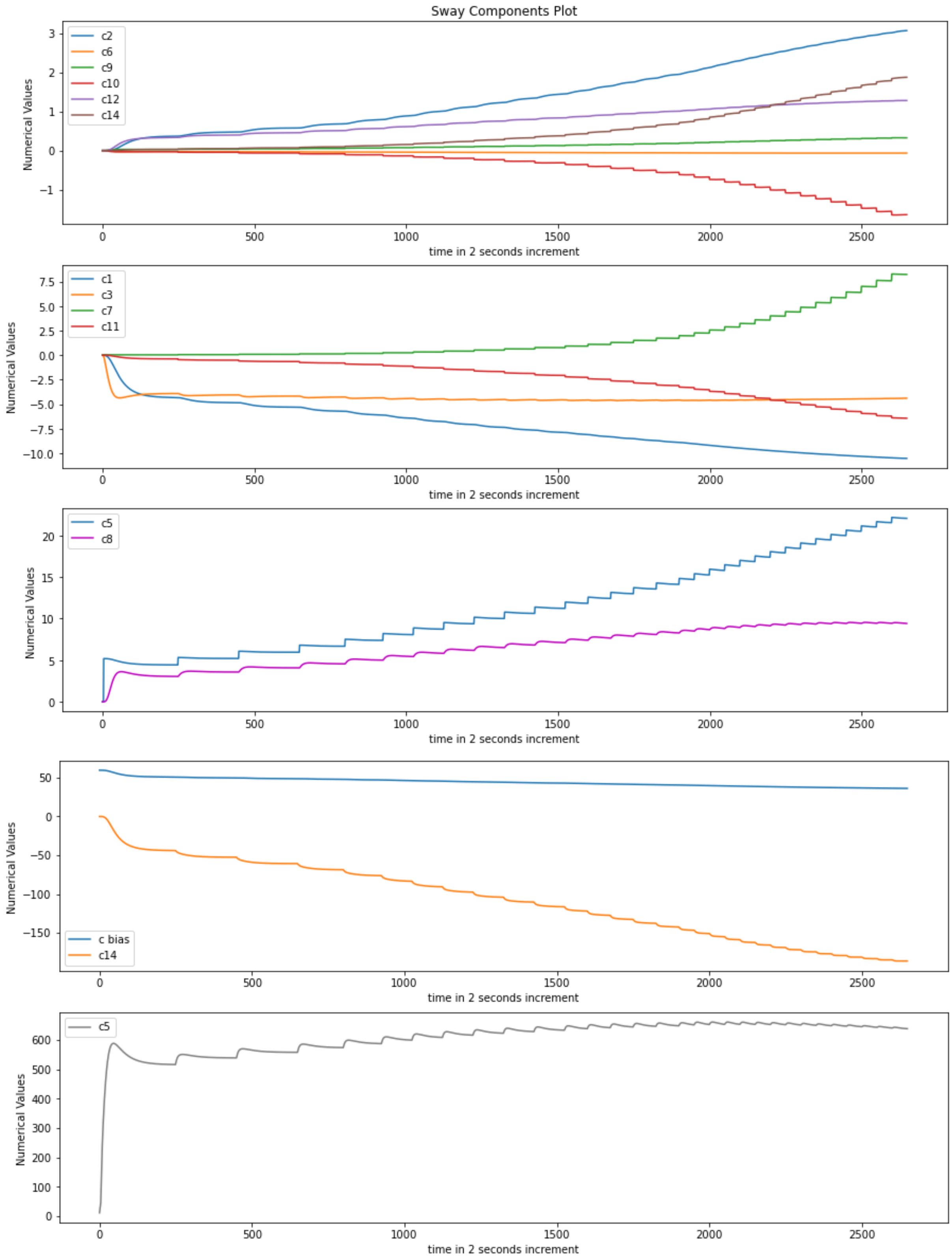

Figure 27. Sway & Yaw Components Plot

As we mentioned earlier, We tend to find the Hydrodynamic Derivatives values in Non-dimensional and we calculate the Train set accuracy as well.

Validation set accuracy of Surge on LinearSVR method: 0.94
Validation set accuracy of Sway on LinearSVR method: 1.00
Validation set accuracy of Yaw on LinearSVR method: 0.59

Train set accuracy of Surge on LinearSVR method: 0.93
Train set accuracy of Sway on LinearSVR method: 0.99
Train set accuracy of Yaw on LinearSVR method: 1.00

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	367	366
2	X`uu	-110	-184	-183
3	X`uuu	-215	55	55
4	X`vv	-899	1	1
5	X`rr	18	-8	-9
6	X`δδ	-95	-658	-658
7	X`δδu	-190	212	212
8	X`vr	798	9	9
9	X`vδ	93	124	124
10	X`vδu	93	-46	-46

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	177	177
2	Y`ou	-8	60	47
3	Y`ouu	-4	2011	1962
4	Y`v	-1160	233	228
5	Y`r	-499	1297	1196
6	Y`δ	278	-212	-214
7	Y`vvv	-8078	336	342
8	Y`δδδ	-90	4	4
9	Y`vvr	15356	-365	-356
10	Y`vvδ	1190	-113	-76
11	Y`vδδ	-4	32	32
12	Y`δu	556	-60	-60
13	Y`vu	-1160	-412	-405
14	Y`ru	-499	-35	-34
15	Y`δuu	278	117	104

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	0	0
2	N`ouu	6	-438	-392
3	N`v	3	-2373	-2078
4	N`r	-264	-441	-395
5	N`δ	-166	453	1362
6	N`vvv	-139	883	892
7	N`δδδ	1636	5934	5835
8	N`vvr	45	4	7
9	N`vvδ	-5483	-3545	-3631
10	N`vδδ	-489	-1165	-1595
11	N`δu	13	-110	-111
12	N`vu	-278	703	711
13	N`ru	-264	2014	1979
14	N`δuu	0	64	62

Source : *code file* 13

Observation:
Function estimation on spiral test is good for surge and sway. But, for Yaw it needs to be improved.

As we have seen in clock wise or counter clock wise spiral test, yaw's function estimation is not good. In order to avoid this, here, we train the SVM with both data(cloak wise and counter clock wise) and it gives good results.

Train set accuracy of Surge on LinearSVR method: 0.91
Train set accuracy of Sway on LinearSVR method: 1.00
Train set accuracy of Yaw on LinearSVR method: 1.00

sl_no	Surge_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	X`u	-184	726	724
2	X`uu	-110	-345	-345
3	X`uuu	-215	99	98
4	X`vv	-899	2	2
5	X`rr	18	-9	-3
6	X`ðð	-95	-1146	-1147
7	X`ððu	-190	385	383
8	X`vr	798	10	10
9	X`vð	93	216	215
10	X`vðu	93	-85	-85

sl_no	sway_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	Y`o	-4	483	482
2	Y`ou	-8	29	57
3	Y`ouu	-4	-83	-133
4	Y`v	-1160	-143	-133
5	Y`r	-499	4144	4058
6	Y`ð	278	-199	-199
7	Y`vvv	-8078	-82	-85
8	Y`ððð	-90	10	10
9	Y`vvr	15356	-261	-251
10	Y`vvð	1190	-178	-168
11	Y`vðð	-4	97	96
12	Y`ðu	556	-287	-288
13	Y`vu	-1160	-1332	-1331
14	Y`ru	-499	-107	-107
15	Y`ðuu	278	205	199

sl_no	yaw_hydrodynamic_derivatives	Original	case 1(C = 10^8)	case 2(C= 10^4, ramp added)
1	N`ou	3	-4	-4
2	N`ouu	6	-79	-96
3	N`v	3	495	490
4	N`r	-264	-77	-93
5	N`ð	-166	-4612	-3847
6	N`vvv	-139	849	853
7	N`ððð	1636	7506	7489
8	N`vvr	45	-7	-6
9	N`vvð	-5483	-4105	-4142
10	N`vðð	-489	-1196	-1269
11	N`ðu	13	-260	-259
12	N`vu	-278	1252	1253
13	N`ru	-264	4213	4185
14	N`ðuu	0	217	215

Source : *code file* 13

Trajectory Comparison on Spiral Test:

Even though there is no coincide in predicted Hydrodynamic Derivatives Values(regression coefficients),SVM shows good accuracy in function estimation of all three governing equation. from plot, we can understand it.

Train Data : sample at odd number(10,30,50,.....,5990 second)
Test Data : sample at even number(20,40,60,.....,6000 second)

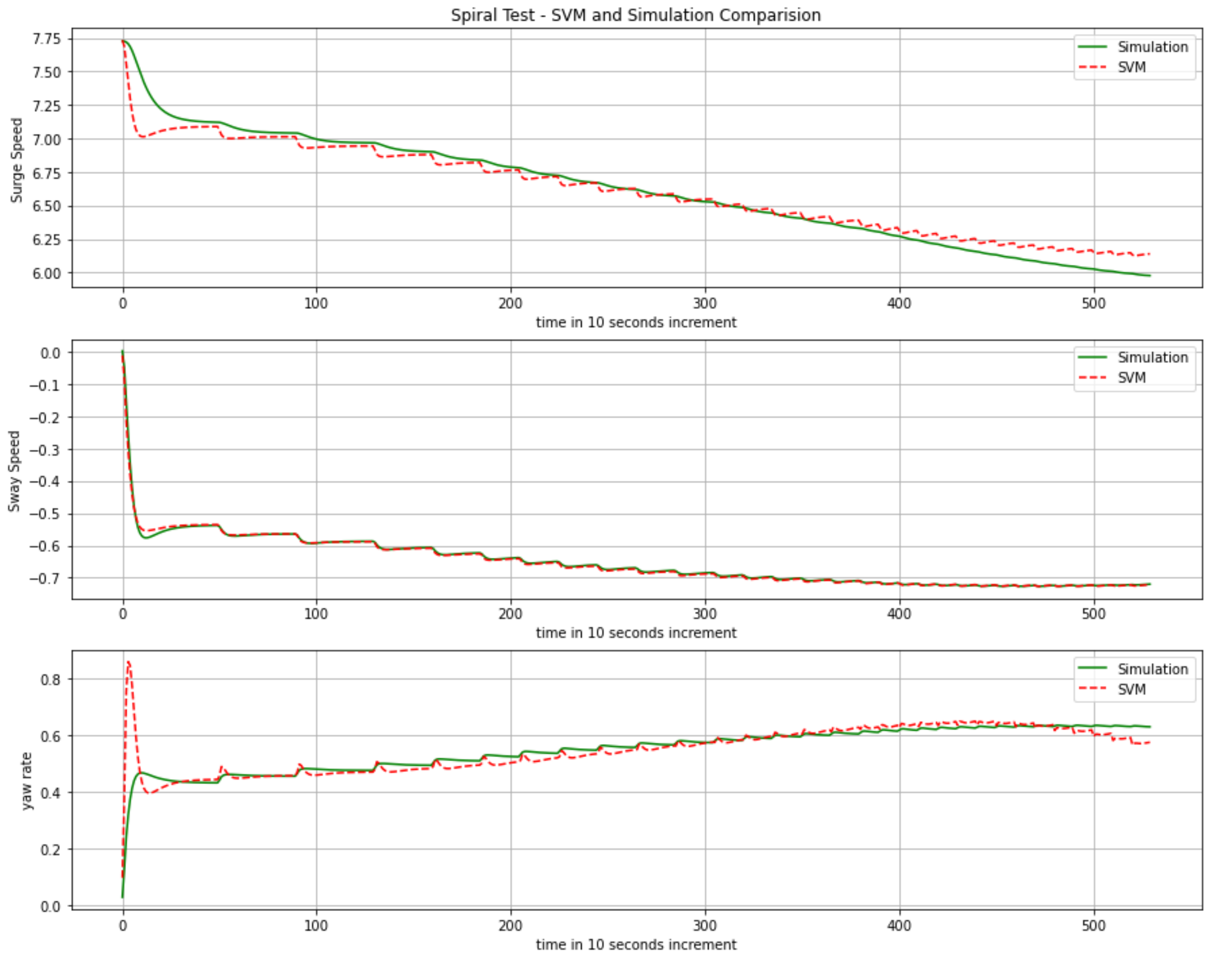

Figure 28. Function Estimation in SVM for CW or CCW spiral test
Source : *code file* 13

Train Data : Combined clock wise and counter clockwise data in 10 seconds time interval
Test Data : Sample at even number(20,40,60,.....,6000 second)

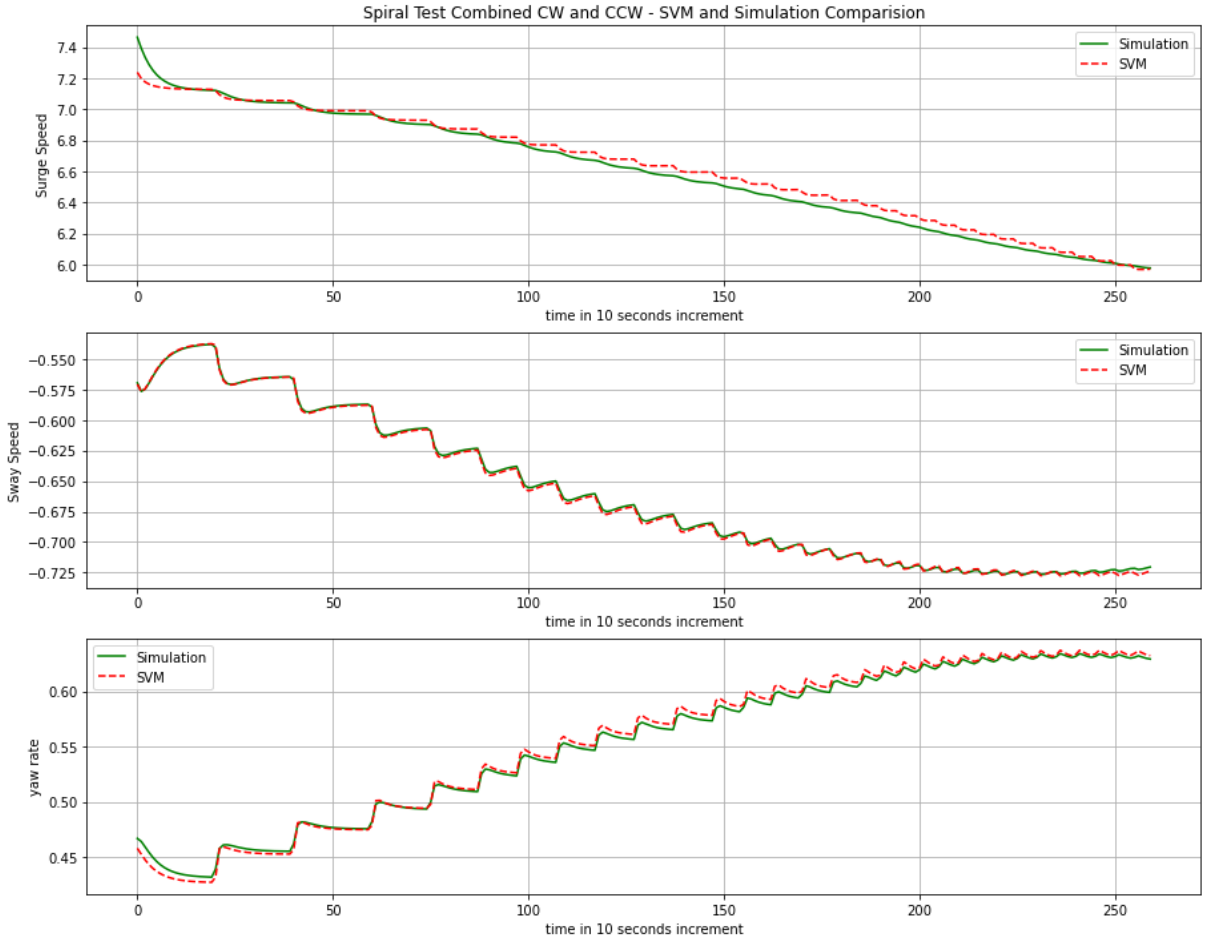

Figure 29. Function Estimation in SVM for combined CW or CCW spiral test
Source : *code file* 13

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Conclusion

- Study on Parametric Identification has performed for various tests.
- Support Vector machine is good for Function Estimation
- Among all the trials, we can say "**Combined Spiral Test (clock and counter clock wise combined)** gave nearest values in HDV.
- "**Building Kernel**" would be the future scope for getting matched HDV.