11th International Conference on Fast Sea Transportation
FAST 2011, Honolulu, Hawaii, USA, September 2011

Trimaran Resistance Artificial Neural Network

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1.0 ABSTRACT

The location of trimaran side-hulls (amas) plays an important role in the wave-making resistance of the vessel. This research investigated interference effects for a Naval Surface Warfare Center, Carderock Division (NSWCCD) sealift concept design. The experiments were conducted at Webb Institute's Robinson Model Basin over a two year period. This data is thought to be one of the most comprehensive sets of test data on side-hull placement for a single model.

The experimental results have been incorporated into four artificial neural networks (ANN). The end result is a series of matrix equations that continuously predicts residuary resistance, trim and sinkage, over a range of staggers and transverse spacings for the concept hull. While the ANN results are specific to the vessel in question, they shed light on the level of sensitivity of side-hull placement on trimaran calm water resistance.

KEY WORDS: Trimaran, Multi-hull, Interference, Resistance

1.0 INTRODUCTION

Interest in trimaran hull forms has increased dramatically during the past twenty years. This type of hull form can offer substantial resistance reduction at high speeds compared to conventional monohull vessels. While trimarans typically have greater wetted surface area compared to monohulls of similar displacement, the slenderness of the component hulls results in significant reductions in the wave-making resistance. Additionally, this hull form can offer improved motions in a seaway. Further, it has become apparent that trimarans offer greater options regarding both overall deck space and space utilization.

In the early 1990's a study was undertaken to investigate the use of a trimaran for a 4,200 ton Anti-Submarine Warfare frigate (Bastisch, 1992). The favorable findings of that study sparked significant interest in side-hull placement for both calm water resistance and seakeeping characteristics. There are a large number of numerical investigations reported in the literature including: Suzuki and Ikehata, 1993; Larsson et. al, 1997; and Doctors and Scrace, 2003.

The number of systematic experimental studies are somewhat more limited. The 1996 Webb Senior thesis of Landen et. al. investigated an FFG-7 center-hull with three different configurations of side-hulls. In the following year Ackers et. al. (1997) continued the work of Landen et. al. using four variations of arrangements including: side-hull symmetry, side-hull longitudinal and transverse locations, side-hull angles of attack, and side-hull displacement. The same year Zhang (1997) tested a 7 m self-propelled trimaran model for both powering and seakeeping. The test matrix consisted of five longitudinal locations that were spaced along a large portion of the center-hull.

More recently, the Office of Naval Research funded efforts by Carr and Dvorack (2007), Qi (2008) and Royce et.al. (2010). These efforts investigated the interference effects for a NSWCCD sealift concept in which the side-hulls were placed at nine different locations. Both efforts recorded the total resistance as well as the side-hull resistance in order to provide insight to the interference process. The latter effort involved two different model scales and found that there is a small effect due to scaling. A newly published Webb Senior thesis (Klag and McMahon, 2011) investigates the use of a small water-plane center-hull (TRI-SWACH) with the same side-hulls of the Carr and Dvorack (2007) effort.

It is not clear that the processes that generate the interference effects are fully understood. Understanding of the interference process, and its effect on resistance, is further complicated due to the variability of the relative size, shape and placement of the side-hulls. A final complication that arises in the evaluation of model-scale trimarans is that the form factor appears to have a Froude number dependency and the residuary resistance has been shown to have a Reynolds number dependence (Mizine et al., 2004).

There is limited collective knowledge relating trimaran hydrodynamic performance. This implies that it is unlikely that a naval architect will select a "good" hull to start an optimization process associated with a numerical model. Based on this assumption, it would be extremely helpful to have a design tool based on pertinent hull parameters that would aid in the selection process. Clausen et al. (2001) have shown the utility in Bayesian and neural networks for preliminary design based on prior built container ships. In essence, they developed sophisticated regression models to aid in preliminary design. It is proposed that a similar type

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **SEP 2011**	2. REPORT TYPE	3. DATES COVERED **00-00-2011 to 00-00-2011**
4. TITLE AND SUBTITLE **Trimaran Resistance Artificial Neural Network**		5a. CONTRACT NUMBER
		5b. GRANT NUMBER
		5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER
		5e. TASK NUMBER
		5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Naval Surface Warfare Center, Carderock Division (NSWCCD),Center for Innovation in Ship Design,Bethesda,MD,20817**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR’S ACRONYM(S)
		11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
The location of trimaran side-hulls (amas) plays an important role in the wave-making resistance of the vessel. This research investigated interference effects for a Naval Surface Warfare Center, Carderock Division (NSWCCD) sealift concept design. The experiments were conducted at Webb Institute?s Robinson Model Basin over a two year period. This data is thought to be one of the most comprehensive sets of test data on side-hull placement for a single model. The experimental results have been incorporated into four artificial neural networks (ANN). The end result is a series of matrix equations that continuously predicts residuary resistance, trim and sinkage, over a range of staggers and transverse spacings for the concept hull. While the ANN results are specific to the vessel in question, they shed light on the level of sensitivity of side-hull placement on trimaran calm water resistance.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**10**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

of model that incorporates both ship dimensions and hydrodynamic characteristics would significantly improve the probability of selecting a "good" design early in the design stage.

This paper presents a simplified parametric model based on the results of a systematic series of trimaran configurations. The model is based on the Carr and Dvorack (2007) effort extended to include data for a total of 21 different side-hull locations, covering a range of Froude numbers from 0.12 to 0.50. The parametric model is based on an Artificial Neural Network and is restricted to the center and side-hull configurations tested. The value in the parametric model is that it is able to predict the residuary resistance for an infinite number of positions with the bounds of the test matrix.

2.0 MODEL

The trimaran hull form explored in this study featured a slender transom-stern center hull stabilized by two small side hulls, with the center hull providing 94 percent of displacement. The prototype is a concept design developed at the Naval Surface Warfare Center, Carderock Division for the Joint High Speed Sealift (JHSS) mission. The lines drawing is presented in Figure 1 and the principal characteristics are given in Table 1.

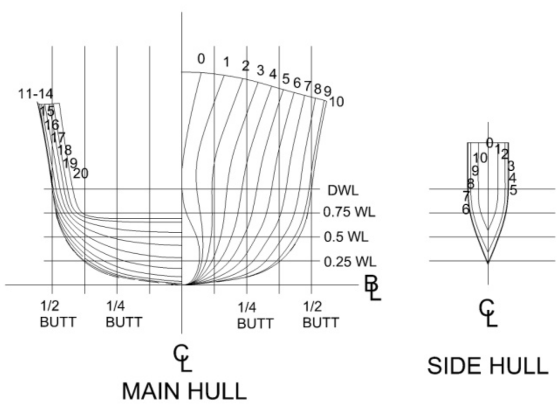

Fig. 1. The Trimaran Lines

The 1/125th scale model was fabricated from General Plastics FR 4520 foam at Webb Institute. To allow for adjustment of the side hull transverse and longitudinal positions, an apparatus of 80/20 aluminum bars and plywood was built on the model (Figure 2). A force block was attached on the apparatus to measure the side-hull resistance directly.

3.0 TEST MATRIX

Eight longitudinal and five transverse side hull locations were used during testing. The longitudinal side hull locations were such that the midship of the center-hulls were positioned at: 73.1%, 75.6%, 76.9%, 78.2%, 79.5%, 80.7%, 82% and 83.3% of the length between perpendiculars (relative to the forward perpendicular). The transverse spacings were located such that the distance between center-hull and side-hull centrelines were: 8.9%, 9.8%, 10.7%, 11.7%, and 12.7%. The spacing of 8.9% matched the design configuration originally provided by NSWCCD. These configurations cover likely positions on a high speed naval ship. In addition to the 21 configurations, the center-hull and side-hulls were tested separately to obtain the individual resistances. The tranverse and longitudinal side hull locations are illustrated in Figure 3. The actual positions tested are shown in figure 4.

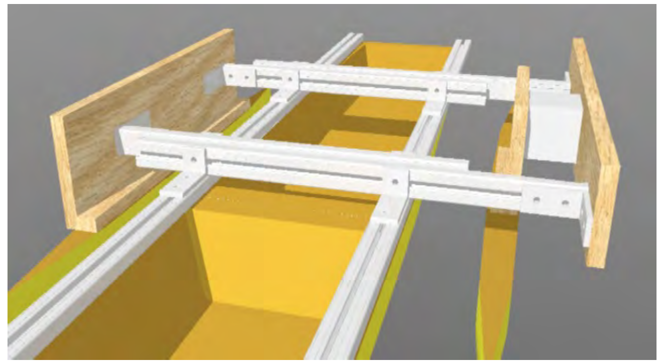

Fig 2. Model Apparatus

Table 1. Principal Characteristics

Centre Hull	
Displacement	30,321 MT
LOA	268.3 m
BOA	25.9 m
LCB (forward of transom)	121.2 m
LWL	262.5 m
BWL	24.4 m
Draft	9 m
Static Wetted Area	7,523 m2
Block Coefficient (Cb)	0.525
Prismatic Coefficient (Cp)	0.634
Midship Coefficient (Cx)	0.828
Waterplane Coefficient (Cwp)	0.762
Side Hull	
Displacement	948 MT
LOA	77 m
BOA	3.8 m
Draft	7.1 m
Static Wetted Area	911.1 m2
Trimaran	
Total Static Wetted Area	9,345 m2
Total Displacement	32,200 MT

Each configuration was tested at speeds corresponding to Froude numbers 0.12~0.5 at an increment of 0.02 (Froude number based on center-hull length between perpendiculars). Additional speeds were considered wherever humps and hollows in the resistance curves needed further investigation.

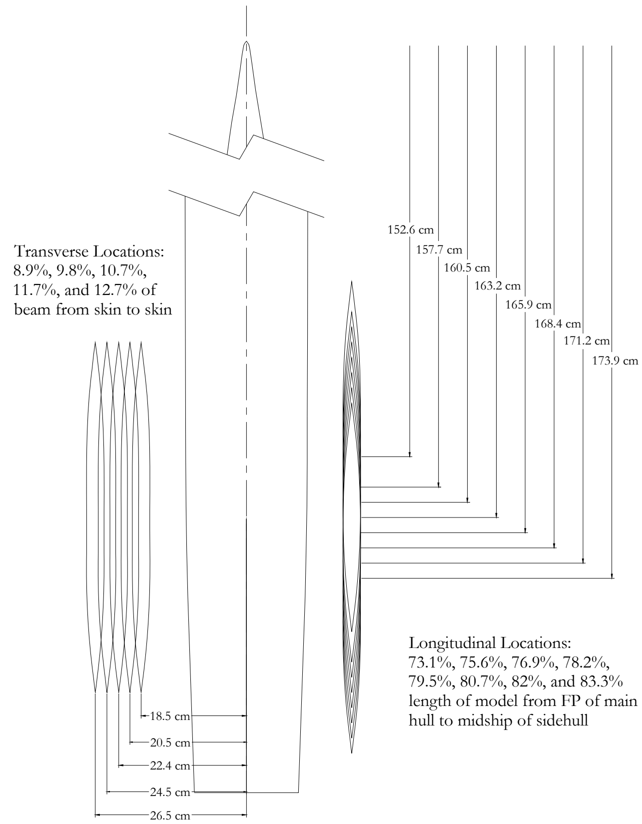

Fig. 3. Side Hull Locations in Test Matrix

4.0 ARTIFICIAL NEURAL NETWORK

As identified, the goal of this effort was to develop a regression model that predicts the residuary resistance, trim, and sinkage of a trimaran. Currently, it is proposed that a neural network be used to identify the non-linear relationships between side-hull transverse separation and fore and aft placement based on a systematic series of model tests. Neural networks are able to "learn" non-linear relationships between input variables and output variables based on a training data set (Statsoft, 2003). The process of training the neural network involves hypothesizing the complexity of the network (number of hidden layers and number of perceptrons), determining a training algorithm, and testing the learned capabilities on a sufficiently populated, random training set. The error of the trained neural network is checked against a selection set (data not included in the training sample). This type of modeling has been shown to be effective for predicting the appropriate principal characteristics of container ships by Clausen et al. (2001).

A schematic of a simple neural network is shown in Figure 4 below. In this figure, the input vector is on the right-hand side. Input data are assigned weights (through the training process) and the biases are determined. As shown in the figure, all of the weighted inputs are passed to neurons in the middle (hidden) layer. The hidden layer applies a transfer function and additional weights are applied. From the hidden layer, the transformed data is weighted, biases are determined, and then the data is passed to the neurons in the output layer. Finally, a transfer function is applied to the output layer data and the final output is scaled back to real units. It is possible to include more than one hidden layer, depending on the complexity of the problem at hand.

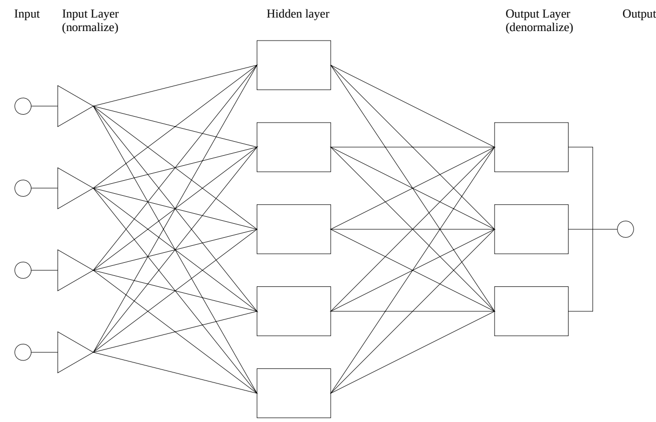

Fig. 4. Single hidden layer artificial neural.

Due to the complicated nature of the interference effects, four different ANN's have been developed: trimaran residuary resistance, composite residuary resistance, trimaran trim, and trimaran sinkage. The data provided in the figures below compares experimental data with predicted data for configurations that were not considered in the training of the ANN. The matrix equations developed by the four ANN's are provided in the appendix.

5.0 RESULTS AND DISCUSSION

The measurements included speed, Vm, total resistance, R_{Tm}, trim and sinkage. The residuary resistance coefficient is obtained by subtracting the frictional resistance coefficient from the total resistance coefficient. Side-hull and center-hull Reynolds numbers were considered when calculating the friction coefficient. Generally the equation for residuary resistance coefficient is given as:

$$CR = CT_m - CF_m \quad (1)$$

Where

CR	=	Residuary Resistance
CT_m	=	RT_m / ½ $\rho_m S_m V_m^2$
CF_m	=	$0.075/(\log_{10}(Re_m) - 2)^2$
RT_m	=	Model total resistance
ρ	=	Mass Density of tank Water
V_m	=	Model Velocity
S_m	=	Wetted surface area (static)
Re_m	=	Model Reynolds number = VmLm/ν
N	=	Kinematic viscosity of tank water

Specifically, friction coefficients were found for the side and center hulls and a total frictional coefficient was derived as follows:

$$CF_{tot} = CF_{cent} \frac{SA_{cent}}{SA_{tot}} + 2CF_{side} \frac{SA_{side}}{SA_{tot}} \qquad (2)$$

Where:

SA_{cent}	=	Surface Area Center Hull
SA_{side}	=	Surface Area Side Hull
CF_{tot}	=	Total friction coefficient
CF_{cent}	=	Friction coefficient based on center-hull Reynolds number
CF_{side}	=	Friction coefficient based on side-hull Reynolds number

5.1 Resistance Comparison

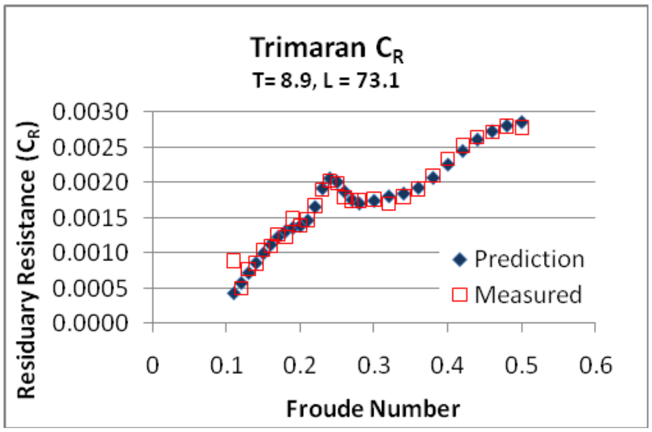

Fig. 5. Trimaran CR, training data

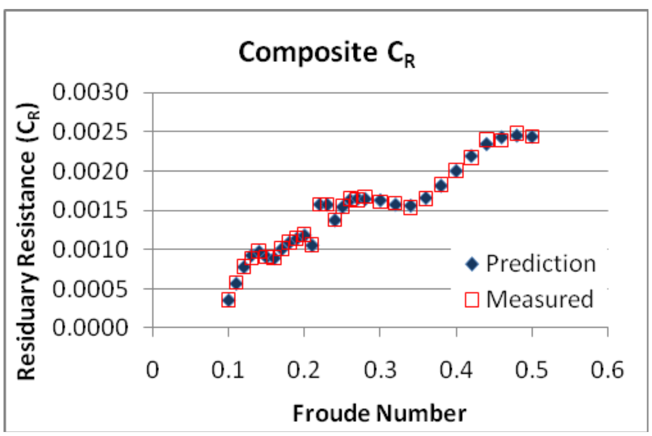

Fig. 6. Composite CR, training data

Figure 5 shows a comparison of the predicted CR and the measured CR for part of the training data in the trimaran configuration. Figure 6 shows a comparison of the predicted CR and the measured CR for a composite trimaran (summation of center-hull and side-hull data when tested separately). The agreement between prediction and measured is very good, however, this provides little insight in the model's ability to predict residuary resistance at other positions. Figures 7 and 8 show the predicted and measured residuary resistance for configurations that were not part of the ANN training data (production data). The agreement at higher Froude numbers is extremely good, while the agreement at lower Froude numbers is acceptable.

Since all of the composite data was used in training there is no comparable plot for the summed configuration. The matrix equations for the trimaran and composite trimaran configurations are provided in the appendix and are identified as models C_{Rtri} and C_{Rcomp}, respectively. Both of the neural networks used to predict residuary resistance utilize a single hidden layer.

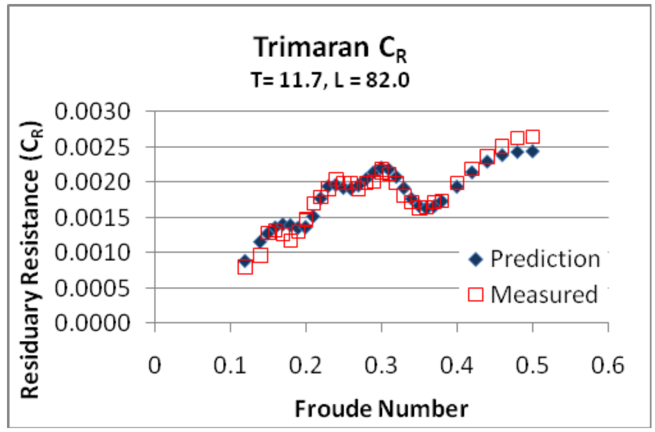

Fig. 7. Trimaran CR, production data

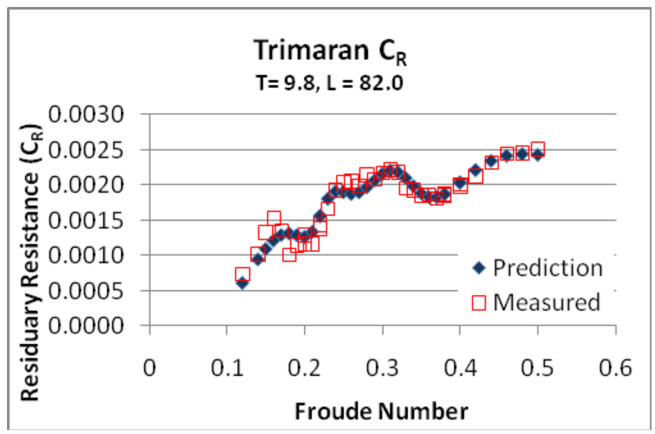

Fig. 8. Trimaran CR, production data

5.2 Trim and Sinkage Comparison

Figure 9 shows a comparison of the predicted trim and the measured trim for part of the training data in the trimaran configuration. Figures 10 and 11 provide comparisons of the predicted and measured trim for configurations that were not part of the neural network training (production data). The matrix equations for the trim predictions are provided in the appendix and are identified as model Trim. Surprisingly, this model required two hidden layers in order to produce reasonable predictions. This is most likely due to the small random error at the lower Froude number conditions.

Figure 12 shows a comparison of the predicted sinkage and the measured sinkage for part of the training data in the trimaran configuration. Figures 13 and 14 provide comparisons of the predicted and measured sinkage (in inches) for configurations that were not part of the neural network training (production data). The matrix equations for the sinkage predictions are provided in the appendix and are identified as model Sinkage. This model also required two hidden layers in order to produce reasonable predictions.

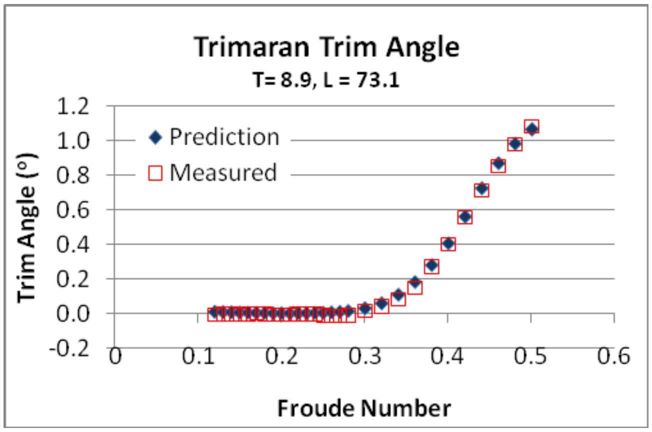

Fig. 9. Trim, training data

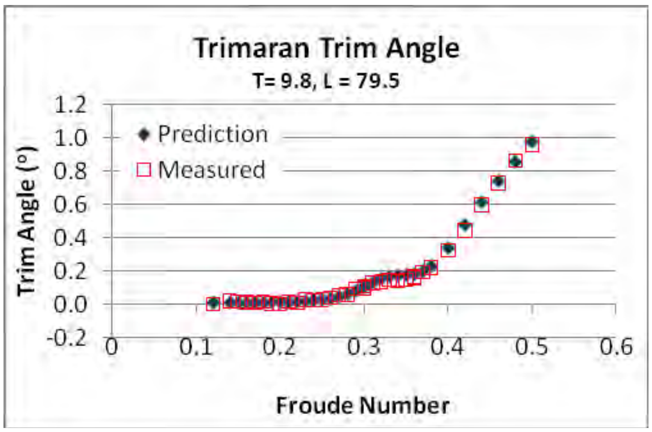

Fig. 10. Trim, production data

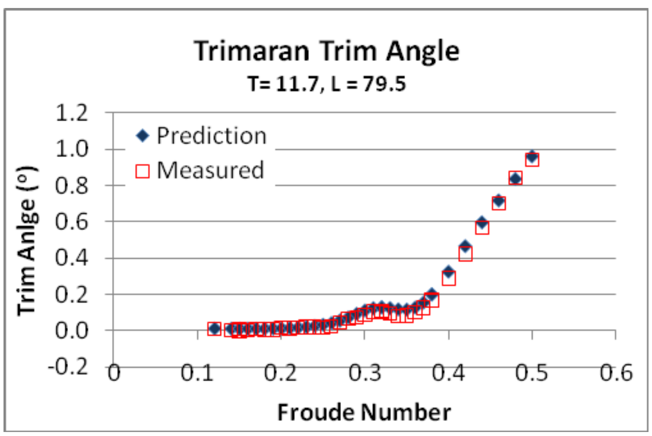

Fig. 11. Trim, production data

6.0 DISCUSSION AND CONCLUSION

Generally, the four different ANN's used in this effort provided excellent agreement with measured data at the higher Froude numbers. It is obvious that the models presented here have limited utility. This analysis was restricted to a single center-hull and one side-hull configuration at a single total displacement. As with any regression analysis, extrapolation outside the bounds of the underlying test matrix should be avoided.

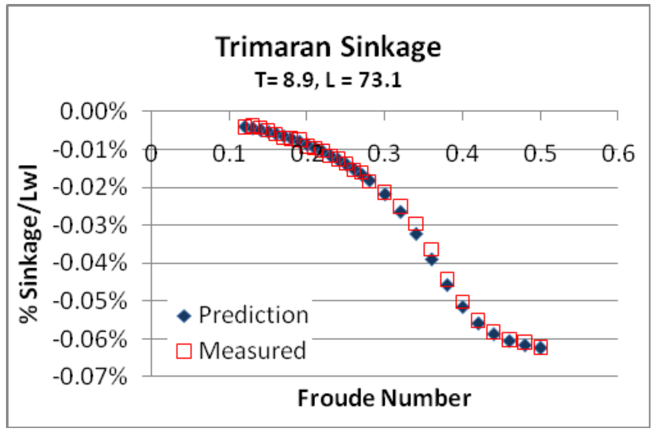

Fig. 12. Sinkage, training data

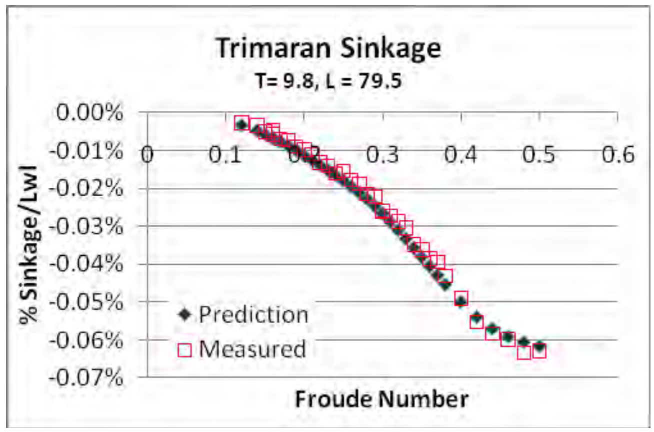

Fig. 13. Sinkage, production data

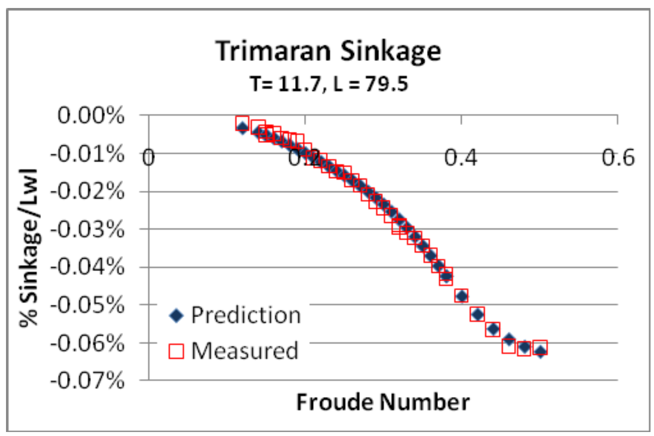

Fig. 14. Sinkage, production data

It is extremely encouraging that the artificial neural networks were able to predict the actual model behaviour for conditions other than those used for training. This effort represents a first step toward developing a synthesis model for trimaran design. It is recognized that design analysis beyond the capabilities of a synthesis model are warranted, however this type of model will enable designers to rapidly arrive at a "good" initial design

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ACKNOWLEDGMENTS

This work is supported by the Office of Naval Research (ONR) under grant no. N00014-10-1-0652. The authors gratefully acknowledge the support of Ms. Kelly Cooper, ONR program manager, and Dr. Colen Kennel, technical director of the Center for Innovation in Ship Design (CISD), for providing the lines drawings and engaging in various discussions throughout the trimaran research program development.

APPENDIX

The following tables provide the matrix data that is required for the calculations of the residuary resistant coefficients (composite and trimaran respectively), trim and sinkage. The tables identify the required inputs for each regression model and provide the ranges of values investigated. Each matrix in the calculations is identified by the nature of the operation, matrix name, and size of the matrix. The matrix formula operations (using matrix names) are provided at the lower right of each table.

Table A1. Composite Residuary Resistance

MODEL: C_{Rcomp}

Input (1x1 array) - User Provided

FN

Range of Investigation

FN	0	0.5

Normalization Weight, NW (1X1 matrix)

4.4974

Normalization Bias, NB (1X1 array)

-1.3499

Hidden Layer1 Synapse, HLS_1 (1x12 matrix)

-17.3236	10.7029	-12.6221	12.2650	-23.5236	9.9967	-6.4086	-0.2930	-0.2752	-2.6644	-2.9922	-6.0343

Hidden Layer1 Axon, HLA_1 (1x12 array)

-7.1428	4.2356	-9.0825	-1.0810	-7.5989	7.0560	-3.0358	-1.2715	-0.3695	1.7321	2.1688	-3.9871

Output Layer Synapse, OLS (12x1 array)

3.7222
8.5179
-1.8472
-0.0998
1.5725
-5.3573
5.3053
0.5079
0.2703
-2.5675
2.0216
-6.3622

Output Layer Axon, OLA

Gain	Bias
1.0000	0.2873

Rescaling, R

Gain	Bias
848.7892	-1.2054

The following operation include matrix multiplication, (order important)

$Input*NW+NB = A_1$

$\tanh(A_1*HLS_1+HLA_1) = A_2$

$(A_2*OLS)*OLA\ Gain + OLA\ Bias = A_3$

$(A_3-R\ Bias)/(R\ Gain) = C_{rcomp}$

Table A2. Trimaran Residuary Resistance Coefficient

MODEL: C_{Rtri}

Input (1x4 array) - User provided

Trans %	Long %	LCB %	FN

Note LCB % relative to midship, forward positive.

Normalization Weight, NW (4X4 matrix)

0.4737	0.0000	0.0000	0.0000
0.0000	0.1765	0.0000	0.0000
0.0000	0.0000	3.0508	0.0000
0.0000	0.0000	0.0000	4.7347

Range of Investigation

Transverse	8.9	12.7	(CL to CL)/Lwl
Longitudinal	73.1	83.3	(FP to Midship (ama))/Lwl
LCB	-4.92	-5.51	
FN	0	0.5	

Normalization Bias, NB (1X4 array)

-5.1158	-13.8000	15.9102	-1.4686

Hidden Layer1 Synapse, HLS_1 (4x18 matrix)

Note: Matrix broken for printing

1	2	3	4	5	6	7	8	9 Columns
0.9909	-0.2483	-0.2729	1.5099	-0.4011	-0.1140	-1.5656	-0.1546	0.1331
1.2718	1.0694	0.0141	0.8692	1.0959	-0.5158	-1.4209	0.4743	1.5070
0.0375	1.1447	0.4379	-1.7190	0.0587	2.0180	1.0561	0.5585	-0.1809
0.2769	-9.2568	-5.5583	2.7829	2.0946	-0.1348	-0.1012	-5.9794	-3.1713

10	11	12	13	14	15	16	17	18 Columns
0.4276	-0.1896	-3.7817	0.1196	0.1445	1.0360	-0.6414	-0.3808	-0.0374
-1.8588	0.7887	-0.5586	-1.5890	-0.6155	1.6240	-0.0173	0.0013	-0.0084
-0.1748	-0.2364	-0.3193	-1.2461	-0.8130	-1.7923	1.5153	1.6450	-0.1767
-0.2361	-2.8714	1.2793	-1.5635	4.6995	0.0551	1.1447	3.1503	-2.6574

Hidden Layer1 Axon, HLA_1 (1x18 array)

Note: Array broken for printing

1	2	3	4	5	6	7	8	9 Columns
-0.5680	-3.9550	0.1977	-0.5979	1.5429	0.8533	0.8430	-2.5225	-0.0002

10	11	12	13	14	15	16	17	18 Columns
0.6465	0.0972	2.8698	-1.2434	-0.3163	-0.9961	-1.6843	0.0770	0.1928

Output Layer Synapse, OLS (18x1 array)

-1.8361
-1.7518
-1.6126
0.1171
-0.7026
-1.8135
-1.6265
2.5145
-2.5897
1.2764
2.4473
-0.1698
-2.7586
-3.5892
-1.4147
-0.4111
-1.7482
-4.3040

Output Layer Axon, OLA

Gain	Bias
1.0000	-1.3396

Rescaling, R

Gain	Bias
759.855	-1.2806

The following operation include matrix multiplication, (order important)

Input*NW+NB = A_1

tanh(A_1*HLS_1+HLA_1) = A_2

(A_2*OLS) *OLA Gain + OLA Bias = A_3

(A_3-R Bias)/(R Gain) = C_{rtri}

Table A3. Trimaran Trim

MODEL: Trim

Input (1x4 array) - User Provided

Trans %	Long %	LCB %	FN

Note LCB % relative to midship, forward positive.

Normalization Weight, NW (4X4 matrix)

0.4737	0.0000	0.0000	0.0000
0.0000	0.1765	0.0000	0.0000
0.0000	0.0000	3.0508	0.0000
0.0000	0.0000	0.0000	4.7347

Range of Investigation

Transverse	8.9	12.7	(CL to CL)/Lwl
Longitudinal	73.1	83.3	(FP to Midship (ama))/
LCB	-4.92	-5.51	
FN	0	0.5	

Normalization Bias, NB (1X4 array)

-5.1158	-13.8000	15.9102	-1.4686

Hidden Layer1 Synapse, HLS_1 (4x5 matrix)

-0.5757	1.0092	0.0633	-0.1292	0.0961
0.0035	-5.0610	-1.6457	-1.7750	1.0173
-1.5627	-3.1264	-1.9786	-2.4812	1.5015
-0.1609	0.2077	1.7997	-0.5831	1.2957

Hidden Layer1 Axon, HLA_1 (1x5 array)

-0.2008	0.1714	-0.1596	0.4478	-0.6330

Hidden Layer2 Synapse, HLS_2 (5x3 matrix)

2.6823	6.3740	1.6916
1.2483	3.5436	0.6854
-2.2961	-4.1868	-1.4662
-3.0006	-1.5563	-3.8118
-0.4077	1.9417	-2.2241

Hidden Layer2 Axon, HLA_2 (1x3 array)

2.1809	1.3775	1.5294

Output Layer Synapse, OLS (3x1 array)

3.3701
-0.1861
-3.2853

Output Layer Axon, OLA

Gain	Bias
1.0000	-0.8010

Rescaling, R

Gain	Bias
1.6312	-0.8676

The following operation include matrix multiplication, (order important)

Input*NW+NB = A_1
tanh(A_1*HLS_1+HLA_1) = A_2
tanh(A_2*HLS_2+HLA_2) = A_3
(A_3*OLS) *OLA Gain + OLA Bias = A_4
(A_4-R Bias)/(R Gain) = Tri_{trim}

Table A4. Trimaran Sinkage (negative means increased draft)

MODEL: Sinkage

Input (1x4 array) - User Provided

Trans %	Long %	LCB %	FN

Note LCB % relative to midship, forward positive.

Normalization Weight, NW (4X4 matrix)

0.4737	0.0000	0.0000	0.0000
0.0000	0.1765	0.0000	0.0000
0.0000	0.0000	3.0508	0.0000
0.0000	0.0000	0.0000	4.7347

Range of Investigation

Transverse	8.9	12.7	(CL to CL)/Lwl
Longitudinal	73.1	83.3	(FP to Midship (ama))/
LCB	-4.92	-5.51	
FN	0	0.5	

Normalization Bias, NB (1X4 array)

-5.1158	-13.8000	15.9102	-1.4686

Hidden Layer1 Synapse, HLS_1 (4x5 matrix)

-0.7050	0.0075	-0.0155	-0.6036	0.0348
51.8912	-48.6066	-10.2240	48.1152	4.1117
48.2641	-45.5331	-9.9571	45.0211	3.8798
0.7426	1.2881	3.1765	0.6433	1.6522

Hidden Layer1 Axon, HLA_1 (1x5 array)

-2.4945	1.2653	-1.1203	-2.0879	0.5631

Hidden Layer2 Synapse, HLS_2 (5x4 matrix)

-21.5909	1.2194	-2.6368	18.1978
0.6737	1.5502	-0.3599	-0.4484
-0.2526	-0.6186	-0.0058	0.1663
22.8882	-0.2695	2.5286	-19.2115
-0.9645	0.2663	-0.3896	0.8197

Hidden Layer2 Axon, HLA_2 (1x4 array)

1.1828	-0.2694	0.4685	-1.0472

Output Layer Synapse, OLS (4x1 array)

3.3473
0.5116
2.9095
4.2561

Output Layer Axon, OLA

Gain	Bias
1.0000	-0.3622

Rescaling, R

	Gain	Bias	
	32.8982	0.9094	in.
-or-	39.16449	1.0826	% sink/Lwl

The following operation include matrix multiplication, (order important)

Input*NW+NB = A_1

$\tanh(A_1*HLS_1+HLA_1) = A_2$

$\tanh(A_2*HLS_2+HLA_2) = A_3$

(A_3*OLS) *OLA Gain + OLA Bias = A_4

(A_4-R Bias)/(R Gain) = Tri_{sink}