Experimental Validation of Artificial Neural Network (ANN) Model for Scramjet Inlet Monitoring and Control

Azam Che Idris, Mohd Rashdan Saad, Mohd Rosdzimin Abdul Rahman, Fakroul Ridzuan Hashim, Konstantinos Kontis

ABSTRACT--- ***A hypersonic flight vehicle, viewed as an engineering system, must have a real-time monitoring and control of its performance, in order for it to be safe and practical for operation. The scramjet engine is the most suitable for hypersonic flow regime and its performance depends mostly on its inlet. There are multiple strategies to measure the performance of a scramjet inlet but they are limited to on-ground operations only. A number of empirical relations exist to easily calculate the scramjet inlet performance using only its internal throat Mach number but they are somewhat hit-and-miss. Using Artificial Neural Network (ANN) algorithm and data from the literature, we investigated the optimum ANN structures that can be used to model scramjet inlet performance. The optimum ANN model is then tested and validated against our own experimental measurement of our generic scramjet inlet. The optimum ANN model with 10-nodes in a single hidden layer was able to match perfectly with our experimental data.***

Index Terms— Artificial neural network, hypersonic, SBLI, scramjet, shockwave.

I. INTRODUCTION

Hypersonic flight has been the ultimate dream of aviation. It has been envisioned since the early days of aviation and researched upon since the 50s but practical flight has never materialized resulting in waning interest from the aerospace community. However, Boeing's X-51A success in flight demonstration has revitalized the awareness in hypersonic flight. In recent years, hypersonic arms race has reached fever pitch with the coming of a new player, China, in addition to the old aerospace superpowers of USA and Russia. Lately, the United States has been teasing the aviation enthusiast with new concepts from Boeing and Lockheed, which are capable of hypersonic flight, to be the successor for the infamous SR-71. The key enabler for hypersonic flight is the scramjet engine, which can operate in flow speed of more than Mach 5 [1].

As scramjet engine operates without a mechanical compressor to compress the air for combustion, its overall performance is heavily influenced by the performance of its inlet [2]. Many studies have been done to understand the flow passing through the inlet [3]-[8], but its performance was still hard to measure with too many parameters to be considered. Using the concept of 'stream-thrust', the performance of a scramjet inlet can be modelled by using the input of mass flow rate, drag and heat transfer from experimental measurement [9]-[12]. Although deemed the most comprehensive method, the 'stream-thrust' method has too many uncertainties contained inherently in the three measurements of inputs required. Another method relies on a set of pitot rake to measure the stagnation pressure of the flow exiting the scramjet inlet [3], [13]-[16]. This value will be combined with the static pressure of the exit area to predict the overall performance of the inlet. Both the stream-thrust and pitot rake techniques are limited as on-ground measurement of scramjet performance, thus making them unsuitable for real-time monitoring and control of a scramjet engine.

In order to create an effective control system, the onboard computer on a hypersonic aircraft needs to monitor in real-time the performance of the scramjet. Thus, the computer needs a simplified mathematical model of the scramjet performance. In [17] were the first to introduce a simple equation that relates the kinetic energy efficiency of a scramjet inlet to a single parameter of throat Mach number ratio. The equation has been modified later by [18], [19]. In recent years, Smart suggested that instead of relying only on a single parameter, the equation should also consider the freestream Mach number of the scramjet [20].

$$\eta_{KE} = 1 - 0.2(1 - M_r)^5 \quad (1)$$

$$\eta_{KE} = 1 - 0.4(1 - M_r)^4 \quad (2)$$

$$\eta_{KE} = 1 - 0.528(1 - M_r)^{3.63} \quad (3)$$

$$\eta_{KE} = 1 - \left(\frac{9}{M_o}\right)^{0.7} [0.018(1 - M_r) + 0.12(1 - M_r)^4] \quad (4)$$

where $\left(M_r = \frac{M_{th}}{M_o} = \frac{throat\ Mach\ number}{freestream\ Mach\ number}\right)$

The listed equations gave a simplified strategy for scramjet inlet performance monitoring and control due to the fact that its internal flow Mach number at throat can be measured easily using laser absorption spectroscopy [21], [22]. However, we found that none of the equation listed above can fully fit against published scramjet inlet performance data. This is due to each equation originated from small empirical data or experimental testing done in isolation of each other. This is also due to the complex shock-boundary layer interactions (SWBLI) that can occur inside the inlet-isolator [2]; and each scramjet inlet in the published data are somewhat unique in their internal flow

Revised Manuscript Received on February 11, 2019.

Azam Che Idris, Faculty of Engineering, UPNM, Kuala Lumpur, Malaysia.
Mohd Rashdan Saad, Faculty of Engineering, UPNM, Kuala Lumpur, Malaysia.
Mohd Rosdzimin Abd Rahman, Faculty of Engineering, UPNM, Kuala Lumpur, Malaysia.
Fakroul Ridzuan Hashim, Faculty of Engineering, UPNM, Kuala Lumpur, Malaysia.
Konstantinos Kontis, Mechan Chair of Engineering, University of Glasgow, United Kingdom.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

structures. Thus, to be able to create a unified mathematical model that is robust enough to be used across large segment of scramjet inlet design and shape is the holy grail of scramjet inlet monitoring and control.

The aim of this current work is to investigate the suitability of using ANN technique to build a mathematical model that can fit most of published scramjet inlet performance data [16], [23]-[29]. Variations of ANN technique has been used to model scramjet nozzle [30], combustor [31], [32] and inlet geometry [33]. However, there is yet an attempt in the hypersonic community to utilize ANN to model the complex aerothermodynamics phenomena inherent in measuring the performance of a scramjet inlet. This technique has not been widely utilized in the hypersonic community and we want to promote its usefulness.

II. ARTIFICIAL NEURAL NETWORK (ANN) THEORY

Artificial Neural Networks (ANN) is the latest addition to the vast library of tools in the Machine Learning concept, that can be used to model multivariate phenomena that are too complex to be modelled using basic statistics [34]-[37]. The idea behind ANN is to recreate the neurological process of a thinking brain in processing and storing information [38], [39].

A good ANN algorithm that is available commercially or in open-source should be able to build a random network of nodes connected to each other in order to process the input signal (the input parameters). The input signal (a_i) will be fed forward by multiplying it with weights (w_{ij}) before being summed together at summing junction. The summed value X will be fed through a transfer function $F(X)$. The ANN software should then train the model by 'back-propagation' process where the value of weights and bias will be adjusted in order to match the output with the available target data (see Fig. 1).

$$X = \left[\sum_{i=1}^{n} w_{ij} a_i\right] + b_j \quad (5)$$

$$F(X) = \frac{e^{X} - e^{-X}}{e^{X} + e^{-X}} \quad (6)$$

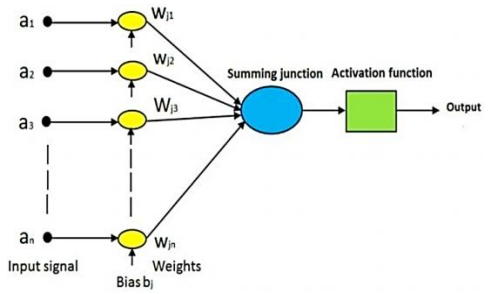

Fig. 1: Diagram of ANN concept where every input signal, *a*, will be amplified by its junction weight, *w*, before being summed together with bias, *b*, at a summing junction. The summed value will be manipulated using activation function, *F(X)*, before being transferred to output layer

III. DEVELOPMENT OF ANN MODEL

In this study, 36 data points of scramjet inlet performance has been utilized to train suitable ANN models. The input and output are normalized to -1 and 1 by using (7) and (8). The number of hidden layers connecting the input and output are varied between 1 and 3. As for the input, we derive three different cases, each with different type of input. In Case 1, the inputs are the Mach number ratio (M_r) and freestream Mach number (M_o) similar to 4 (see Fig. 2). For Case 2, the inputs are the throat Mach number (M_{th}) and freestream Mach number (M_o). In Case 3, the input is only a single input of Mach number ratio (M_r), similar to (1) – (3).

All ANN models will calculate only one output, namely the kinetic energy efficiency (η_{KE}) as the main indicator of the scramjet inlet performance. Each ANN model will be judged based on minimum root mean square error (RMSE in (9)) and maximum correlation coefficient (R in (10)). The best model will be selected and validated against current experimental data done in this study. The details of the ANN parameters are listed in the Table 1.

$$Normalized\ Input = 2 * \left(\frac{Input - Input_{min}}{Input_{max} - Input_{min}}\right) - 1 \quad (7)$$

$$Normalized\ Output = 2 * \left(\frac{Ouput - Output_{min}}{Output_{max} - Output_{min}}\right) - 1 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{target} - Y_{output}\right)^2} \quad (9)$$

$$R = \frac{\sum_{i=1}^{n}(Y_{target} - \overline{Y_{target}})(Y_{output} - \overline{Y_{output}})}{\sqrt{\sum_{i=1}^{n}(Y_{target} - \overline{Y_{target}})^2 (Y_{output} - \overline{Y_{output}})^2}} \quad (10)$$

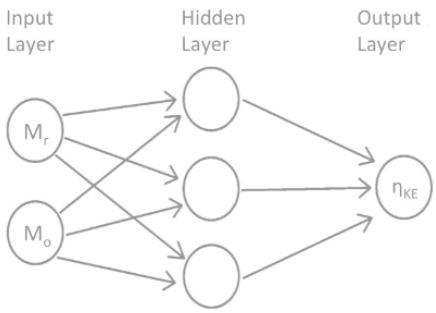

Fig. 2: Diagram of the ANN model used in this study. The inputs are varied depending on case. Number of hidden layers are varied between 1 and 3 with each layers set at default 10 nodes

Table 1: Network parameters used to train our ANN model

Neural Network Parameters	Value
Network type	Feed-forward with back-propagation
Number of hidden layers	Between 1 to 3 layers
Number of input	Between 1 to 2 nodes
Number of nodes in the hidden layer	10
Learning algorithm	Levenberg-Marquardt
Transfer function (input-hidden)	Tangent-Sigmoid function
Transfer function (hidden-output)	Linear function
Learning rate	0.01

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

IV. METHODOLOGY

In our previous work, we introduced the concept of the 'final shock' exiting the scramjet inlet-isolator as the main indicator for its performance [8]. We can measure the pressure rise across this final shock using pressure sensitive paint (PSP) signal from the inner sidewall. By inserting pressure rise and shock angle, both the stagnation pressure, P_{t3}, and total temperature, T_{t3}, at the throat area can be calculated. Finally, the kinetic energy efficiency can be calculated using the relation below [10]:

$$\eta_{KE} = 1 - 5 * \left(\frac{1}{M_o^2}\right)\left[\left(T_{t3}\left(\frac{P_o}{P_{t3}}\right)^{0.286} \Big/ T_o\right) - 1\right] \qquad (11)$$

The experiments were conducted in the High Super Sonic Tunnel (HSST) capable of Mach number up to 6 depending on the nozzle dimension. The stagnation pressure and the stagnation temperature were set to be 6.5bar and 375K respectively, and the Mach 5 nozzle was selected for this current study. The setup of the PSP measurement system is depicted such as in Fig. 3. The specialized PSP formulation capable of hypersonic flow measurement has been mixed in-house. The software used to process the raw PSP images is the Davis 7.0 software. A generic scramjet inlet with modular cowl section is utilized in this study (see Fig. 4). The cowl length, height and deflection angle can be changed independently in order to control the throat Mach number.

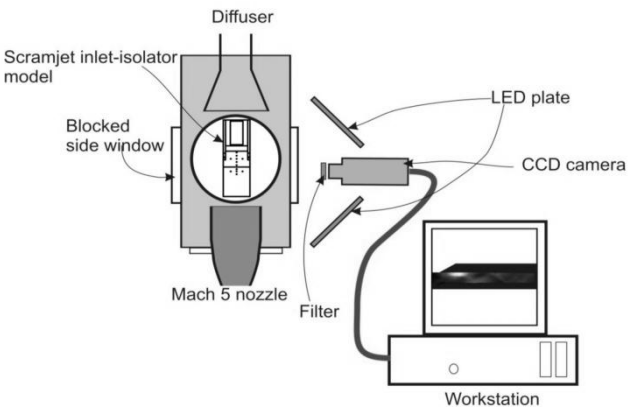

Fig. 3: Diagram of the experimental setup from the plan view. The camera used to capture PSP signal was placed on the side of test section

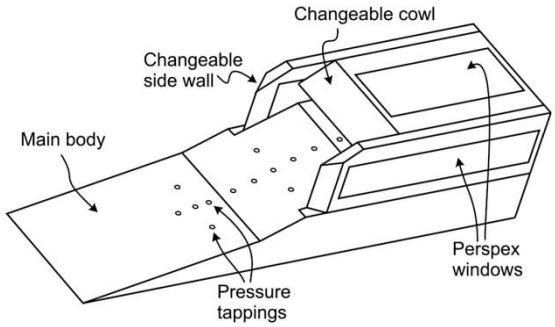

Fig. 4: Simplified sketch of the modular scramjet inlet model used in this experiment. The cowl component of the inlet can be changed in order to modify its height, length and cowl tip deflection angle

V. RESULTS AND DISCUSSION

A. ANN Model Evaluation

This study tested different ANN architectures with varying input types and number of hidden layers. However, for every layer, the number of nodes are kept constant at 10. For each ANN model, the weights and biases were adjusted in more than 50 epoch. The models are compared to each other in Table 2. It can be observed that Case 1 with 1 hidden layer has the lowest RMSE which means it has the lowest error between the produced output and the target data obtained from published literature. It also has the highest R value with the closest fit to the target data. The regression plot between targets and output is shown in Fig. 5 below. In the figure, we plotted the fitness of the best ANN model from each case. We could make an inference that the Case 1, where the inputs are the Mach number ratio (M_r) and freestream Mach number (M_o), is the best since it consistently outperforms Case 2 and Case 3 regardless of number of hidden layers. From here, it is decided that Case 1 with 1 hidden layers will be validated against data from our own experimental measurement.

Table 2: Comparison of training results of ANN models with different number of hidden layers

Case	RMSE	R
Case 1: 1 layer	0.3335	0.9746
Case 1: 2 layers	0.6130	0.9624
Case 1: 3 layers	0.7149	0.9602
Case 2: 1 layer	0.4075	0.9623
Case 2: 2 layers	0.4815	0.9592
Case 2: 3 layers	0.7179	0.9564
Case 3: 1 layer	1.0669	0.7669
Case 3: 2 layers	0.7536	0.8915
Case 3: 3 layers	0.7293	0.9467

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

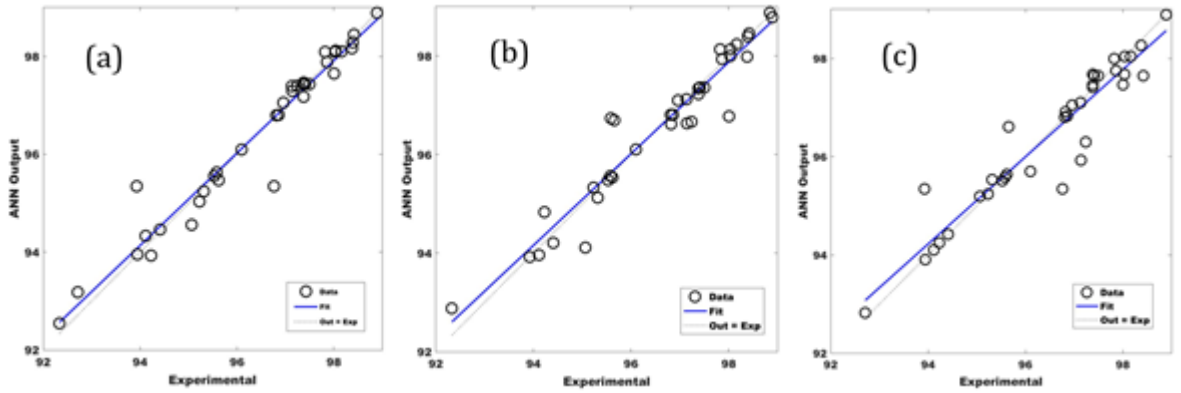

Fig. 5: Fitness of (a) Case 1:1, (b) Case 2:1, (c) Case 3:3

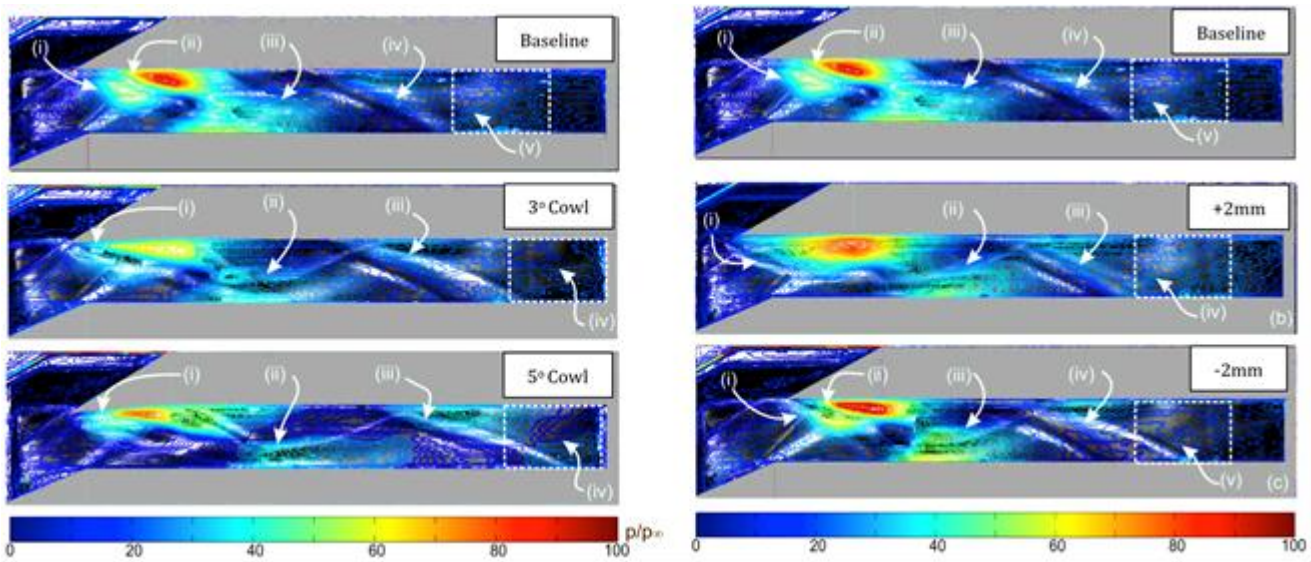

Fig. 6: Comparison of scramjet inlet internal pressure

A. Results

The geometry of the scramjet inlet was varied by deflecting the cowl inwards by 3 and 5 degrees. The cowl length was also modified by 2mm forward and backward. Generally, the inward deflection of cowl tip reduces the cowl tip shock strength thus reducing the total pressure loss. This in turn improve the performance of the scramjet inlet. This can be observed by the pressure map produced using PSP signal in Fig. 6.

The cowl tip shock was intensified in the case of cowl with forward extension. The shock from the external compressive ramp impinged directly on the inside surface of the cowl thus creating a massive separation (see Fig. 6). This will results in performance deterioration in comparison to the baseline case where the compression shock impinge exactly at cowl tip. By missing the shock completely, such as in the case where the cowl length was reduced by 2mm, the inlet achieved better internal flow uniformity, thus resulting in better performance.

The performance for all cases were calculated using the 'final shock' concept and were plotted against the curve of in 1 – 4 (see Fig. 7). Generally, our data lies between the curve of [18], [19]. The data from other researchers were also plotted together and they are more scattered although none ventured too far away from the area bounded by the curves from [17], [19].

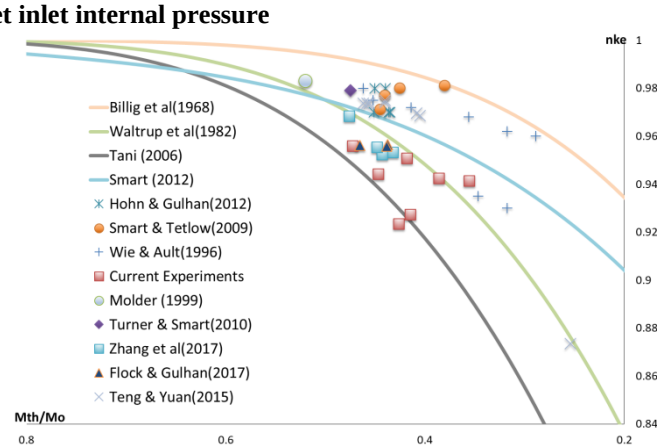

Fig. 7: Comparison of our experimental data and data found from literatures plotted together with performance curves of in (1) to (4)

B. Validation of ANN Model against Experimental Data

The ANN model of Case 1 with 1 hidden layer was tested against our experimental measurement. The RMSE between our experimental data and the output from the ANN model was found to be 0.9513. This value is larger than the RMSE of the same ANN model tested against the published performance data. However, this is still less than 1% error and proves that this ANN model is robust

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

enough to be used with wide range of scramjet geometry and operating conditions. The fit of the ANN output against our experimental data is plotted in Fig. 8. It can be observed that only two experimental data points can be predicted exactly by the ANN model. Nevertheless, all other data points lies very closely to the 45-degree line in the graph. Ideally, a perfect fit would see that all data points lie on this line, but if further optimization of the ANN is performed, we are wary of an overfit of the model that would render the ANN model to become useless against future experimental measurement.

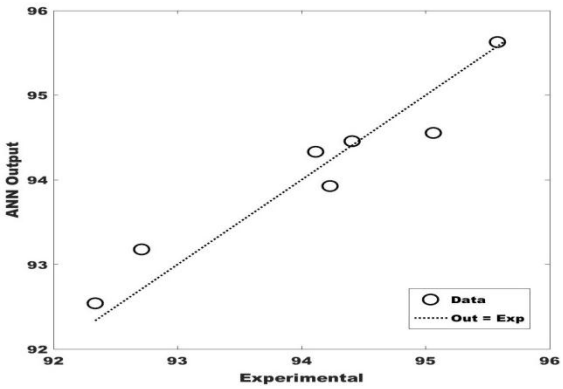

Fig. 8: Comparison of our experimental data with output predicted using the optimum ANN model. Perfect fit is indicated on the 45-degree line between the horizontal and vertical axis of the plot

VI. CONCLUSION

Researchers of scramjet engine technology has been debating on the most effective way of measuring and quantifying the performance of the scramjet inlet. All of the suggested empirical relations that relate the scramjet inlet performance to the throat Mach number has been shown to be not robust enough for a wide range of scramjet geometry and operating conditions. The work done in this article utilized ANN technique to create a mathematical model that could fit the published data. The analysis found that the inlet performance is dependent on both the throat Mach number and freestream Mach number explicitly and not implicitly (as a ratio) as suggested by prior works. The ANN model has been validated against our own measurement of performance of a generic scramjet model. The ANN model was not overfitted by the training data and agree with out experimental data with very low error margin.

REFERENCES

1. K. N. Roberts and D. R. Wilson, "Analysis and design of a hypersonic scramjet engine with a transition Mach number of 4.00," 47th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, 2009, pp. 5–8.
2. R. S. Fry, "A century of ramjet propulsion technology evolution," Journal of Propulsion and Power, 20, 2004, pp. 27–58.
3. P. Gruhn and A. Gülhan,"Experimental investigation of a hypersonic inlet with and without sidewall compression," Journal of Propulsion and Power, 27, 2011, pp. 718–729.
4. J. Häberle and A. Gülhan, "Investigation of two-dimensional scramjet inlet flowfield at Mach 7," Journal of Propulsion and Power, 24, 2008, pp. 446–459.
5. O. M. Hohn and A. Gülhan, "Experimental investigation on the influence of sidewall compression on the flowfield of a scramjet inlet at Mach 7," 17th AIAA International Space Planes and Hypersonic Systems and Technologies Conference, 2011, pp. 1-17.
6. O. Hohn and A. Gulhan, "Experimental investigation of the influence of yaw angle on the inlet performance at Mach 7," 48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, 2010, pp. 1-16.
7. H. Tan, S. Sun, and H. Huang,"Behavior of shock trains in a hypersonic inlet/isolator model with complex background waves," Experiments in Fluids, 53, 2012, pp 1647–1661.
8. A.C. Idris, M. R. Saad, H. Zare-Behtash, and K. Kontis, "Luminescent measurement systems for the investigation of a scramjet inlet-isolator," Sensors, 14, 2014, pp. 6606–6632.
9. E. T. Curran and R. R. Craig, The use of stream thrust concepts for the approximate evaluation of hypersonic ramjet engine performance. 1973, Available: https://apps.dtic.mil/dtic/tr/fulltext/u2/769481.pdf.
10. W. H. Heiser and D. T. Pratt,Hypersonic Airbreathing Propulsion. Washington: AIAA, 1994.
11. A. Matthews, T. Jones, and T. Cain, "Design and test of a hypersonic isentropic-spike intake with aligned cowl," Journal of Propulsion and Power, 21, 2005, pp. 838–843.
12. A. Matthews and T. Jones, "Design and test of a modular waverider hypersonic intake," Journal of Propulsion and Power, 22, 2006, pp. 913–920.
13. R. C. Haefeli and H. Bernstein, Performance of Separation Nose Inlets at Mach Number 5.5. Washington: National Advisory Committee for Aeronautics, 1953.
14. H. Bernstein and R.C. Haefeli, Investigation of Pressure Recovery of a Single-Conical-Shock Nose Inlet at Mach Number 5.4. Washington: National Advisory Committee for Aeronautics, 1953.
15. H. Bernstein and R. C. Haefeli, Performance of Isentropic nose Inlets at Mach number of 5.6. Washington: National Advisory Committee for Aeronautics, 1954.
16. O. M. Hohn and A. Gülhan, "Analysis of a three-dimensional, high pressure ratio scramjet inlet with variable internal contraction," 18th AIAA/3AF International Space Planes and Hypersonic Systems and Technologies Conference, 2012, pp. 1-18.
17. F. Billig, M. Lasky, and R. Orth, "Effects of thermal compression on the performance estimates of hypersonic ramjets," Journal of Spacecraft and Rockets, 5, 1968, pp. 1076–1081.
18. P. Waltrup, F. Billig, and R. Stockbridge, "Engine sizing and integration requirements for hypersonic airbreathing missile applications," AGARD Ramjets and Ramrockets for Mil. Appl., 41, 1982, p (SEE N82-32256 22-99).
19. K. Tani, T. Kanda, and K. Kudo, "Aerodynamic performance of scramjet inlet models with a single strut," Journal of Propulsion and Power, 22, 2006, pp. 905–912.
20. M. K. Smart, "How much compression should a scramjet inlet do?" AIAA Journal, 50, 2012, pp. 610–619.
21. S. O'Byrne, S. Wittig, J. Kurtz, Y. Krishna, C. Rodriguez, M. Aizengendler, and J. Davies, "Diode laser sensor for scramjet inlets," Canberra: Australian Defence Force Academy, 2011.
22. J. Kurtz, M. Aizengendler, Y. Krishna, P. Walsh, and S. B. O'Byrne, "Flight test of a rugged scramjet-inlet temperature and velocity sensor," 53rd AIAA Aerospace Sciences Meeting, 2015, pp. 1-18.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

23. M. K. Smart and M. R. Tetlow, "Orbital delivery of small payloads using hypersonic airbreathing propulsion," Journal of Spacecraft and Rockets, 46, 2009, pp. 117–125.
24. D. Van Wie and D. Ault, "Internal flowfield characteristics of a scramjet inlet at Mach 10," Journal of Propulsion and Power, 12, 1996, pp. 158–164.
25. S. Molder, "Performance of three hypersonic inlets," 22nd International Symposium on Shock Waves, 1999.
26. J. C. Turner and M. K. Smart, "Application of inlet injection to a three-dimensional scramjet at Mach 8," AIAA Journal, 48, 2010, pp. 829–838.
27. Y. Zhang, H. J. Tan, S. Sun, H. Chen, and C. H. Li, "Experimental and numerical investigation of a fluidically variable hypersonic inlet," AIAA Journal, 55(8), 2017, 2597-2606.
28. A. K. Flock and A. Gülhan, "Experimental and numerical performance analysis of a self-starting three-dimensional scramjet intake," Journal of Propulsion and Power, 33(6), 2017, 1570-1580.
29. J. Teng and H. Yuan, "Variable geometry cowl sidewall for improving rectangular hypersonic inlet performance," Aerospace Science and Technology, 42, 2015, pp. 128–135.
30. A. Govinda, M. K. K. Devaraj, Y. Singh, N. Thakor, V. R. Kulkarni, S. N. Omkar, and G. Jagadeesh, "Design of optimized two-dimensional scramjet nozzle contour for hypersonic vehicle using evolutionary algorithms," 30th International Symposium on Shock Waves, 2017, pp. 119–124.
31. C. D. Ghodke, J. Pranatharthikaran, G. J. Retaureau, and S. Menon, "Numerical and experimental studies of flame stability in a cavity stabilized hydrocarbon-fueled scramjet," 17th AIAA International Space Planes and Hypersonic Systems and Technologies Conference, 2011, pp. 1-16.
32. Q. Chen, L. H. Chen, H. B. Gu, X. Y. Zhang, and P. Wang, "Study on judgment method of combustion mode on dual-mode scramjet," Procedia Engineering, 67, 2013, pp. 147–154.
33. J. Gao, L. Dou, and P. Su, "Multi-model switching control of hypersonic vehicle with variable scramjet inlet based on adaptive neural network," 12th World Congress on Intelligent Control and Automation, 2016, pp. 1714–1719.
34. C. K. Ma, Y. H. Lee, A. Z. Awang, W. Omar, S. Mohammad, and M. Liang, "Artificial neural network models for FRP-repaired concrete subjected to pre-damaged effects," Neural Computing and Applications, 2017, pp. 1–7.
35. H. Nozari and S. Azadi, "Experimental evaluation of artificial neural network for predicting drainage water and groundwater salinity at various drain depths and spacing," Neural Computing and Applications, 2017, pp. 1–10.
36. H. R. Aidinlou and A. Nikbakht, "Intelligent modeling of thermohydraulic behavior in solar air heaters with artificial neural networks," Neural Computing and Applications, 2017, pp. 1–15.
37. S. Elkatatny, Z. Tariq, M. Mahmoud, A. Abdulraheem, and I. Mohamed, "An integrated approach for estimating static Young's modulus using artificial intelligence tools," Neural Computing and Applications, 2018, pp. 1–13.
38. S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach. New Jersey: Prentice Hall, 2010.
39. R. Rojas, Neural Networks: A Systematic Introduction. Berlin: Springer Verlag, 1996.