Thermal Fluid Model Development of Steam Methane Reformer using Artificial Neural Network

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Overview

- Background and Motivation
- Modeling Objective
- Experimental Setup
- Artificial Neural Network Structures
- Statistical Model Verification
- Results
- Conclusions

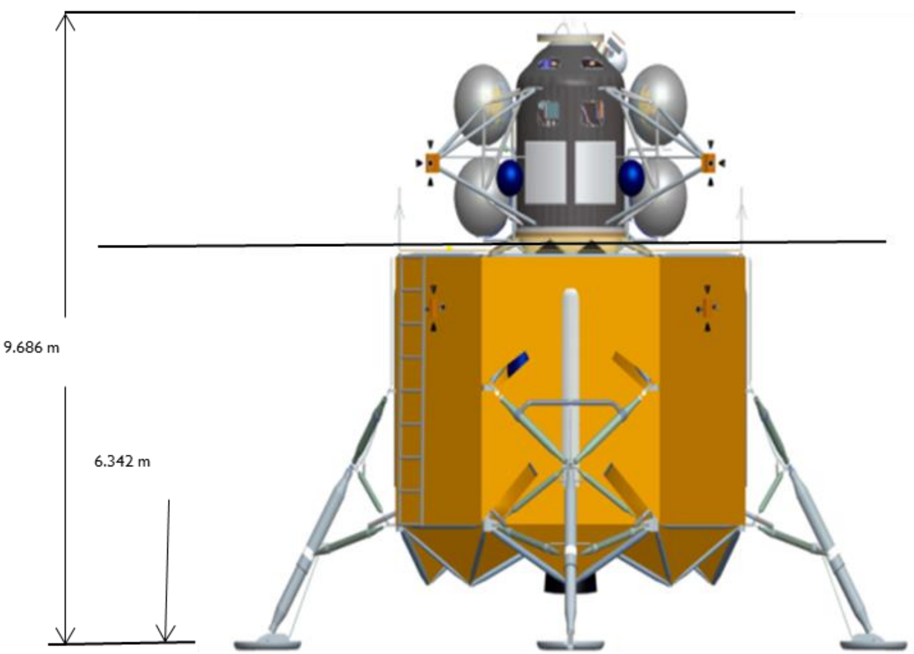
Background

- Gemini, Apollo, and Space Shuttle used fuel cells as main power source for vehicle and water source for life support and thermal
  - PEM (Gemini) and Alkaline (Apollo, Shuttle) fuel cells were used
  - Ideal for short (less than 3 weeks) missions when the required O2 and H2 can be launched with the vehicle

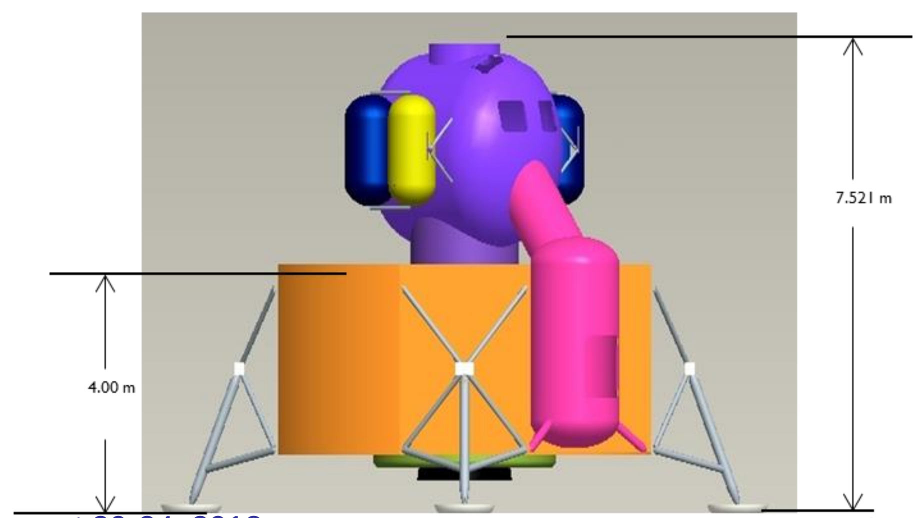
- New missions that might require long-duration stays in orbit or at a habitat, can not rely on the availability of pure reactants but should also aim to be sun-independent – a problem for which Solid Oxide Fuel Cells integrated with a Steam Methane Reformer (SMR) might be the answer

Background

- NASA has investigated & developed LOX/CH4-propelled landers (Altair, Morpheus) to consider fuel cells as a power source to preserve mission flexibility
- Previous work at JSC has the volumetric and mass benefits of LOX/CH4 propelled vehicles vs LH2/LO2
- Using a SMR, steam reformation of methane into a H2-rich mixture is being considered for more efficient fuel cell performance.



LH2/LO2 Lander Size



LOX/Methane Lander Size

Motivation

- To obtain reliable and efficient operation of SMRs to ensure consistent pressure and temperature under different operating conditions.
- Artificial neural networks (ANN) modeling approach can:
  - handle complex and nonlinear characteristics of input and output variables including pressure and <u>temperature</u>
  - converge to a solution quickly with very low error
  - account for <u>dynamic</u> behavior

Objective

- Compare and assess the dynamic models for best fit under given operating conditions
  - SMR Temperature model
  - SMR Pressure model
- Dynamic ANN with Levenberg-Marquardt (LM) algorithm have two different structures:
  - Conventional time delay (TD) only structure
  - Time delay with Nonlinear Autoregressive Network with External Input (NARX) structure

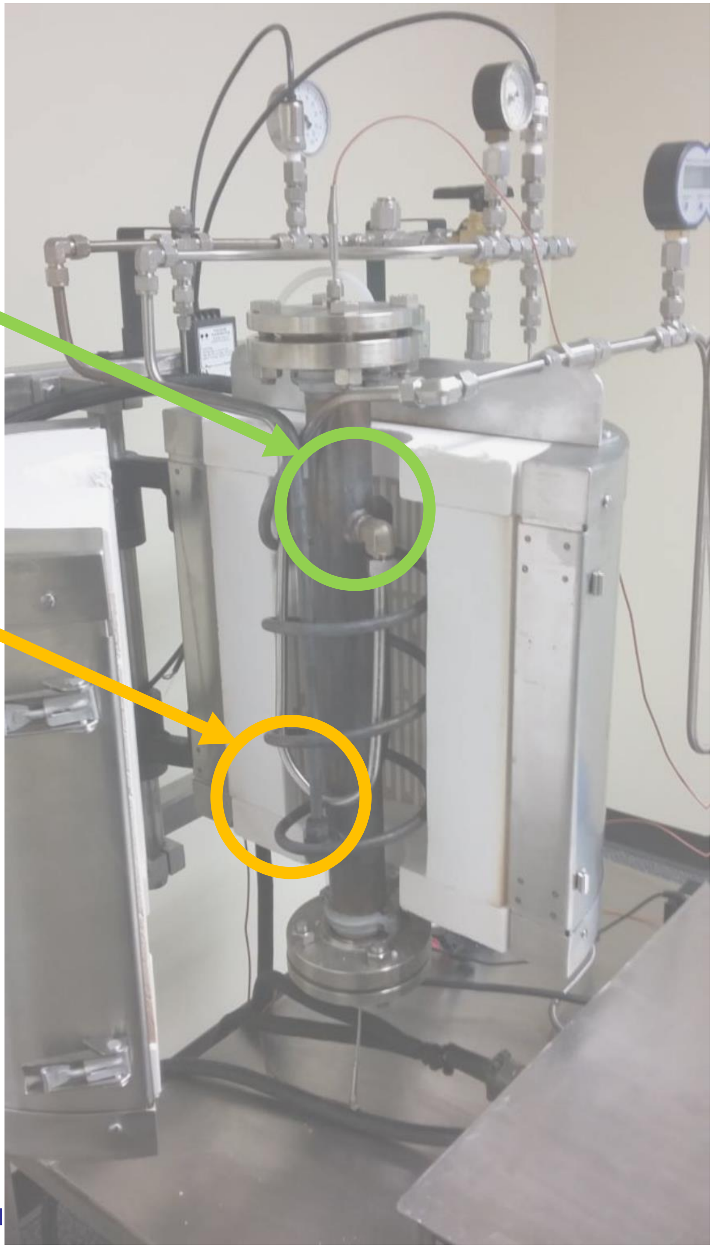
Experimental setup

Variables	Units	Operating range
Methane input temperature	^{o}C (^{o}F)	500-800 (932-1472)
Water input temperature	^{o}C(^{o}F)	500-800 (932-1472)
Methane input pressure	psig	4-6
Water input pressure	psig	9-10
Methane input flow rate	SLPM	4-6
Water input flow rate	SLPM	13-18
SMR (Output) temperature	^{o}C(^{o}F)	500-800 (932-1472)
SMR (Output) pressure	psig	4-6

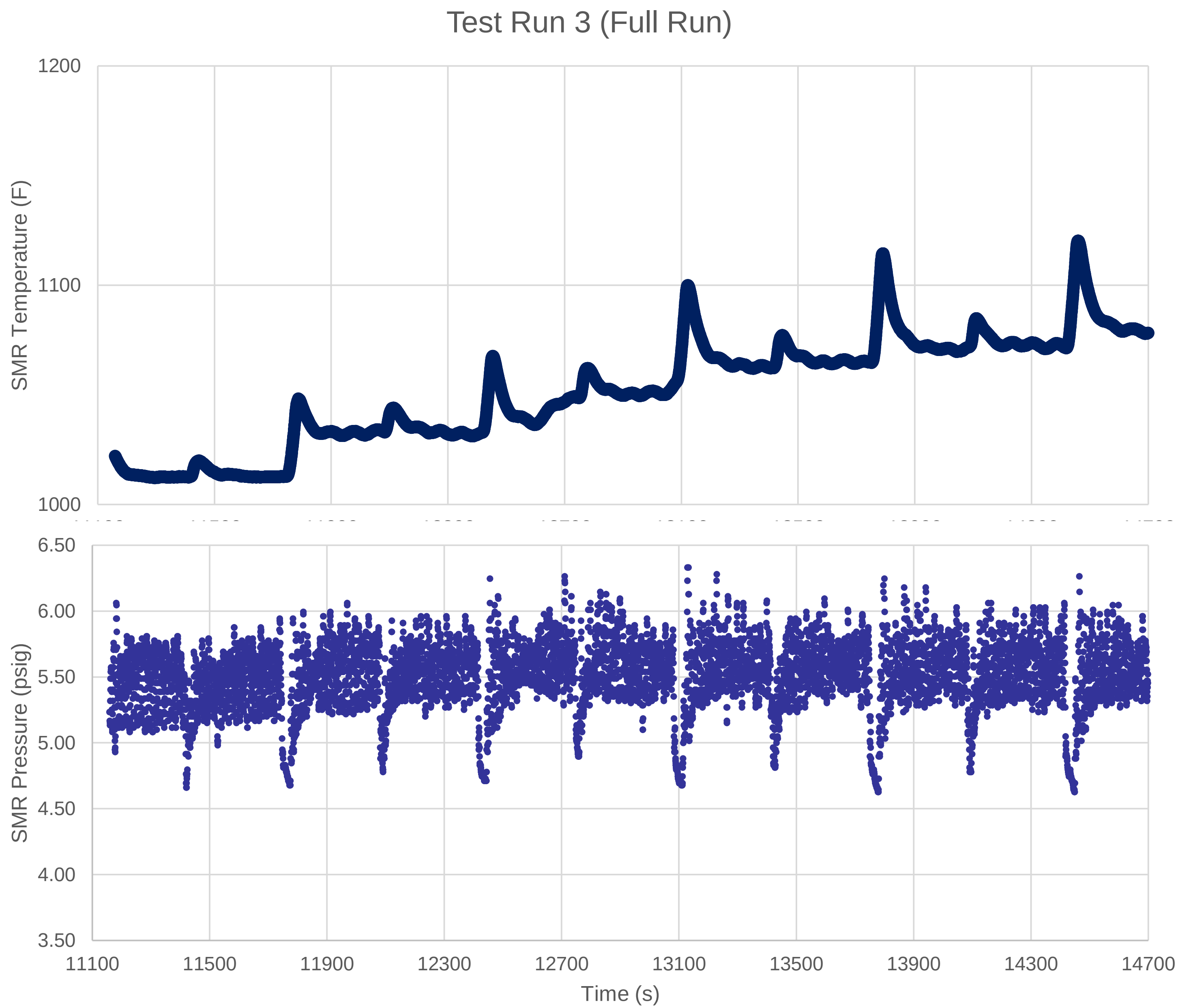
Experimental setup

Methane and Water Inputs

SMR Output

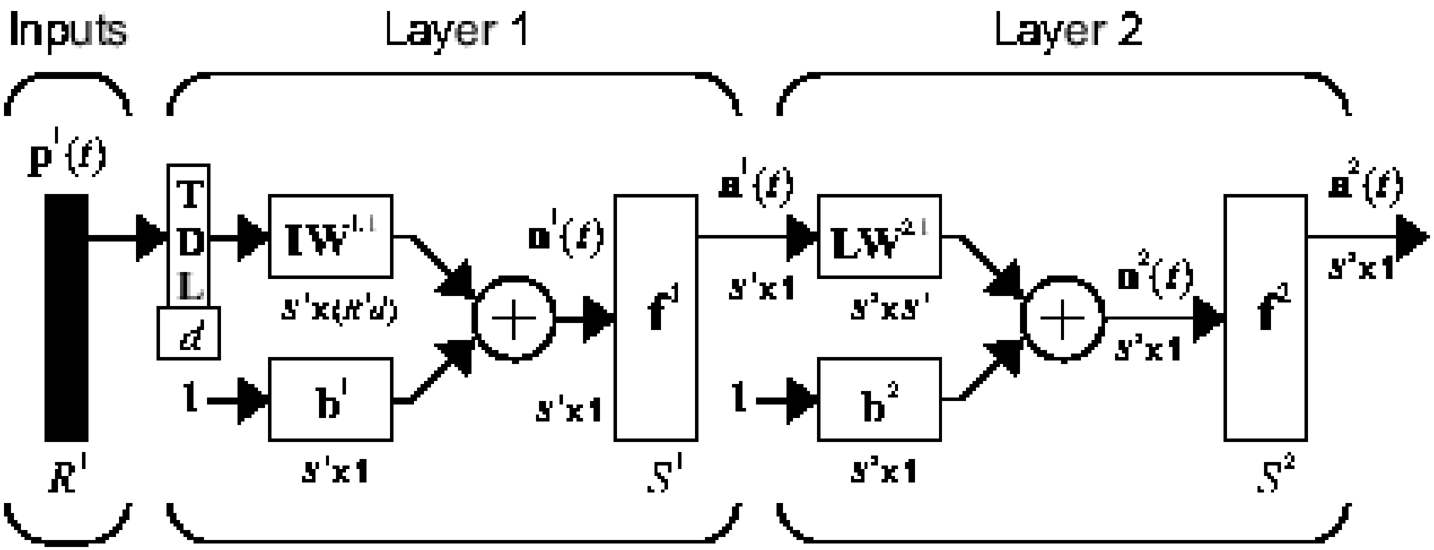


Example Experimental Result



ANN modeling approach

- Dynamic Fitting ANN with LM algorithm and TD structure

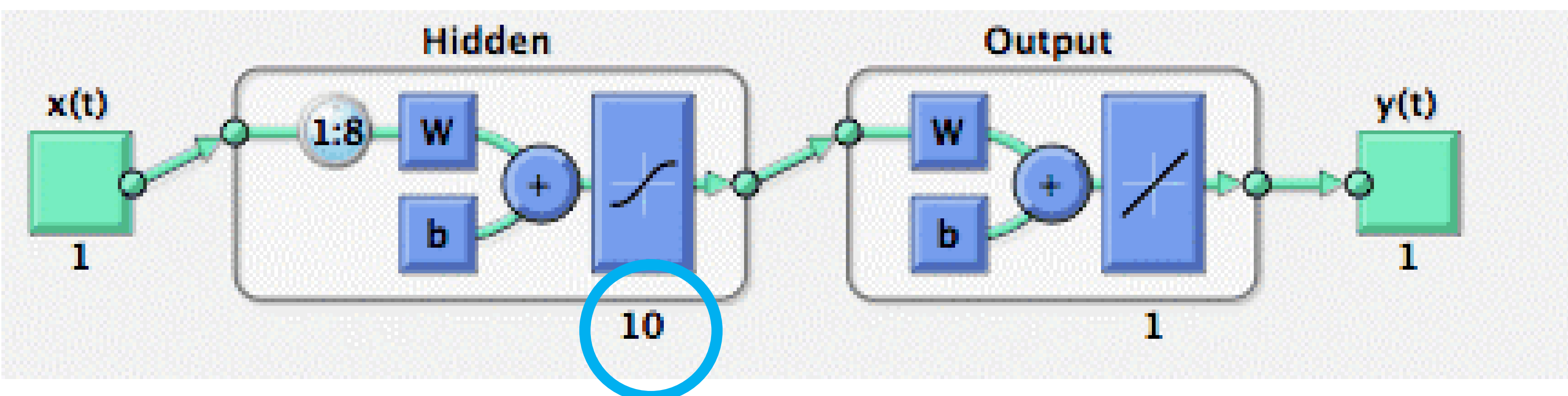


Reference: Mathworks Inc.

ANN modeling approach

- Dynamic Fitting ANN with LM algorithm and TD structure

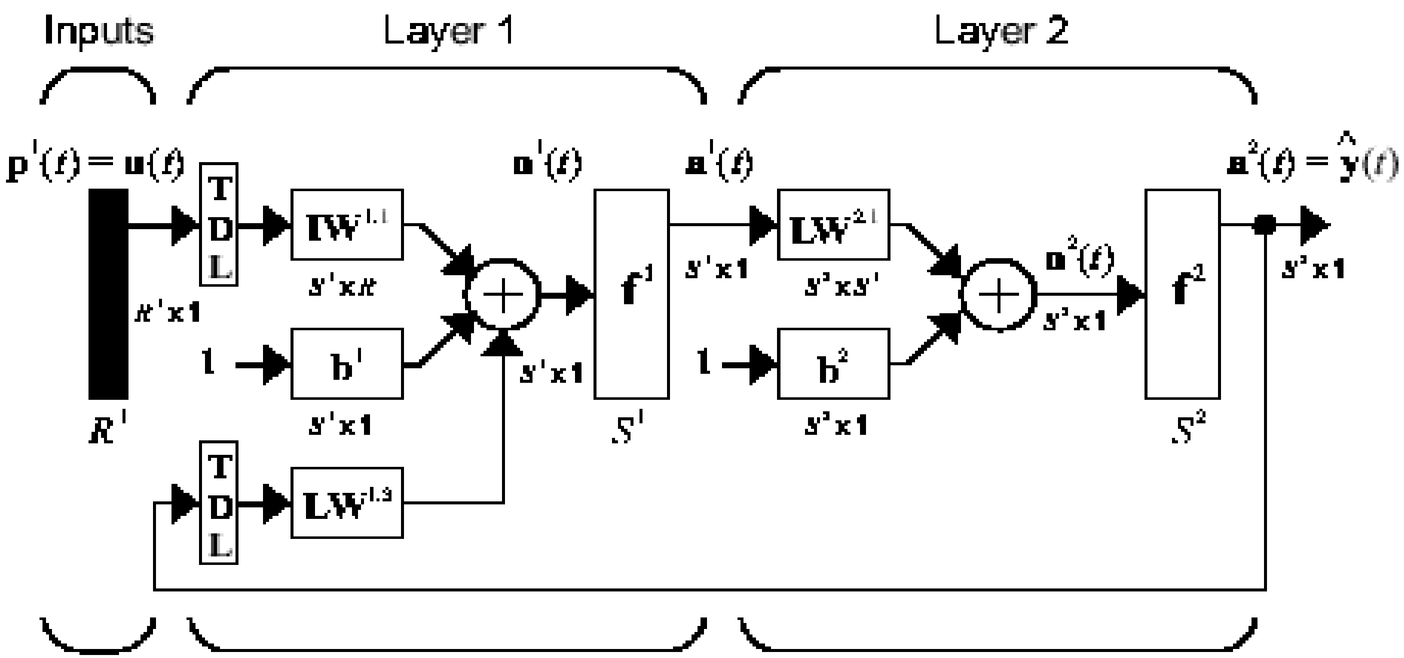
Inputs **Output**



Change # of Hidden neurons

ANN modeling approach

- Dynamic Fitting ANN with LM algorithm and TD & NARX structure



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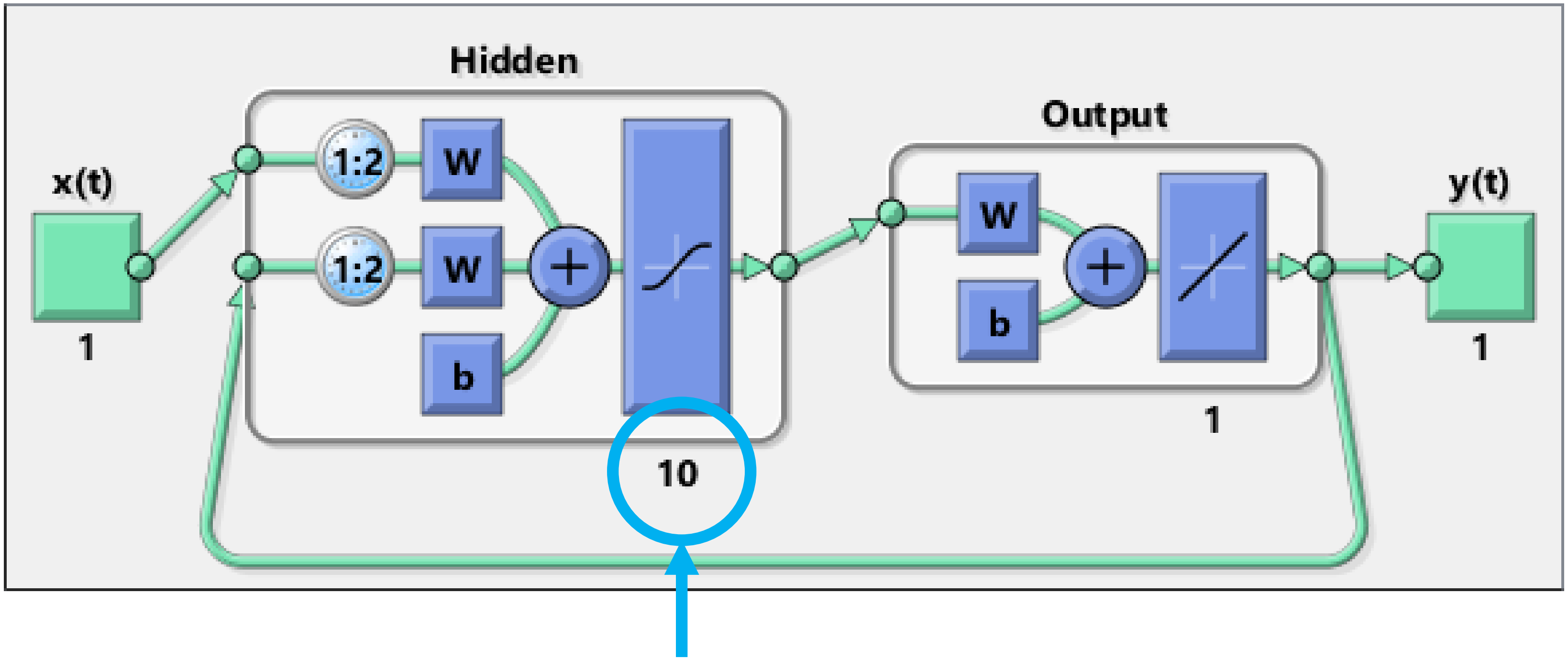
ANN modeling approach

- Dynamic Fitting ANN with LM algorithm and TD & NARX structure



Change # of Hidden neurons

Reference: Mathworks Inc.

Statistical Analysis

- Mean Squared Error - closeness of fit (converge to 0)

$$\mathrm{MSE} = \frac{1}{n}\sum(Z - Y)^2$$

- Coefficient of Determination – strength of fit (closer to 1)

$$R^2 = [Cor(Z,\mathrm{Y})]^2$$
$$= 1 - \frac{\mathrm{SSE}}{\sum(Y - \bar{Y})^2}$$

- Y – experimental data
- Z – model results
- n – number of data points
- $\bar{Y}$ – mean experimental value
- SSE – sum of squared error

Results – Dynamic Fitting LM w/ TD

# of Hidden Neurons	R^2	MSE
1	0.98953	462.54
5	0.9948	230.91
10	0.99705	130.82
15	0.99771	101.67
20	0.99827	76.698
25	0.9995	22.064
30	0.99829	75.666

Results – Dynamic Fitting LM w/ NARX

# of Hidden Neurons	R^2	MSE
1	0.99999	0.37352
5	0.99999	0.31826
10	1	0.19429
15	1	0.14639
20	1	0.13704
25	1	0.15315
30	1	0.13319

Results – Dynamic Fitting LM w/ TD

# of Hidden Neurons	R^2	MSE
1	0.98433	0.086254
5	0.98985	0.056055
10	0.99236	0.042222
15	0.99199	0.044358
20	0.99343	0.036356
25	0.99387	0.033975
30	0.99404	0.033034

Results – Dynamic ANN LM w/ NARX

# of Hidden Neurons	R^2	MSE
1	0.98715	0.070845
5	0.99181	0.045267
10	0.99337	0.036865
15	0.99225	0.042823
20	0.994	0.033211
30	0.99195	0.044516

Conclusions

- Most models showed very good fit to the experimental data for 1-30 hidden neurons.
  - All ANN NARX Temperature models had $R^2 > 0.99$ and $MSE < 0.4$
  - All Pressure models had $R^2 > 0.98$ and $MSE < 0.09$
- ANN model using LM algorithm with NARX structure showed the best fit for both SMR temperature and pressure
- Almost any of these modeling approaches can be applied in predicting thermal and pressure behavior of SMR
  - to improve thermal efficiency
  - stabilize the dynamic operation.

Acknowledgements

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References

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THANK YOU!