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Modeling Electricity Demand: A Neural Network Approach

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Support

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"Implications of Climate Change for Regional Air Pollution and Health Effects and Energy Consumption Behavior"

Co-researchers in the project are

- Frederick Joutz from the George Washington University Department of Economics
- Benjamin Hobbs and Yihsu Chen from the Johns Hopkins University Department of Geography and Environmental Engineering
- Hugh Ellis from the Johns Hopkins University School of Public Health

Outline

I. Context of the Research
II. Introduction to ANN Modeling
III. Basics of Electricity Demand
IV. Developing the Demand Model
V. Results

I. Context of the Research

Context

The modeling efforts of the STAR grant are

1. Electricity load modeling and forecasting
2. …
3. …
4. …

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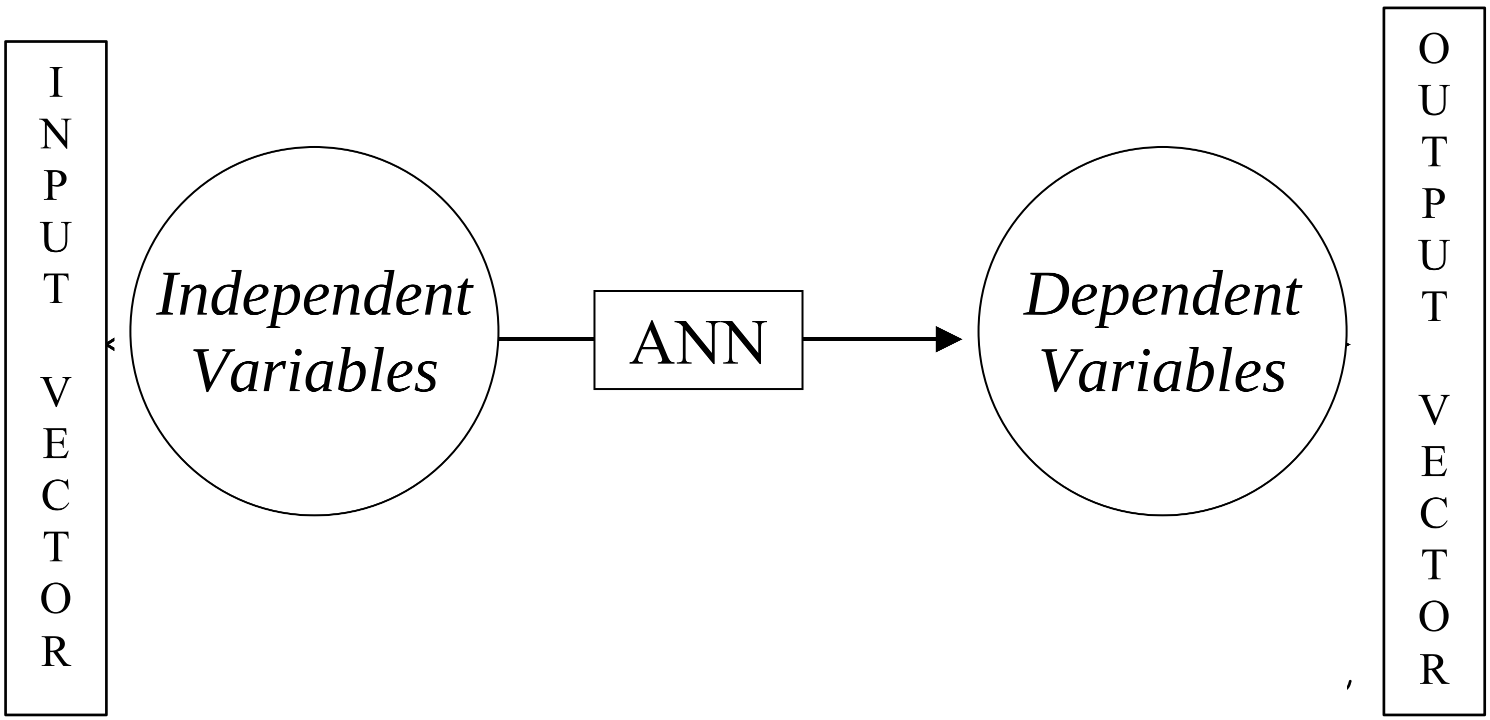
1. Electricity load modeling and forecasting
2. Electricity generation and dispatch modeling
3. Regional air pollution modeling
4. Health effects characterization

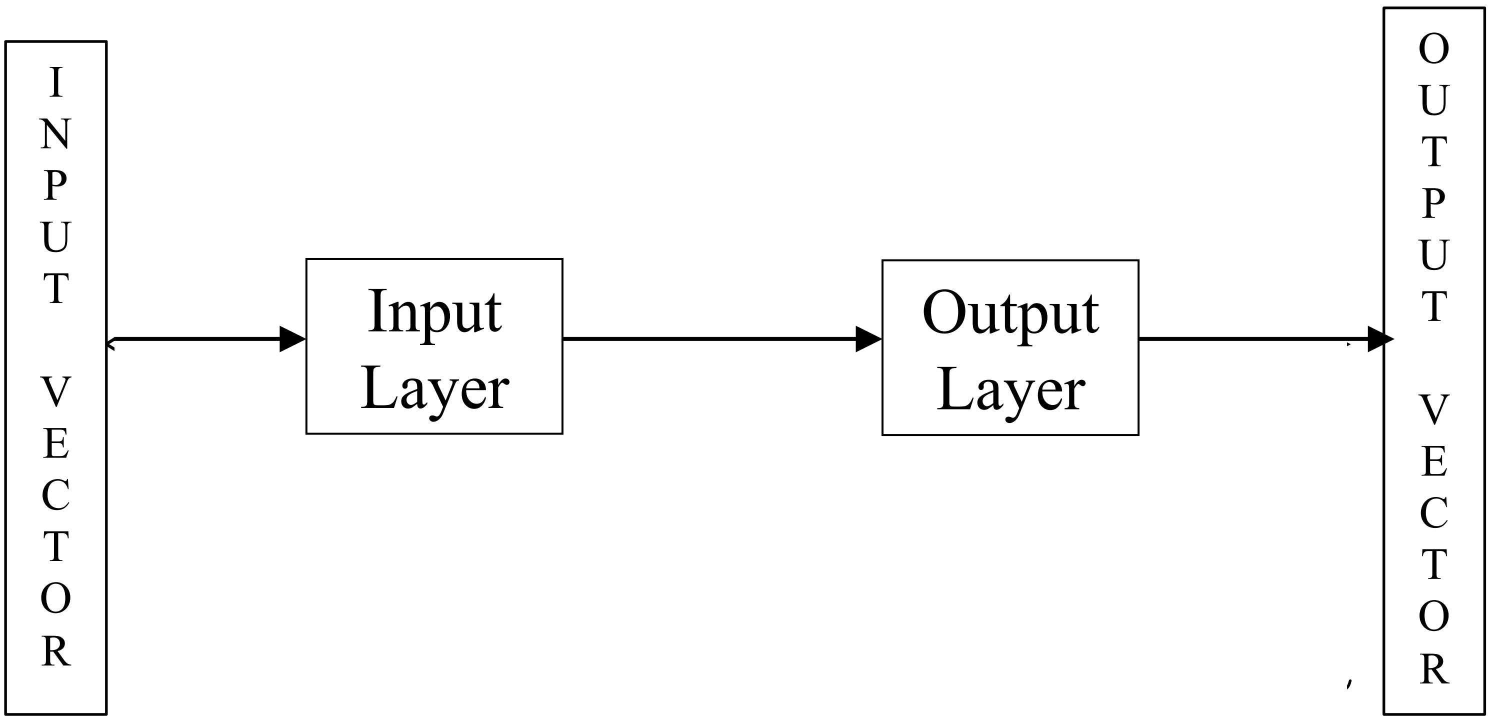
II. Intro to ANN Modeling

ANN Model Architecture



“ANN Electricity Modeling.” Crowley, GWU.

ANN Model Architecture



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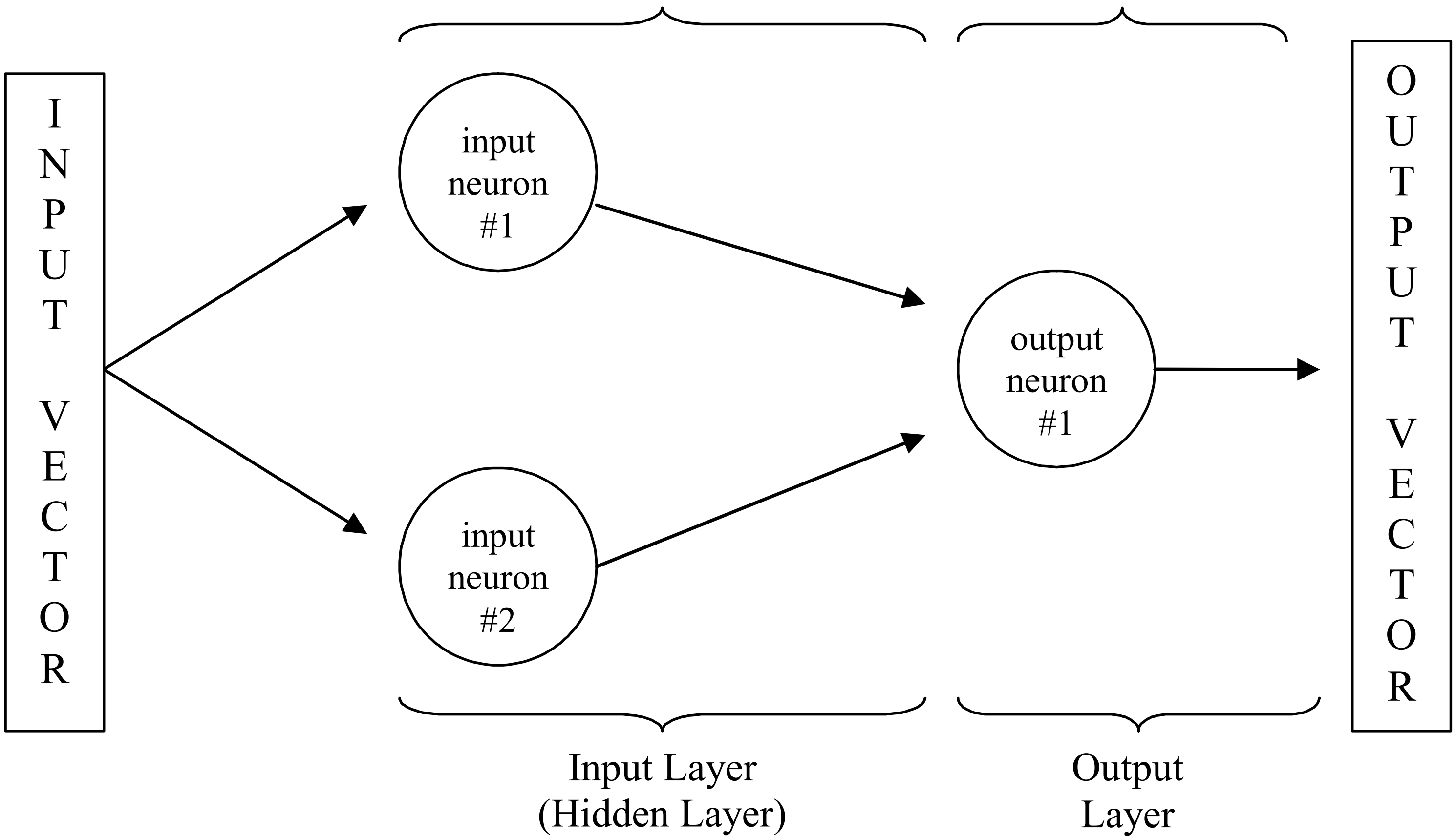

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ANN Model Architecture

Elements of a neuron

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ANN Model Architecture

Elements of a neuron

- Multiplicative Weight (*w*)

ANN Model Architecture

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- Additive Bias (*b*)

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ANN Model Architecture

Elements of a neuron

- Multiplicative Weight (w)
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- Transfer Function (f)

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ANN Model Architecture

Elements of a neuron

- Multiplicative Weight (w)
- Additive Bias (b)
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The Neuron uses these elements in its operation, when it receives an **input** (p) and produces a **result** (a)

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ANN Model Architecture

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  using the weight (w) and bias (b)

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- Application of the Transfer Function (f)

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- Linear Transformation

  using the weight (*w*) and bias (*b*)

- Application of the Transfer Function (*f*)

The neuron then passes the result (*a*) on to the next part of the ANN.

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ANN Model Architecture

<u>Linear Transformation</u>

- Multiply the input (*p*) by a weight (*w*) and add the bias (*b*) to get the intermediate result (*n*):

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ANN Model Architecture

Linear Transformation

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$$n = w \times p + b$$

- Pass the intermediate result (n) to the transfer function

ANN Model Architecture

<u>Transfer Function</u>

- Apply the transfer function (f) to the intermediate result (n) to create the neuron's result (a)

ANN Model Architecture

<u>Transfer Function</u>

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- For neurons in the input layer, the transfer function is typically a hard-limiting switch at some threshold, say $n = 0$:

$$f(n) = (0 \text{ for } n \leq 0;\ 1 \text{ for } n > 0)$$

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ANN Model Architecture

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- For neurons in the output layer, the "pure linear" transfer function typically has no effect:

$$f(n) = n$$

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ANN Model Architecture

INPUT VECTOR

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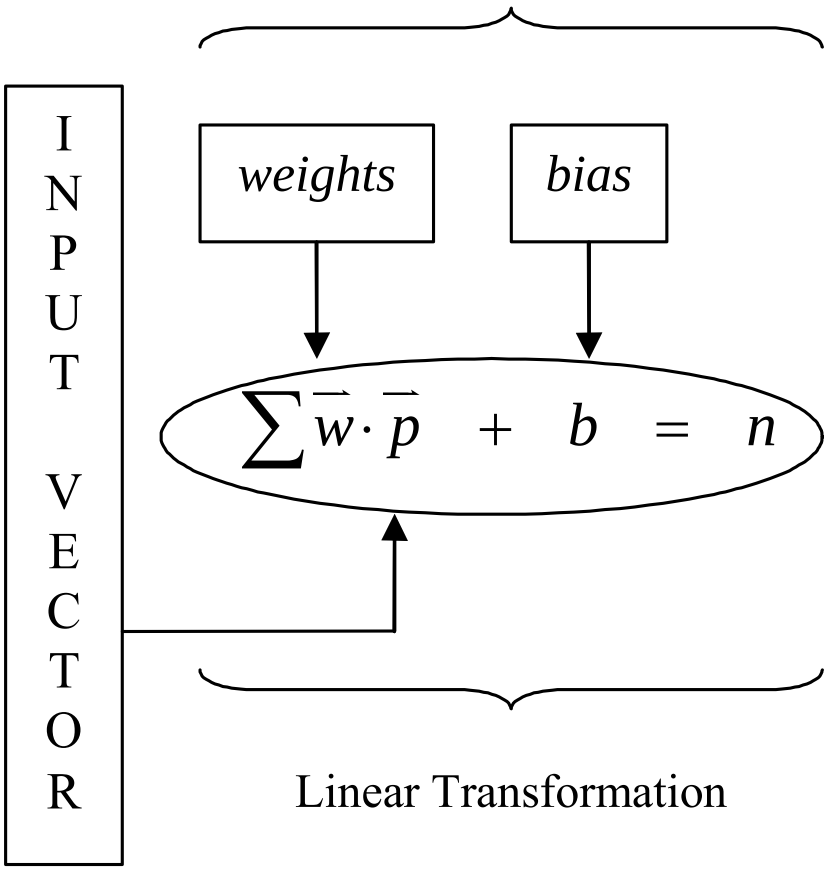
ANN Model Architecture



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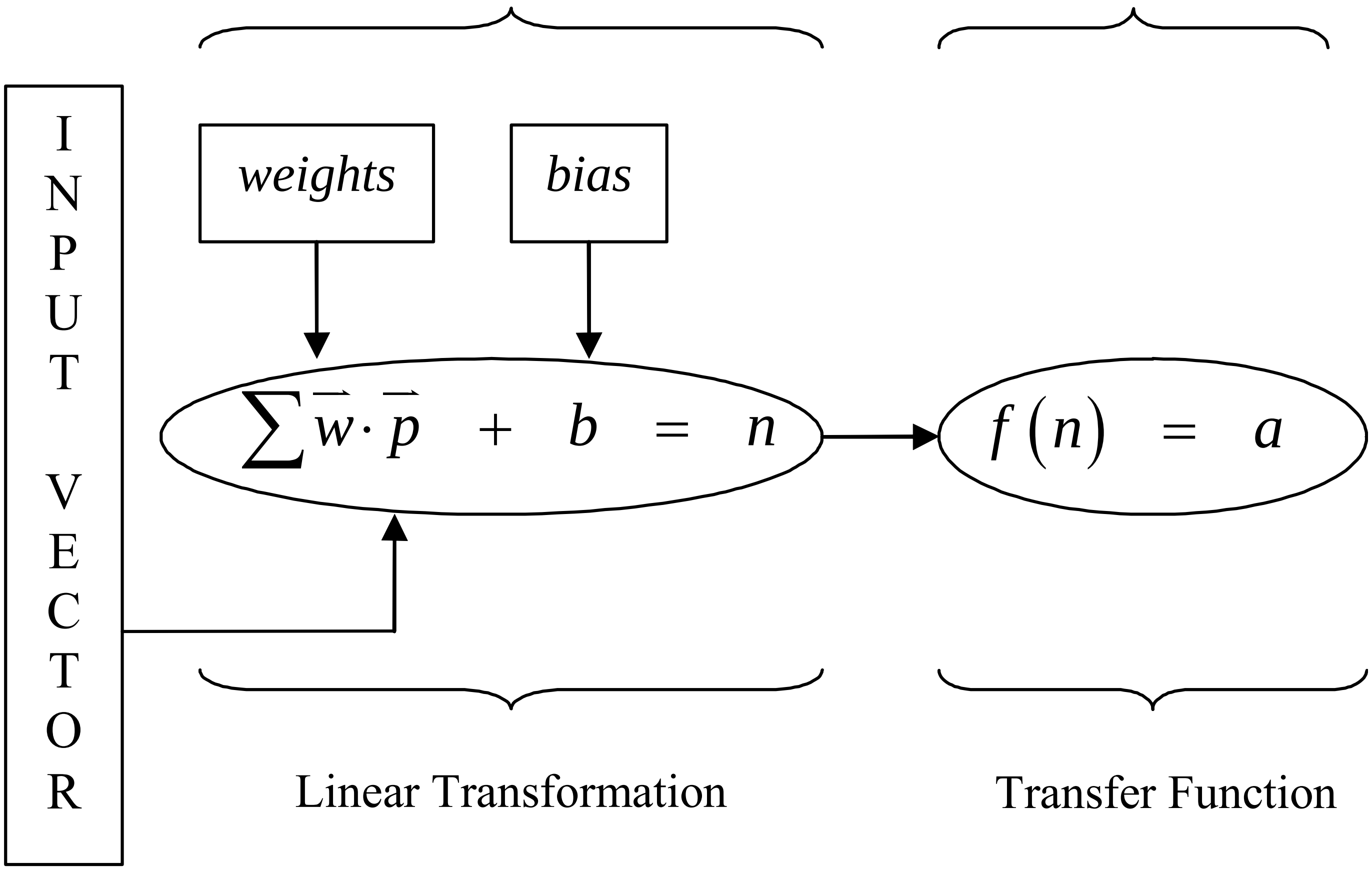

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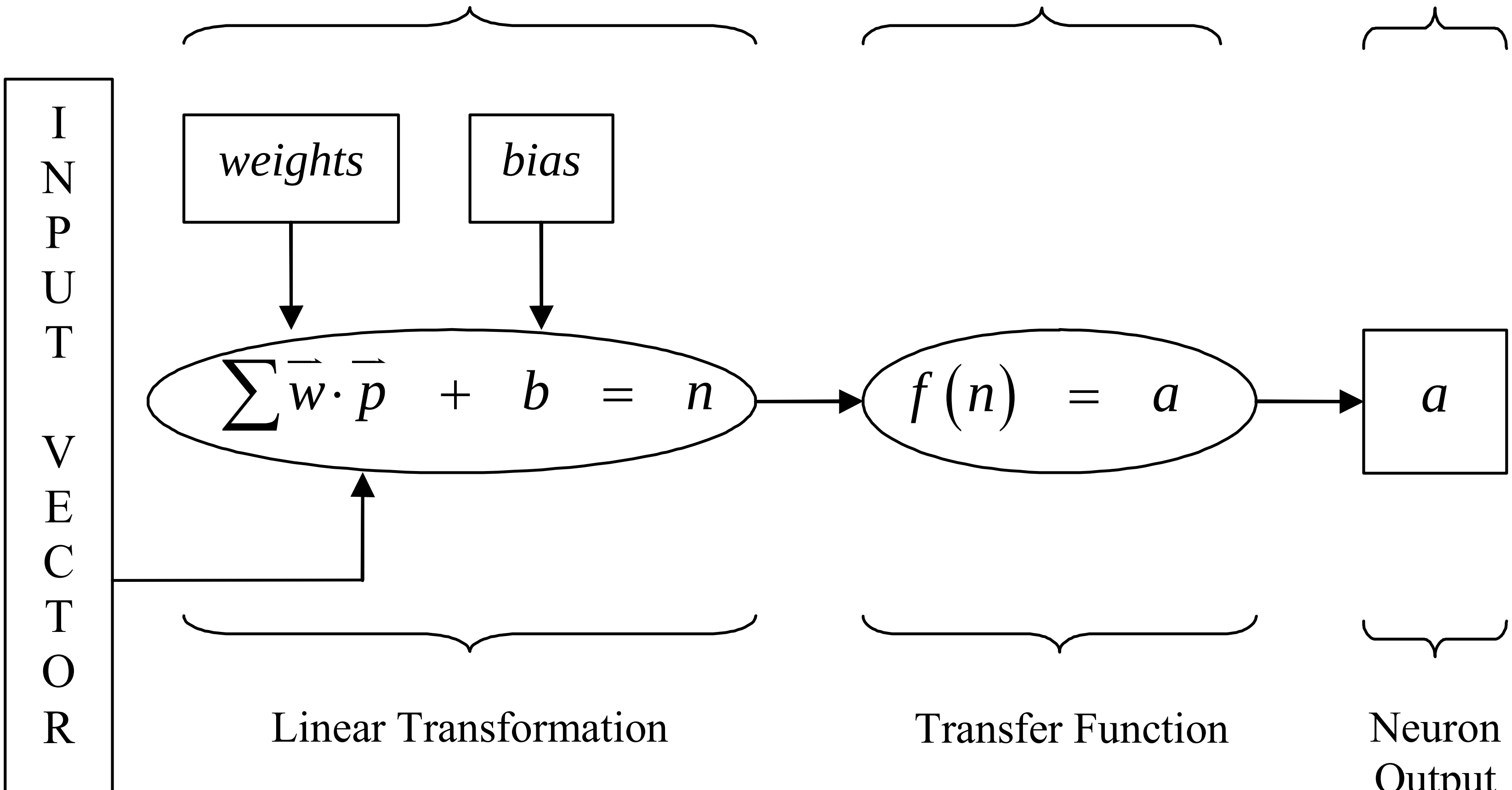

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ANN Model Architecture

Example: A Neuron's Operation

- Say a neuron has a weight of 10, a bias of 100, and a hard-limiting transfer function with a threshold of $n = 0$:

  $w = 10$; $b = 100$

  $f(n) = (0 \text{ for } n \leq 0; 1 \text{ for } n > 0)$

ANN Model Architecture

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ANN Model Architecture

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ANN Model Architecture

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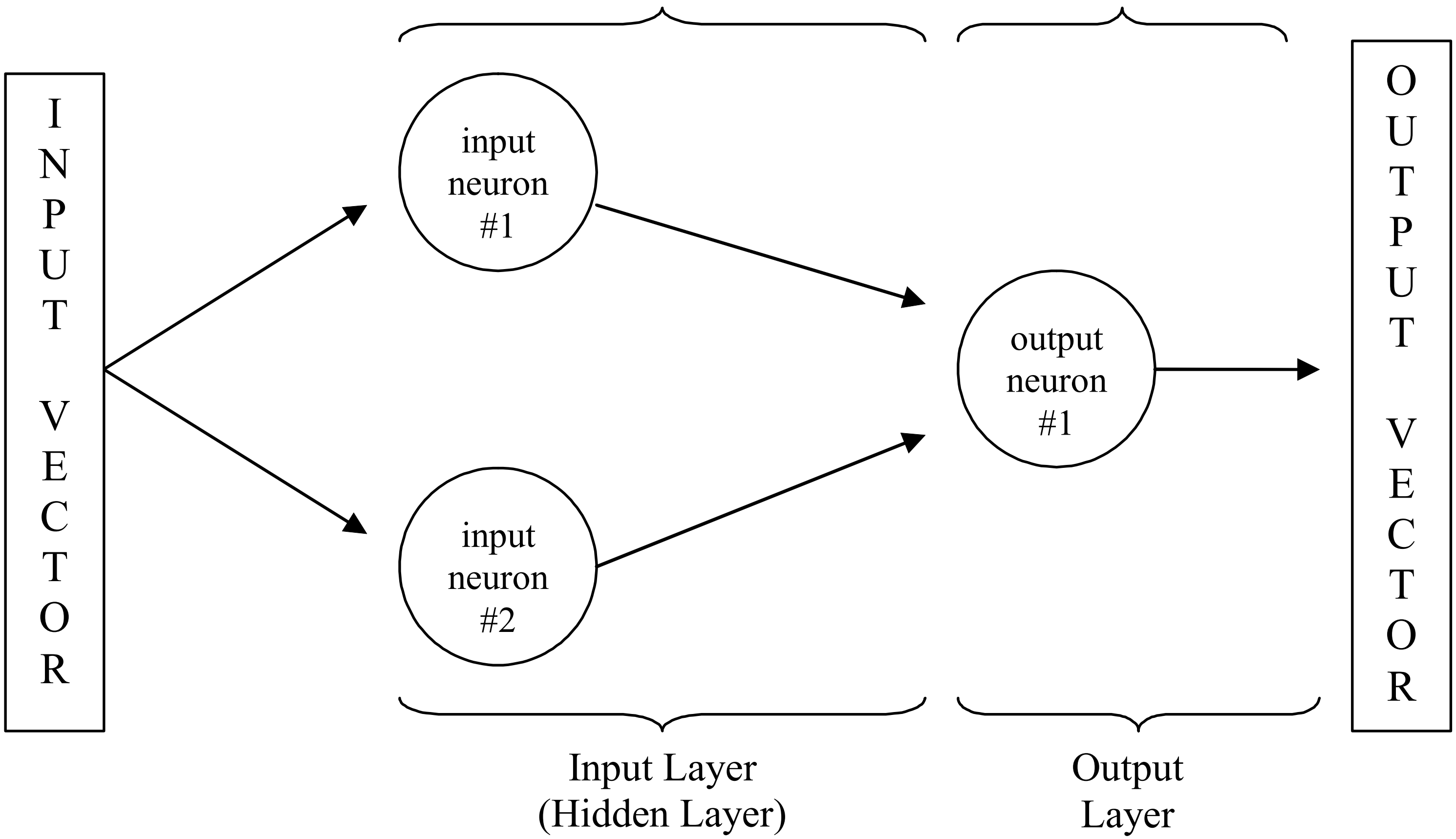
- The neuron's transfer function produces the neuron's result of 1:

  $a = f(n) = 1$

ANN Model Architecture



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- Training is finding the weights and biases that minimize the **performance function**
- The performance function is typically some measure of model error, such as MSE

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    - Input
    - Output
    - Hidden (if any)

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  - typically 1-5 input neurons
  - typically 1 output neuron

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  - input layer: typically hard-limiting (0-1 switch)
  - output layer: typically pure-linear (no effect)
- the *performance function* for the network (MSE)

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III. Basics of Electricity Demand

Electricity Demand

- Utilities are interested in forecasting peak demand

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Electricity Demand

- Utilities are interested in forecasting peak demand
- Peak demand determines how many generators the utility must bring on line
- Overestimating demand is costly, wasteful
- Underestimating peak leads to electricity shortfalls

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Electricity Demand

Hourly peak electricity demand depends on

- Weather
- …
- …
- …
- …

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Electricity Demand

Hourly peak electricity demand depends on

- Weather
- Time of the Year
- …
- …
- …

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Electricity Demand

Hourly peak electricity demand depends on

- Weather
- Time of the Year
- Day of the Week
- …
- …

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Electricity Demand

Hourly peak electricity demand depends on

- Weather
- Time of the Year
- Day of the Week
- Holidays
- …

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Electricity Demand

Hourly peak electricity demand depends on

- Weather
- Time of the Year
- Day of the Week
- Holidays
- Year
- Recent Electricity Demand

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IV. Developing the Demand Model

General Model

Independent Variable (Peak Electric Demand in MWh):

$$Load_d^h$$

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$h = 1 \ldots 24$

is the hour being modeled

General Model

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$$Load_d^h$$

h = 1…24

is the hour being modeled

d = January 1, 1995 … September 30, 2003

is the date of the observation

General Model

Dependent Variables

1. Weather (Temperature in Fahrenheit degrees):

$$Temp_d^h$$

$h = 1 \ldots 24$

is the hour being modeled

$d =$ January 1, 1995 … September 30, 2003

is the date of the observation

General Model

Dependent Variables

2. Time of the Year:

$$Month_i$$

$i = 1 \ldots 12$

is the month of the observation

($Month_1 = 1$ for January, 0 otherwise,

$Month_2 = 1$ for February, 0 otherwise, etc.)

General Model

Dependent Variables

3. Day of the Week:

Day_j

$j = 1 \ldots 7$

is the weekday of the observation

($Day_1 = 1$ for Monday, 0 otherwise,

$Day_2 = 1$ for Tuesday, 0 otherwise, etc.)

General Model

Dependent Variables

4. Holidays:

Holiday

dummy for recording days with different demand profiles due to businesses closing

(*Holiday* = 1 for New Years Day, Independence Day etc., and 0 otherwise)

General Model

Dependent Variables

5. Year of observation:

Year

records the year of the observation to account for trends

General Model

Dependent Variables

6. Recent Electricity Demand:

$$Load_d^{h-1}, \quad Load_d^{h-2}, \quad Load_d^{h-3}$$

electricity demand for the previous three hours

General Model

Dependent Variables

5. Recent Electricity Demand:

$$Load_d^{h-1}, \quad Load_d^{h-2}, \quad Load_d^{h-3}$$

electricity demand for the previous three hours

$$Load_{d-1}^{h}$$

electricity demand for the previous day at this hour

General Model

$$Load_d^h = f\begin{pmatrix} Temp_d^h, \\ Month_i, Day_j, Holiday, Year \\ Load_d^{h-1}, Load_d^{h-2}, Load_d^{h-3}, Load_{d-1}^h \end{pmatrix}$$

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V. Model Selection

Data

- Electricity demand data were obtained from PJM, a large Independent System Operator (ISO) in the mid-Atlantic U.S.

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- Temperature data were obtained from the US National Climatic Data Center (NCDC) for the dates and areas of interest

Model Selection

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  - Input Layer with 1-20 hard-limiting neurons
  - Output Layer with 1 pure-linear neuron

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Model Selection

- I chose to build an ANN with two layers
  - Input Layer with 1-20 hard-limiting neurons
  - Output Layer with 1 pure-linear neuron
- I trained the ANN using the MSE as the performance function
- The optimal number of input neurons was to be determined by evaluating their effect on the ANN

Model Selection

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- But each additional neuron requires estimating several more parameters (weight and bias vectors)
- McMenamin and Monforte (1998) suggest observing the Schwartz Information Criterion (SIC) as additional neurons are added to an ANN

Model Selection

- The SIC is a measure of model performance, based on the MSE, penalized for degrees of freedom.

  (NB the statistic reported is often the natural log of the SIC)

$$SIC \equiv \mathrm{e}^{\frac{2k}{T}} \left[\frac{\sum_{t=1}^{T} e_t^2}{T} \right]$$

$$\begin{cases} e_t \text{ is the model error} \\ T \text{ is the total number of observations} \\ k \text{ is the number of estimated parameters} \\ \mathrm{e} \text{ is the base of the natural logarithm} \end{cases}$$

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- If a neuron's benefit outweighs its cost, SIC falls
- When the SIC starts to rise, the optimal number of neurons has likely been surpassed

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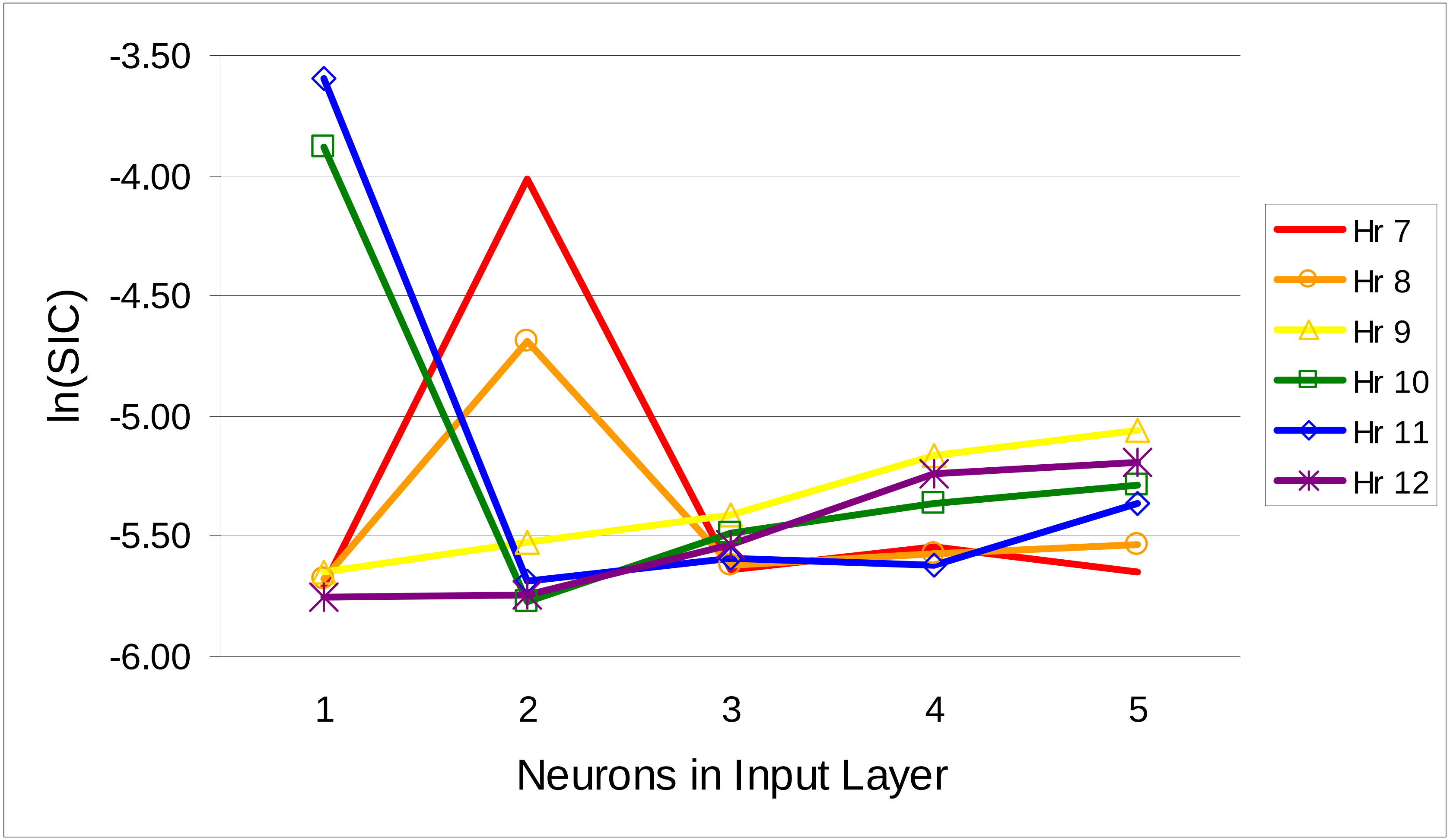
Model Selection

SIC as a Function of Neurons in the Input Layer

Hour 13 – Hour 18



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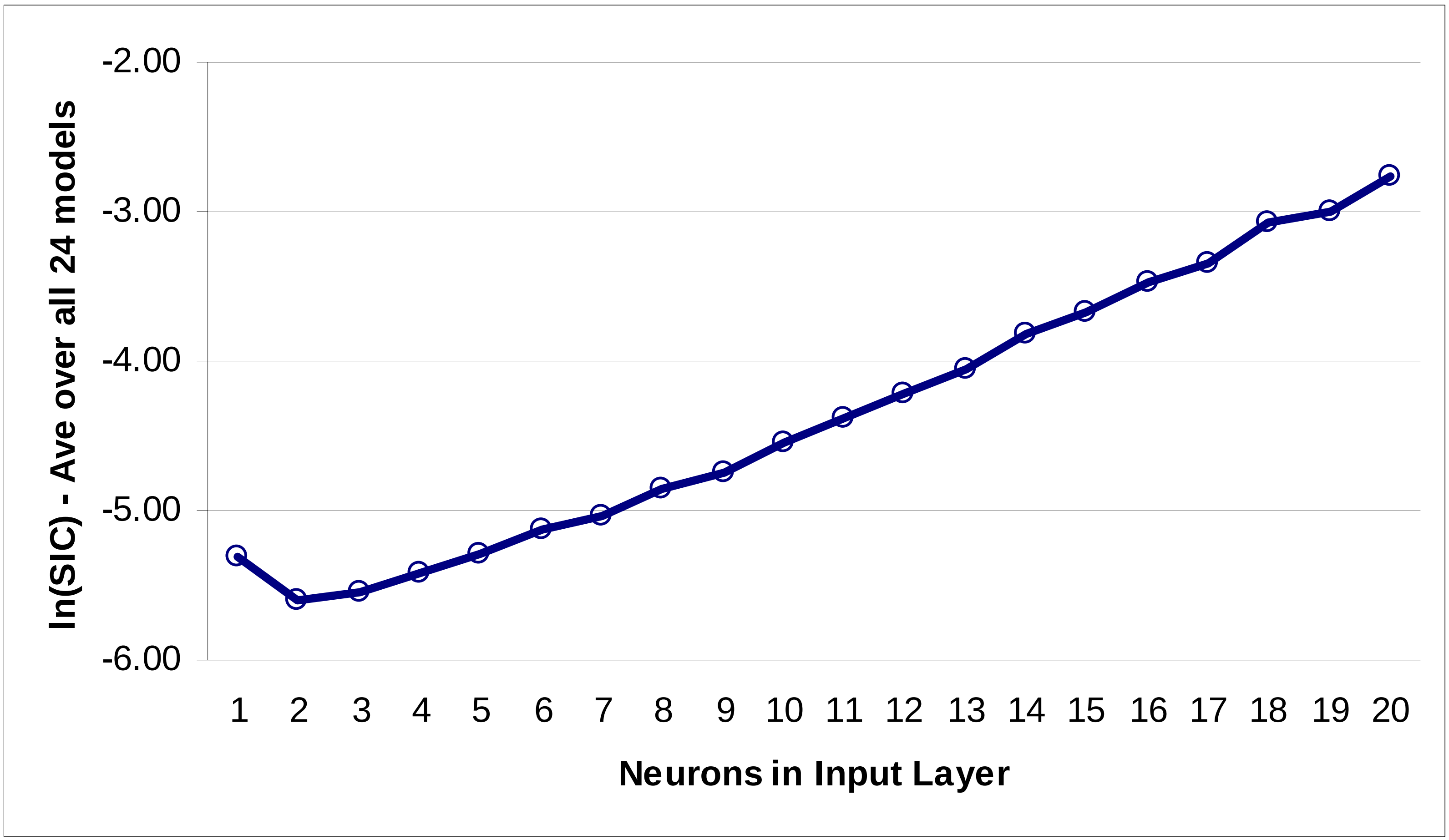
Model Selection

SIC as a Function of Neurons in the Input Layer

Average over all 24 Hours



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V. Model Results

Model Results

CC1

For hourly models estimated for the Summer months:

- four models use 1 input neurons
- fifteen models use 2 input neurons
- four models use 3 input neurons
- one model uses 4 input neurons

CC1 Crow, 5/25/2005

Model Results

ANN models typically perform well with abundant data from non-linear relationships. The hourly models account for about 99% of the variation in the test data, with MAPE around 1.2%.

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Model Results

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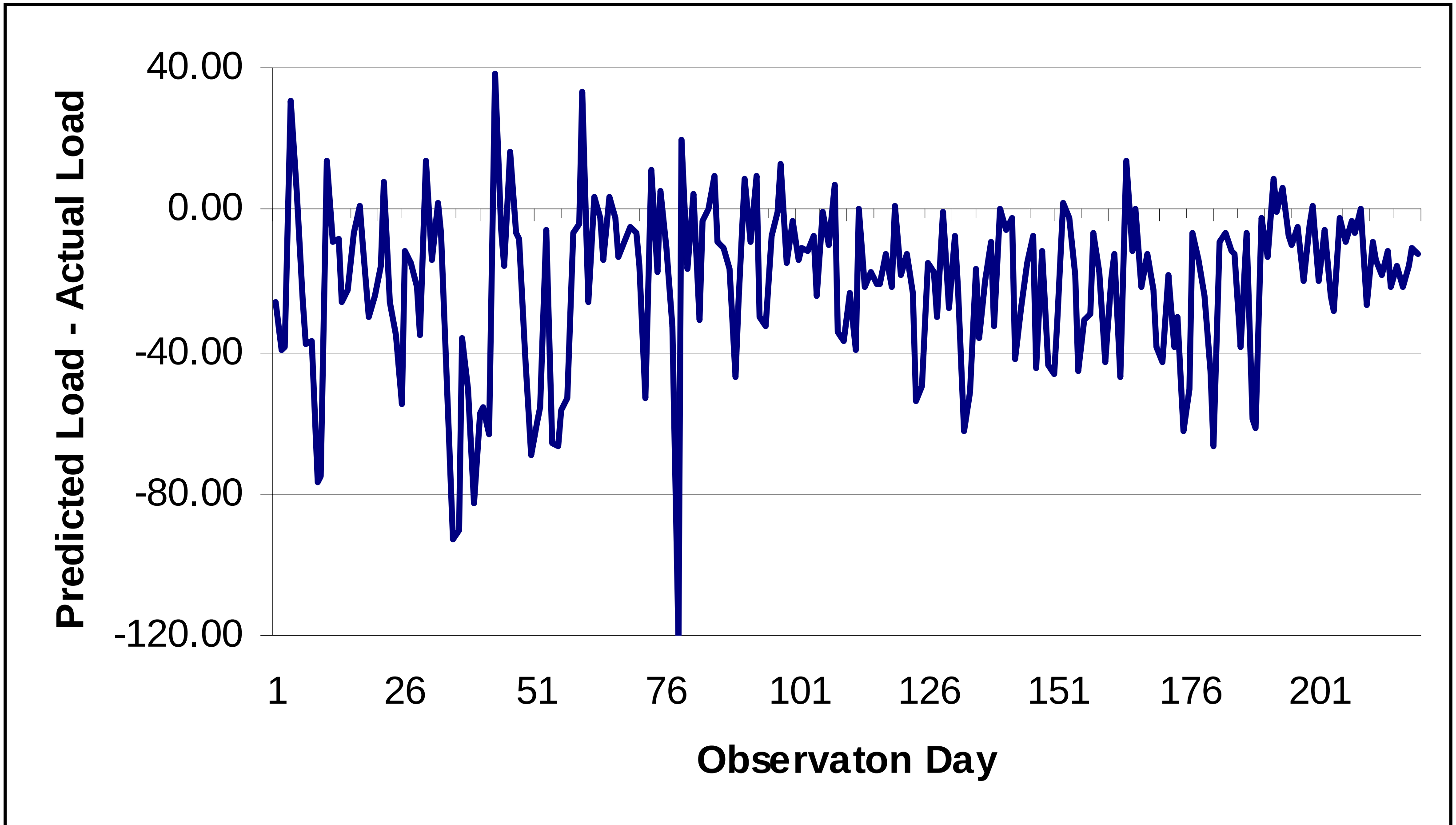
- As the test period is composed of the most recent data, this bias may be due to a growth trend (data were not de-trended)
- Bias could also be due to high demand in the test period, or a structural shift

Model Results

Typical Performer – Hour 12



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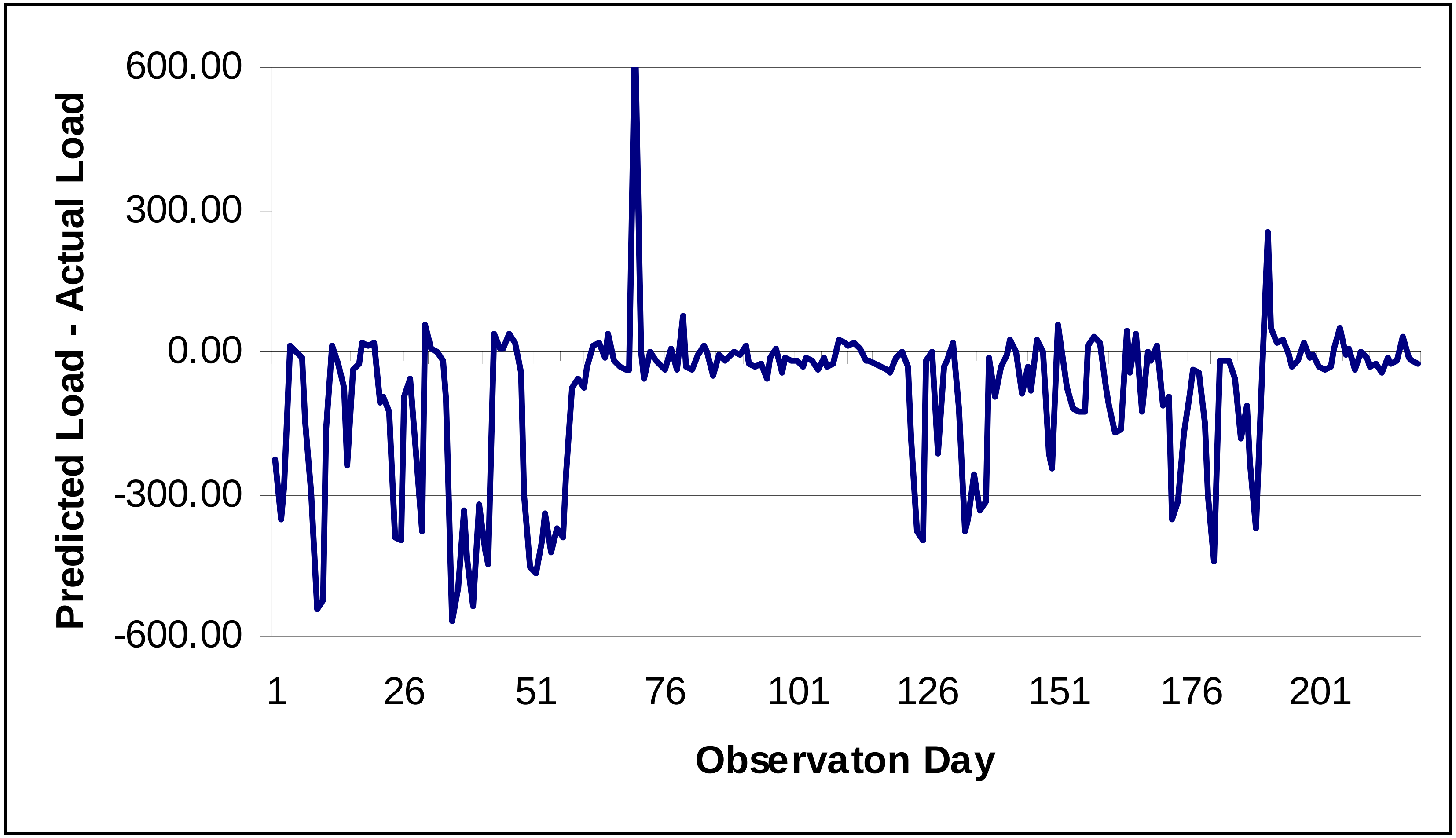
Model Results

Poor Performer – Hour 14



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