BSE Alumni Activity - CPD Lecture and Dinner Gathering on 21 November 2009

Jointly organized by the Department of Building Services Engineering (BSE) and the Alumni Association of Building Services Engineering (AABSE), an alumni event comprising a CPD lecture and a dinner gathering was held on 21 November 2009 (Saturday).

BSE Alumni with Prof. Chow at welcome reception

Commenced at 3:30 pm, the event was attended by over 100 alumni of BSE. After giving a warm welcome at the beginning, Prof. W. K. Chow, Head of Department, shared with the attendees the history and latest development of BSE including its academic programmes, research activities and services to the community, followed by highlighting the opportunities for and the supports needed from BSE alumni.

Welcome by Prof. Chow

Then, a CPD lecture on “Role of Artificial Intelligence in Thermal Science and Engineering as applied to Building Services Engineering” was delivered by an honorable guest - Professor Kwang-Tzu Yang, the Viola D. Hank Professor Emeritus of Engineering at Department of Aerospace and Mechanical Engineering of the University of Notre Dame, USA.

CPD lecture by Prof. K. T. Yang

In the lecture, Prof. Yang explained the theory and principle of artificial intelligence and presented some of its application examples on Thermal Science and Engineering analyses as well as BSE-related problems. Finally, he highlighted the prospects of future research and development in the area of artificial intelligence.

Souvenir presentation to Prof. Yang

Subsequent to the lecture, the former President of AABSE, Mr. Sunny Chan, briefed the alumni about the objectives of AABSE, its recent development and the upcoming activities. The alumni were encouraged to join as members of AABSE, participate in alumni activities and contribute to the continuous development of AABSE.

Introduction to AABSE

After the briefing, nearly 60 alumni stayed behind to join the dinner gathering with some invited guests and staff of BSE.

Dinner Gathering

This wonderful networking function was ended with plenty of joy at 8:00 pm.

Dinner Toasting

Powerpoint file of the CPD lecture

ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN THERMAL SCIENCE AND ENGINEERING (TSE) AS APPLIED TO BUILDING SERVICES ENGINEERING (BSE)

**PRESENTED AT THE
DEPARTMENT OF BUILDING
SERVICES ENGINEERING
HONG KONG POLYTECHNIC UNIVERSITY**

K.T. Yang
University of Notre Dame
Notre Dame, IN 46556 USA

November 2009

HUMAN INTELLIGENCE

- **No clear understanding**
- **Only tentative qualitative cause-effects**
- **Somehow driven by neuro-bio-mental experience**
- **But rather powerful to help making human decisions**
- **Perhaps possible to be “tamed” to do something useful to engineering**

RATIONALE FOR CREATING AND DEVELOPING ARTIFICIAL INTELLIGENCE IN THE SCIENCE AND ENGINEERING COMMUNITY

- Scientific computations based on rigid physical laws are too different and cumbersome in practice, even for simple physical problems
- Hard computing using modern-day computers is still insufficient and not robust enough to deal with ever-increasing complexities, such as, for example, systems involving nonlinearities and unavoidable uncertainties in real-world problems
- New computational paradigms are critically needed. Artificial intelligence (AI) methodologies have shown very desirable attributes and are sometimes referred to as soft computing

GENERAL ATTRIBUTES OF AI APPROACH TO THERMAL ENGINEERING PROBLEMS

- **Functionally different computational algorithms**
- **High tolerance to problem uncertainties and random errors**
- **Much less dependence on complexities and nonlinearities**
- **Little dependence on working-fluid properties**
- **Non-issues of static or dynamic problem behaviors**
- **Readily implementable nonlinear control behaviors**
- **Natural combinations of different AI algorithms without interference to form much more useful AI algorithms**

SIGNIFICANT IMPACT ON AI METHODOLOGIES ON INTELLIGENT BUILDING SYSTEMS

- Much talk in the building industry about intelligent building systems (IBS), worldwide
- Forgone conclusion that eventually IBS will be integrated into building performance-based codes, also worldwide
- The word “intelligent” in IBS only referring to optimum building design, functions, operations, and control, i.e., the “Green” objective, basically independent of AI per se
- Significance of AI lying in the future broad use of the efficient AI methodologies to facilitate the achievement of the “Green” objective, which is very difficult to do at the present time

CURRENT AI METHODOLOGIES IN USE AND UNDER DEVELOPMENT APPLIED TO THERMAL ENGINEERING RELATED TO BSE

- **Artificial Neural Network (ANN)**
- **Genetic Algorithm (GA)**
- **Genetic Programming (GP)**
- **Simulated Annealing (SA)**
- **Interval Analysis (IA)**
- **Fuzzy Logic (FL)**
- **Hybrid Methodologies**

GENERAL CHARACTERISTICS OF AI METHODOLOGIES

- Soft computing, not involving computations based on continuous functions or differential equations
- Each AI methodology being a piece of relatively simple computer software for carrying out a set of calculations many many times until desired results are obtained
- Always feasible to modify software to achieve higher computational effectiveness (e.g., hybrid methodologies)

EMPHASIS OF PRESENT TALK

- No time and neither appropriate to describe each methodology here
- Giving some indication on each methodology in terms of its basis, to give you some idea
- Whenever possible, showing some results from our own recent studies to illustrate the potential advantage of the AI methodologies in certain BSE-related scenarios
- Finally, indicating the availability of recent review publications if you are interested in exploring AI on your own

ARTIFICIAL NEURAL NETWORKS (ANN)

- **Attributes**

Pattern recognition between inputs and outputs

Non-issues in complexity and functional nonlinearity

Account for real and significant physics

Efficient learning capability

Generalization

Potential for new knowledge

High algorithmic flexibility to incorporate innovation

ARTIFICIAL NEURAL NETWORKS (ANN), cont.

- **Critical Requirement and Shortcomings**

  Experimental data for learning

  Large number of free parameters

  Lacking theoretical foundation

  Importance of numerical experimentation and past experience

  Critical area of research

CURRENT ASSESSMENT OF ANN ALGORITHMS

- **Demonstrated ability to accurately model and predict both static and dynamic performance of thermal devices and systems**
- **Demonstrated ability to model complex dynamic behaviors of interacting thermal systems**
- **Real-time responses for thermal system dynamics**
- **Adaptive dynamic system behaviors under changing external parameters**
- **Demonstrated success in the development of dynamic neurocontroller-based robust control strategies for complex dynamic thermal systems**

CURRENT ASSESSMENT OF ANN ALGORITHMS, cont.

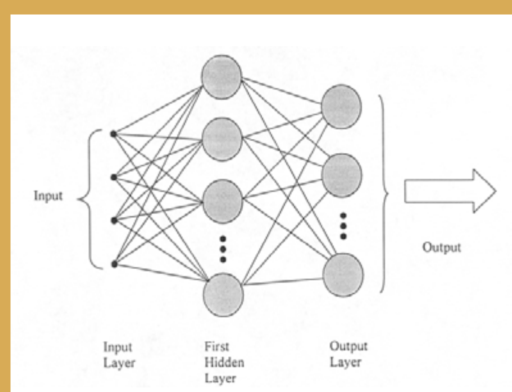
- **Potential and prospect for ANN applications in TSE**
  - **Problems lacking physical models**
  - **High system complexity**
  - **Problems with unavailable or unknown thermo-physical properties**
  - **Problems with unknown or unreliable constitutive relations**
- **Lacking in fundamental studies on ANN implementation practices — a very important area of research**

BASIC ANN CONCEPT AND STRUCTURE

- **Completely deterministic algorithm**
- **Emulating structure and actions of biological neurons in the brain**
- **Massive parallel data processing with simple computations**
- **Layered structure with nodes (neurons) in each layer**
- **Input layer for parameter space, hidden layers, output layer for performance data**

In fully-connected ANN, nodes between adjacent layers are fully inter-connected by connectors characterized by individual weights

Input in each hidden node is characterized by collective connector signals from nodes in the preceding layer and the node bias, and node output is calculated by a step-like activation function



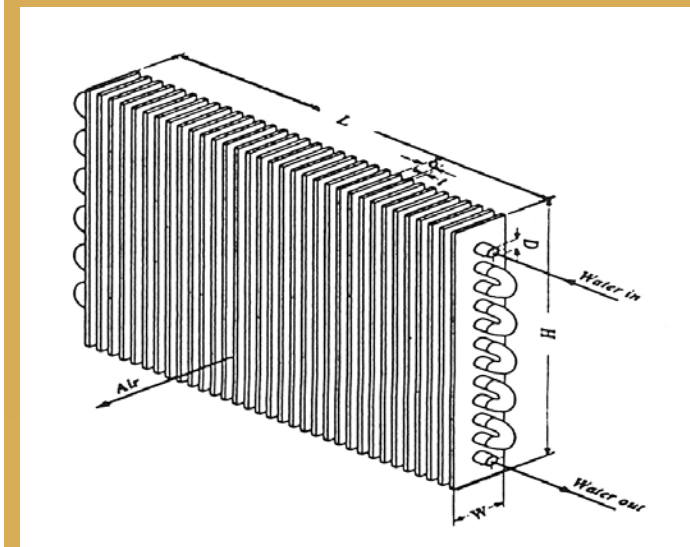
THREE SERIES OF STUDIES
COVERING AREAS OF IMPORTANT
TSE APPLICATIONS

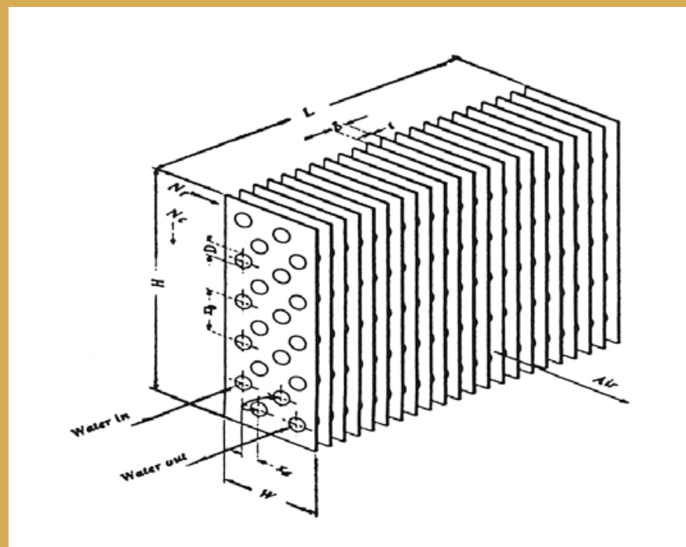
- **Steady performance of thermal devices**
- **Dynamic simulation of thermal device-systems**
- **Robust control strategies for thermal systems**

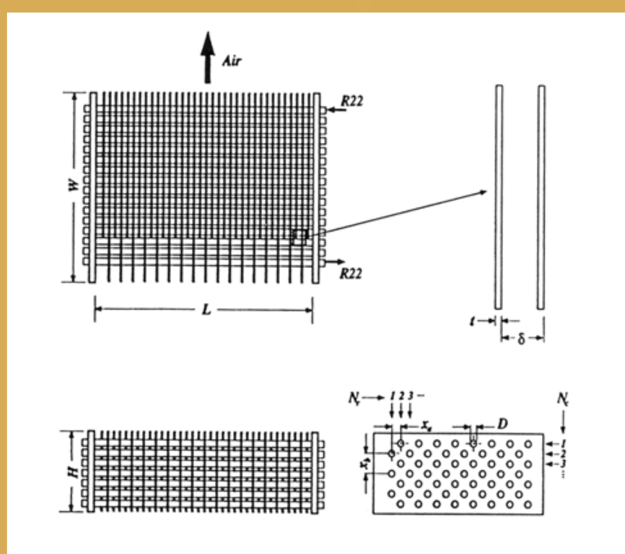
Experiments to Support Studies

- **Providing data for training and testing ANNs under both static and dynamic conditions**
- **Providing data to verify effectiveness of dynamic control strategies**

FIN-TUBE HEAT EXCHANGERS AS THERMAL SYSTEMS







Normalized Inputs (4)

Air flow

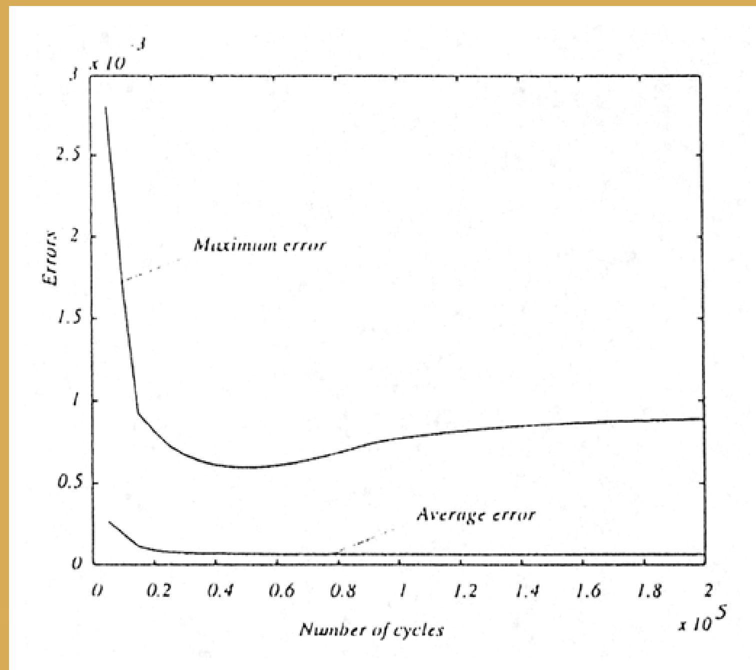
Water flow

Inlet air temperature

Inlet water temperature

Normalized Output (1)

Heat transfer rate



Training error results for configuration 4-5-2-1-1 ANN

197/257 data sets for training

i	j	k	l	$w_{i,j}^{k,l}$
1	1	2	1	−8.744
1	1	2	2	0.401
1	2	2	1	1.321
1	2	2	2	1.120
1	3	2	1	0.772
1	3	2	2	1.356
1	4	2	1	−0.303
1	4	2	2	−0.223
2	1	3	1	−7.741
2	2	3	1	8.576

Values of the weights for configuration 4-2-1.

i	j	$\theta_{i,j}$
2	1	−1.574
2	2	−2.474
3	1	−1.848

Values of the biases for configuration 4-2-1.

Configuration	R	σ
4-1-1	1.02373	0.266
4-2-1	0.98732	0.084
4-5-1	0.99796	0.018
4-1-1-1	1.00065	0.265
4-2-1-1	0.96579	0.089
4-5-1-1	1.00075	0.035
4-5-2-1	1.00400	0.018
4-5-5-1	1.00288	0.015
4-1-1-1-1	0.95743	0.258
4-5-1-1-1	0.99481	0.032
4-5-2-1-1	1.00212	0.018
4-5-5-1-1	1.00214	0.016
4-5-5-2-1	1.00397	0.019
4-5-5-5-1	1.00147	0.022

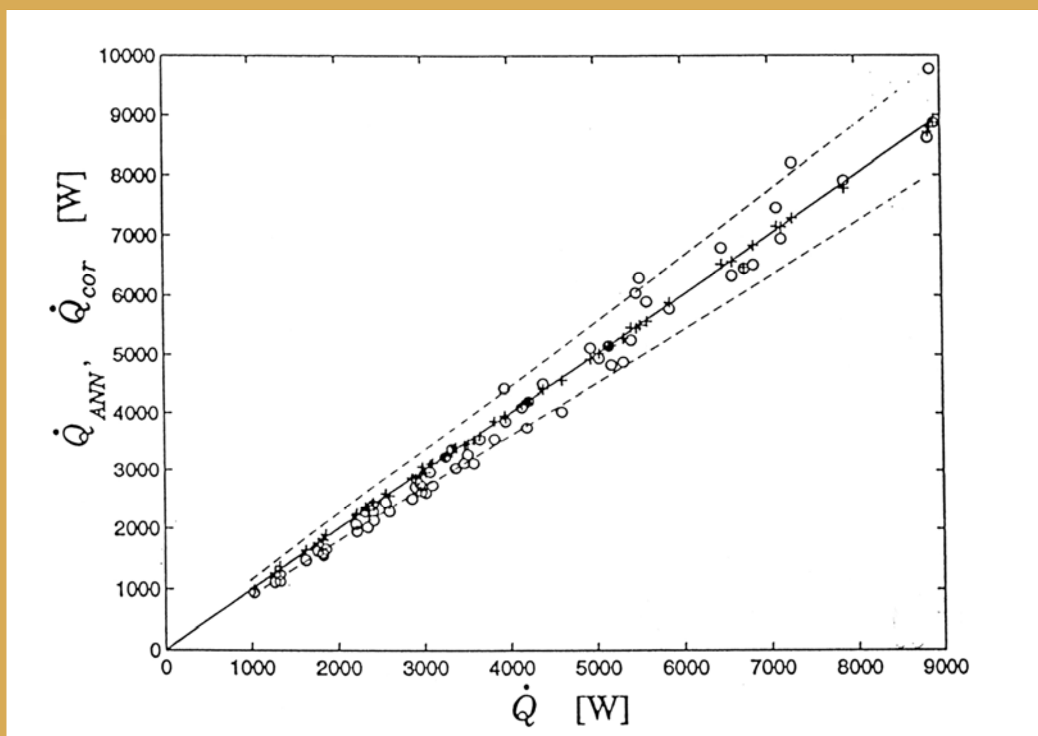
Comparison of heat transfer rates predicted by different ANN configurations for heat exchanger 1.

$$R = \frac{1}{N_p}\sum_{r=1}^{N_p} R_r \qquad \sigma = \sqrt{\frac{1}{N_p}\sum_{r=1}^{N_p}(R_r - R)^2}$$

ANN RESULTS FOR SINGLE-ROW HEAT EXCHANGER

- **ANN configuration with best accuracy   4-1-1-1**
- **ANN configuration with least scatter   4-5-5-1**

with errors with 3.7% and scatter within 0.7%



Comparison of ANN and correlation predictions; ○ correlations; + ANN. Straight line is $\dot{Q}_{ANN} = \dot{Q}$ and $\dot{Q}_{cor} = \dot{Q}$; dotted lines represent $\pm 10\%$ ***deviations***

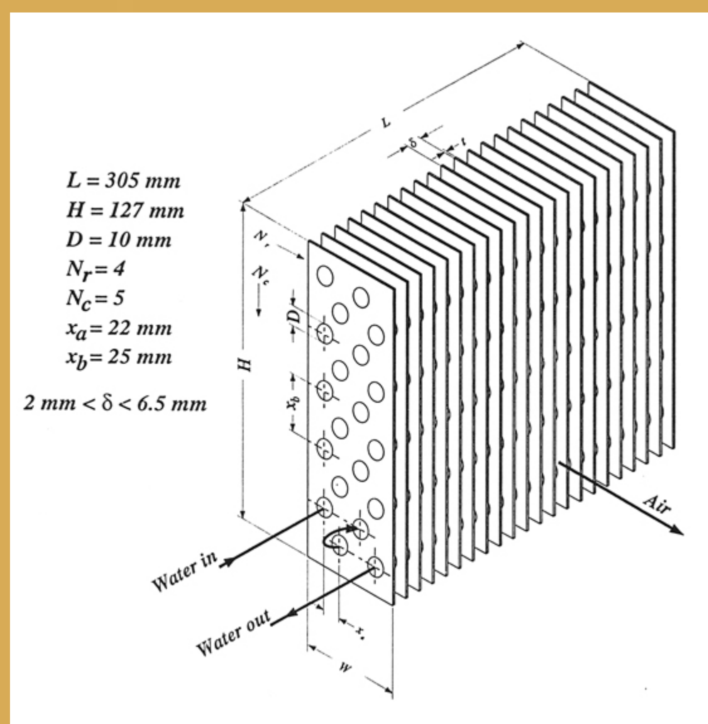
SCHEMATIC OF A HEAT EXCHANGER USED BY MCQUISTON (1978)

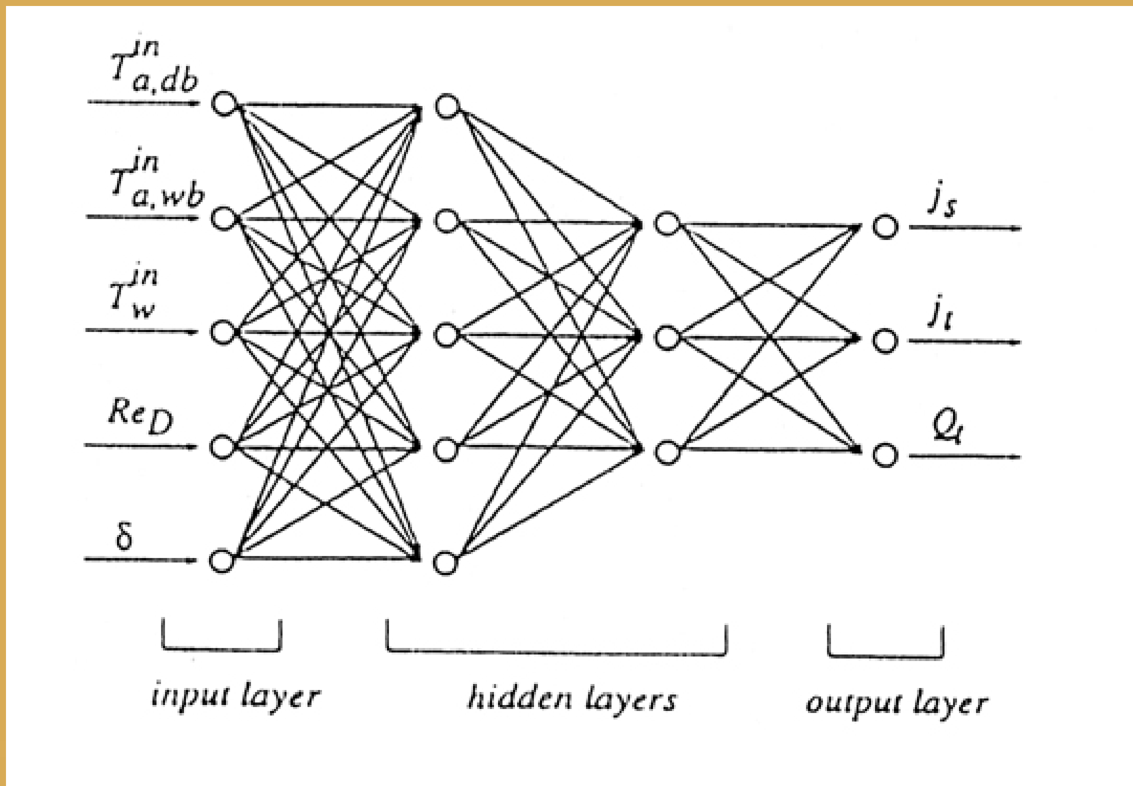
Possible Conditions:

- ***Dry surface (91)***
- ***Dropwise condensation (117)***
- ***Film condensation (119)***

For Prediction Purposes:

$$\dot{Q} = \dot{Q}(\mathrm{Re}_D, T_{a,db}^{in}, T_{a,wb}^{in}, T_w^{in}, \delta)$$

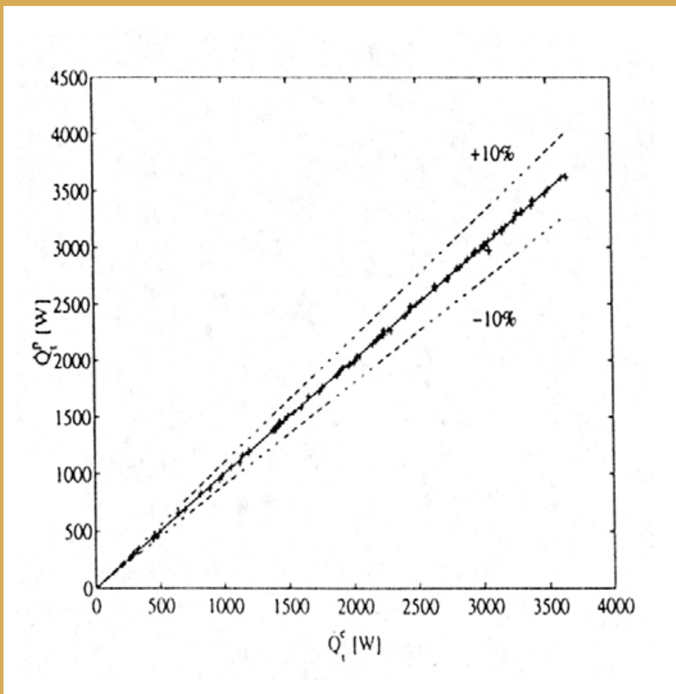




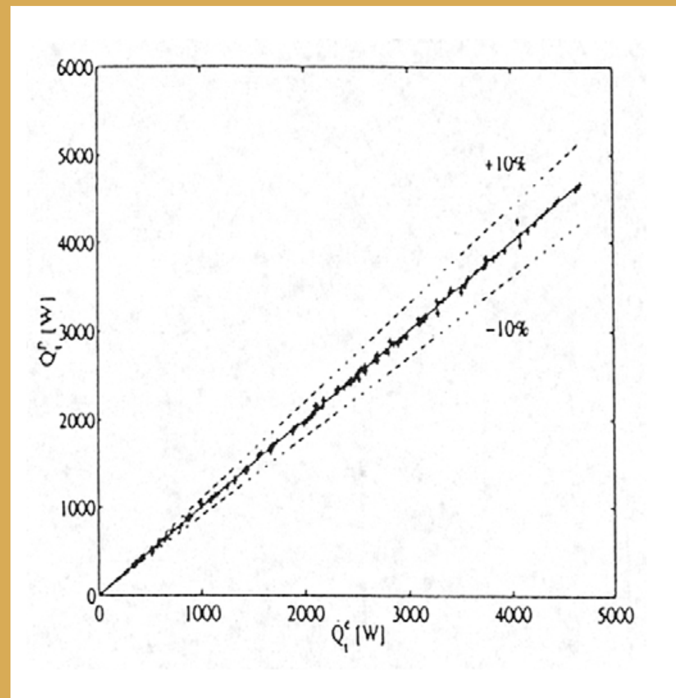
Schematic of a 5-5-3-3 ANN for heat exchanger 2

Surface	*Method*	j_s	j_t	Q_t
Dry	McQuiston	14.57	14.57	6.07
	Gray & Webb	11.62	11.62	4.95
	ANN	1.002	1.002	0.928
Dropwise	McQuiston	8.50	7.55	-
	Gray & Webb	-	-	-
	ANN	3.32	3.87	1.446
Filmwise	McQuiston	9.01	14.98	-
	Gray & Webb	-	-	-
	ANN	2.58	3.15	1.960
Combined	ANN	4.58	5.05	2.69

Comparison of percentage errors in j_s, j_t, and Q_t predictions between the ANN and standard power-law correlations

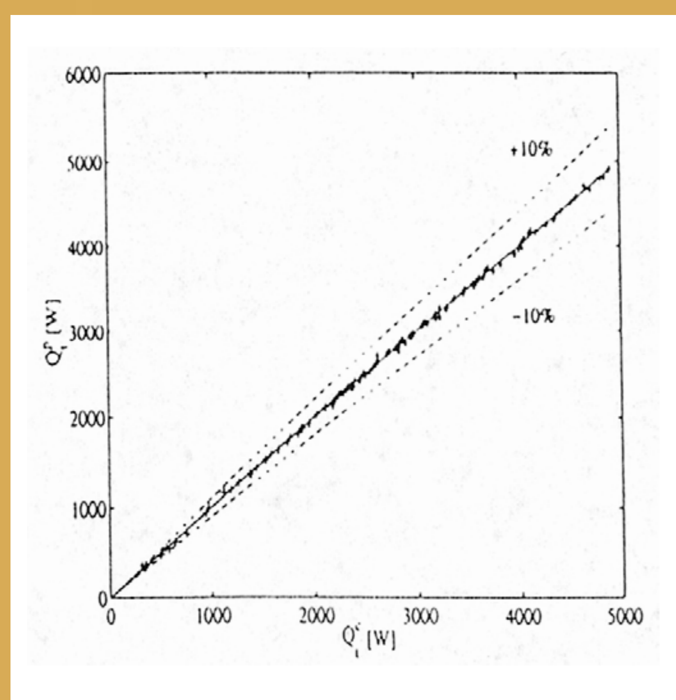


Experimental vs. predicted Q_t for a heat exchanger under dry surface conditions. Straight line is the perfect prediction.



Experimental vs. predicted Q_t for a heat exchanger under dropwise condensation. Straight line is the perfect prediction.

Experimental vs. predicted Q_t for a heat exchanger under film condensation conditions. Straight line is the perfect prediction.



THERMAL SYSTEM DYNAMICS

MODELING BY ANN

- **Characteristics**

  Increased complexity from devices to systems

  Dynamic response to time-dependent change of parameters

  Difficulty in dynamic modeling by traditional approaches

THERMAL SYSTEM DYNAMICS MODELING BY ANN, cont.

- **ANN Application**

  Basic ANN algorithm equally applicable

  Off-line training by treating time variable as an additional input parameter (explicit method)

  Off-line training by advancing input parameters in lagging time step (implicit method)

  Adaptive on-line training for unknown dynamics by using recurrent networks with output becoming input in time steps

  The desirability of using small time steps to simplify network architecture

  Effect of system orders

TWO DEMONSTRATIONS OF ANN

DYNAMIC MODELING

- **Thermal system: single-row fin-tube heat exchanger**
- **Chosen ANN configuration 3-3-5-2**
- **Training data experiment:**

  Constant air and water flow rates and air inlet temperature

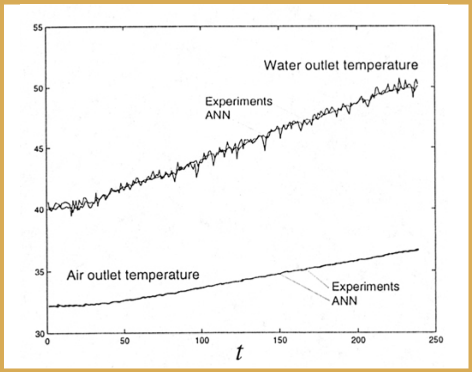
  Changing water inlet temperatures from 32.2 deg. C to 65.5 deg C at 5.56 C step increments

  Resulting changes of water and air outlet temperatures

TWO DEMONSTRATIONS OF ANN DYNAMIC MODELING, cont.

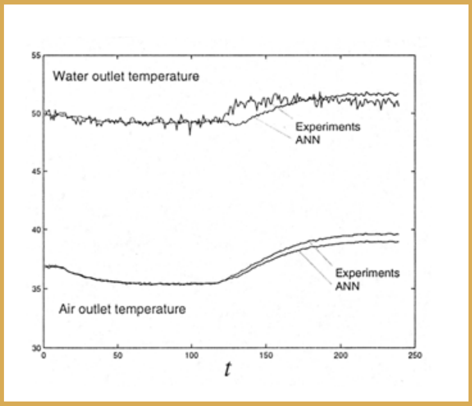
- **Experimental results on**

Ramp-up increase of water inlet temperature



ANN (3-5-5-2) prediction for ramp function

Changing input variable not in the training with air-flow rates changing, first increasing and then decreasing



ANN (3-5-5-2) prediction for change in air mass flow rate

ANN-BASED DYNAMIC

CONTROL OF TSE SYSTEMS

Control Strategy Requirement

- **Ever-increasing TSE system complexity in applications**
- **PID controllers not up to the challenge**
- **Robust controls needed to assure satisfactory system performance, including optimality**
- **Control strategies to guarantee controllability, accuracy, real-time dynamic parameter adaptation, and controller stability at all times**
- **Demonstrated satisfactory system performance by experiments**

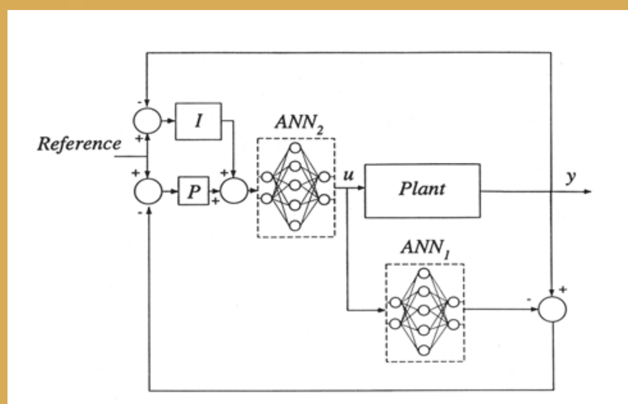
ANN-BASED DYNAMIC

CONTROL OF TSE SYSTEMS, cont.

Promising Strategies Based on Neurocontrollers

- **Exploratory of studies on strategies based on dynamic ANN plant models**
- **Attributes of the use of neurocontrollers: controllers based on inverse ANN plant model, accuracy, stability, on-line real-time adaptation, additional optimization requirement**
- **Promising strategy based on internal model control (IMC) with experimental verification**

Internal model control (IMC)

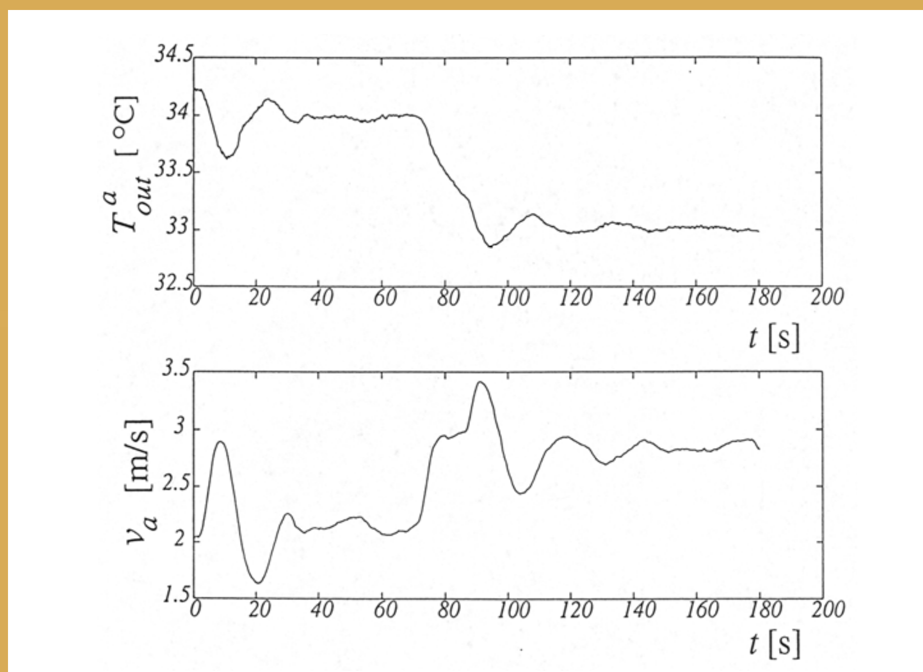


ANN-BASED DYNAMIC CONTROL OF TSE SYSTEMS, cont.

Training for the ANNs in the Temperature Control of HX 1

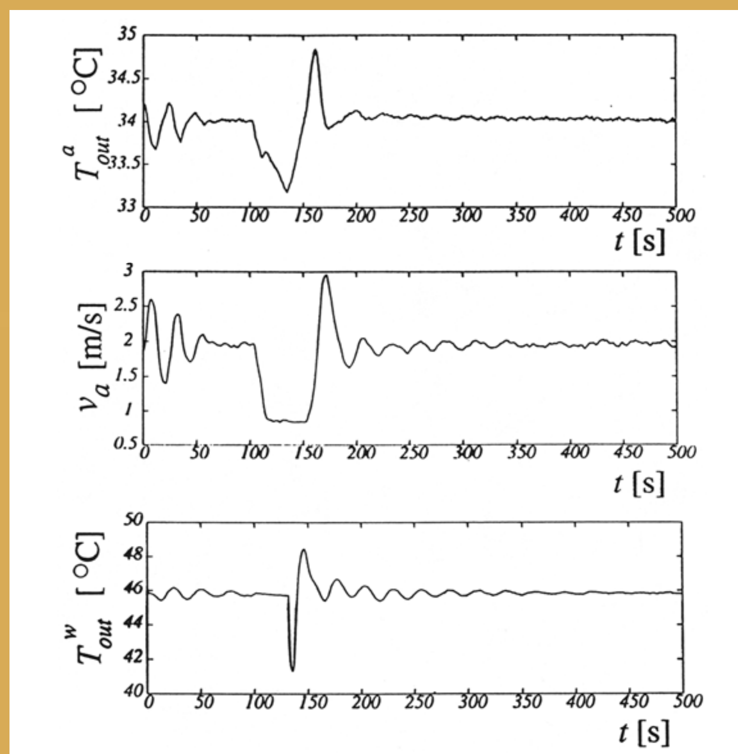
- Changing exit air temperature and air flow
- Keeping inlet air and water temperatures and water flow rate constant
- Small changes in the set target temperatures
- Modifying the ANN parameters in the training cycles to achieve accuracy, controller stability, adaptation, and achieving optimal energy consumption for driving the air flow
- Experimental results for IMC verification with PID back-up

SUDDEN CHANGE OF THE SET POINT IN THE AIR-OUTLET TEMPERATURE FROM 34 DEG. C TO 33 DEG. C



Time (s)	Set Point (deg. C)	Controller
<70	34	PID
70	34 ->33	
70-90	33	NC Adapts
90	33	NC

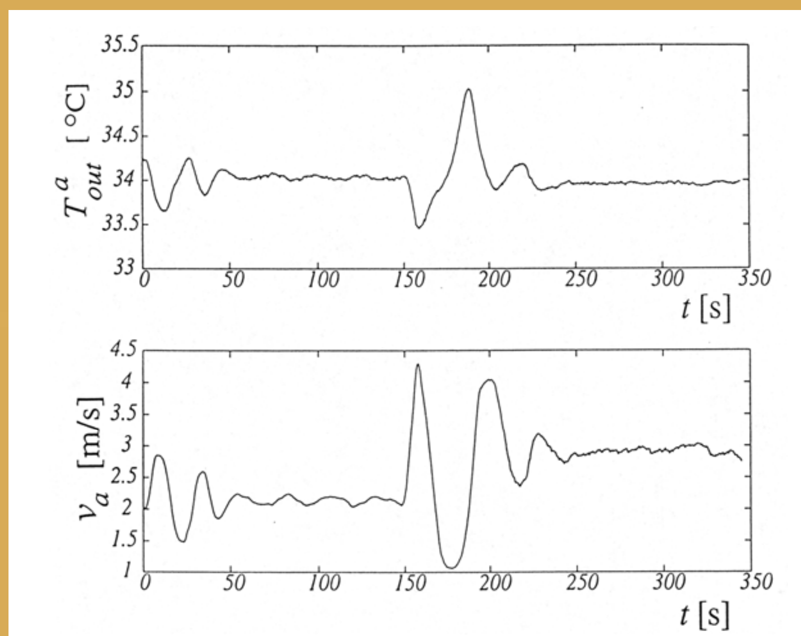
RESPONSE TO WATER-SIDE DISTRURBANCE (WATER FLOW INTERRUPTION)



Time (s)	Disturbance	Controller
<50	on	PID
50-100		NC
100-130	shut off	PID, NC Adapts
130	on	
170		NC

RESPONSE TO AIR-SIDE DISTRURBANCE — SUDDEN REDUCTION IN THE AIR INLET AREA

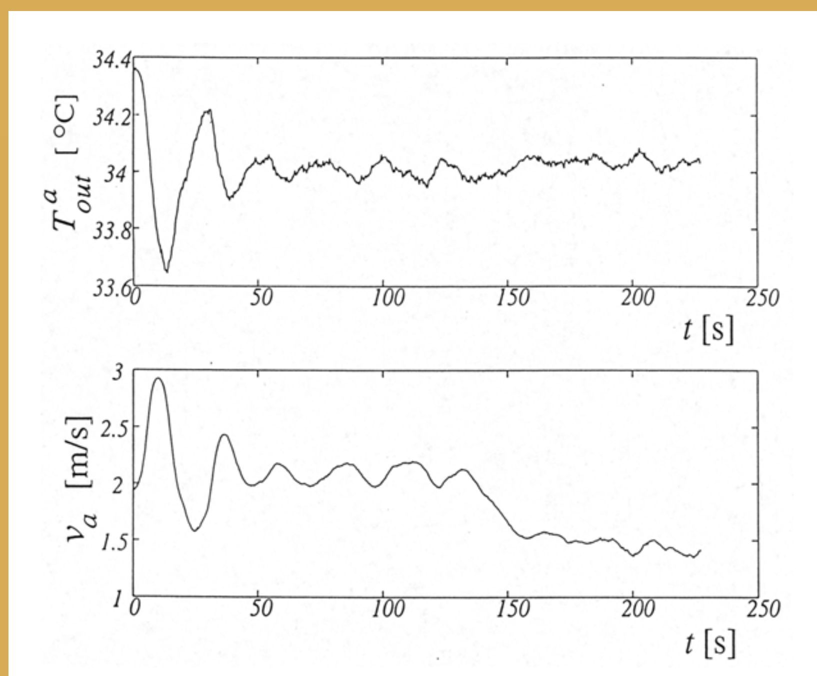
Set temperature 34 deg. C



Time (s)	**Disturbance**	**Controller**
<50	Area 100% open	PID (NC Adapts)
50-150		NC
150	50% blocked	
150-240		PID (NC Adapts)
>240	Continuing	NC

APPLICATION OF ENERGY MINIMIZATION ROUTINE TO REDUCE BOTH FLOW RATES AT THE SAME SET TEMPERATURE

Set temperature 34 deg. C



CONCLUSIONS OF ANN ANALYSIS FOR TSE APPLICATIONS

- Demonstration of excellent ANN results in correlations, dynamic modeling, and control
- Good potential of meaningful treatment of TSE problems not solvable by traditional analysis
- Flexibility in basic ANN methodology permitting modification and innovation in applications, thus broadening its usage
- Exciting prospect of combining ANN analysis with other AI methods
- More research needed to more rationally deal with the free-parameter issue in ANN analysis for TSE
- Increasing ANN analysis expected in TSE

GENETIC ALGORITHM (GA)

- **Search for functional parameters for global optimum**
- **Based on evolutionary principle of natural selection**
- **Fittest members of a species surviving to produce offspring over generations**
- **Characteristics from natural genetics**
- **Fitness function (objective function)**
- **Population (collection of strings)**
- **Generation (each iteration when parents are replaced by offspring)**
- **Offspring (created by genetic operations of crossover and mutation by means of pre-selected probabilities)**
- **Incapable of achieving global optimum with unknown functional forms**
- **Use of GA in other AI methodologies**

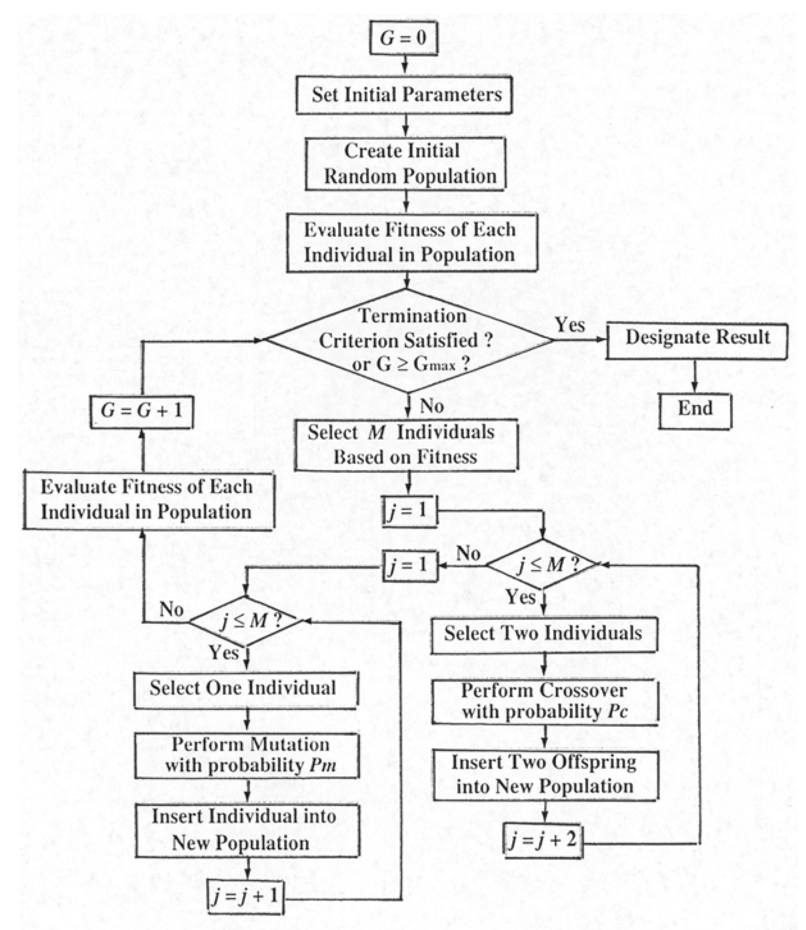
GA APPLICATION TO HX 1 CORRELATIONS

214 experiment data sets, all normalized

9 correlation functional forms with 3 or 4 parameters

Crossover probability 1.0 and mutation probability 0.03

Maximum number of generations 1,000



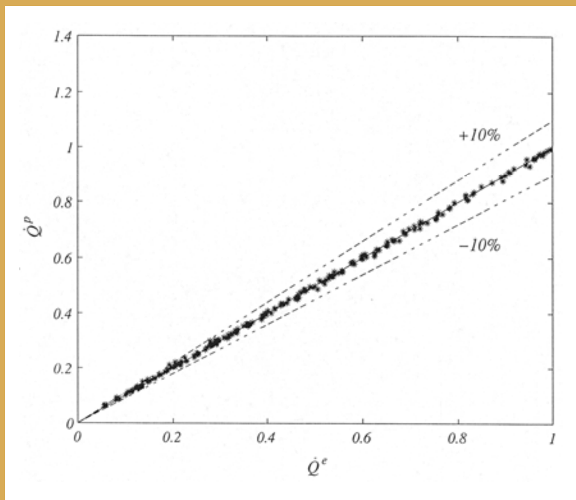
Flow chart for the genetic algorithm.

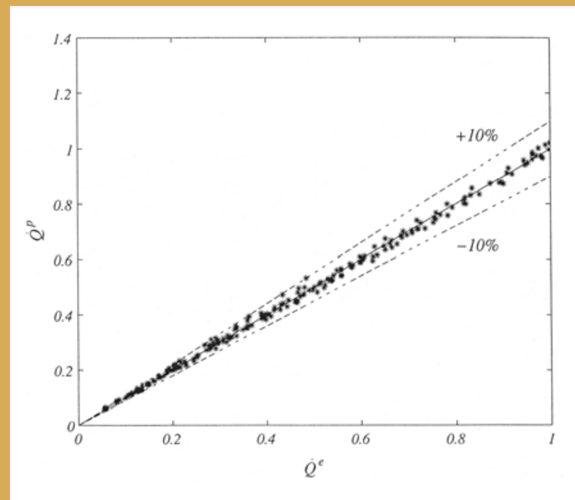
TABLE AND CORRELATION FUNCTIONS

Correlation	*Functional form*
1. Linear	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = n_1 - n_2 \dot{M}_w - n_3 \dot{M}_a$
2. Quadratic	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = n_1 - n_2 \dot{M}_w^2 - n_3 \dot{M}_a^2$
3. Exponential	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = n_1\, e^{-n_2 \dot{M}_w} + n_3\, e^{-n_4 \dot{M}_a}$
4. Logarithmic	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = n_1 - n_2 \ln \dot{M}_w - n_3 \ln \dot{M}_a$
5. Power-law	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = n_1\, \dot{M}_w^{-n_2} + n_3\, \dot{M}_a^{-n_4}$
6. Inverse linear	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = \dfrac{1}{n_1 + n_2\, \dot{M}_w} + \dfrac{1}{n_3 + n_4\, \dot{M}_a}$
7. Inverse quadratic	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = \dfrac{1}{n_1 + n_2\, \dot{M}_w^2} + \dfrac{1}{n_3 + n_1\, \dot{M}_a^2}$
8. Inverse exponential	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = \dfrac{1}{n_1 + e^{n_2 \dot{M}_w}} + \dfrac{1}{n_3 + e^{n_1 \dot{M}_a}}$
9. Inverse logarithmic	$\dfrac{\theta_w - \theta_a}{\dot{Q}^\bullet} = \dfrac{1}{n_1 + n_2 \ln \dot{M}_w} + \dfrac{1}{n_3 + n_4 \ln \dot{M}_a}$

Table Comparison of different correlations.

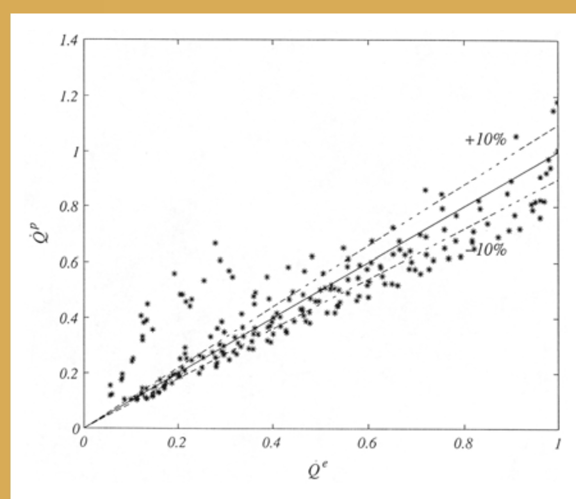
N_C	n_1	n_2	n_3	n_4	$S_{\dot{Q}^\bullet}$	G_g	$\overline{S_{\dot{Q}^\bullet}}$	σ
5	0.1875	0.9997	0.5722	0.5847	4.407×10^{-5}	975	1.408×10^{-4}	7.916×10^{-5}
6	−0.0171	5.3946	0.4414	1.3666	1.601×10^{-4}	984	1.941×10^{-4}	4.902×10^{-5}
8	−0.9276	3.8522	−0.4476	0.6097	6.721×10^{-4}	912	1.278×10^{-3}	7.029×10^{-4}
3	3.4367	6.8201	1.7347	0.8398	1.208×10^{-3}	966	1.255×10^{-3}	1.471×10^{-4}
7	0.2891	20.3781	0.7159	0.7578	1.508×10^{-3}	990	1.509×10^{-3}	1.056×10^{-6}
9	0.4050	0.0625	−0.5603	0.2048	1.680×10^{-3}	830	2.111×10^{-3}	1.131×10^{-3}
4	0.6875	0.4714	0.4902	–	2.411×10^{-3}	917	2.412×10^{-3}	8.798×10^{-7}
1	2.3087	0.8533	0.8218	–	7.551×10^{-3}	976	7.553×10^{-3}	2.330×10^{-6}
2	1.8229	0.6156	0.5937	–	1.196×10^{-2}	896	1.196×10^{-2}	1.508×10^{-6}





Experimental vs. heat predicted flow rates for a power law correlation

Experimental vs. heat predicted flow rates for an inverse linear correlation



Experimental vs. heat predicted flow rates for a quadratic correlation

GENETIC PROGRAMMING (GP)

General Features

- Extension of GA to deal with functional forms and constants rather than just constants in pre-selected functional forms

- Same objectives of searching for global optima

- Also known as symbolic-regression analysis

- Methodology of genetically recombining a population of candidate functions represented by parse trees with branching node serving as specific operators

- Use of penalty function to limit complexity of results

GENETIC PROGRAMMING (GP), cont.

Methodology Steps Different from That of GA

- Taking fitness as reciprocal of variance
- Use of penalized fitness based on sigmoid
- For crossover, the paired parents interchange parts of their trees to provide two offspring by cutting and grafting below a certain operator
- Crossover points being same or different for the parents
- Mutation being applied at a node point randomly
- Constants in succeeding generations in the new functional trees being determined by GA

GP APPLICATION FOR HX 2 WITH DRY SURFACES

- **Colburn j-factor correlation by McQuiston (1978)**

$$j = 0.0014 + 0.2618 RE^{-0.4} AR^{-0.15}$$

- **GP applications**

M=100, Gm=800, pc=0.8, pm=0.2

Two physical parameters Re and AR

$$j = \frac{1.82}{103.81 + 0.0299\,\mathrm{Re} + Ar} \qquad \text{(GP1)}$$

$$= \frac{66.39 - 0.4456 Ar}{3.881.61 + \mathrm{Re}} \qquad \text{(GP2)}$$

$$= \frac{2205.32}{1.39x10^{5} + 24.16\,\mathrm{Re} + Ar\,\mathrm{Re}} \qquad \text{(GP3)}$$

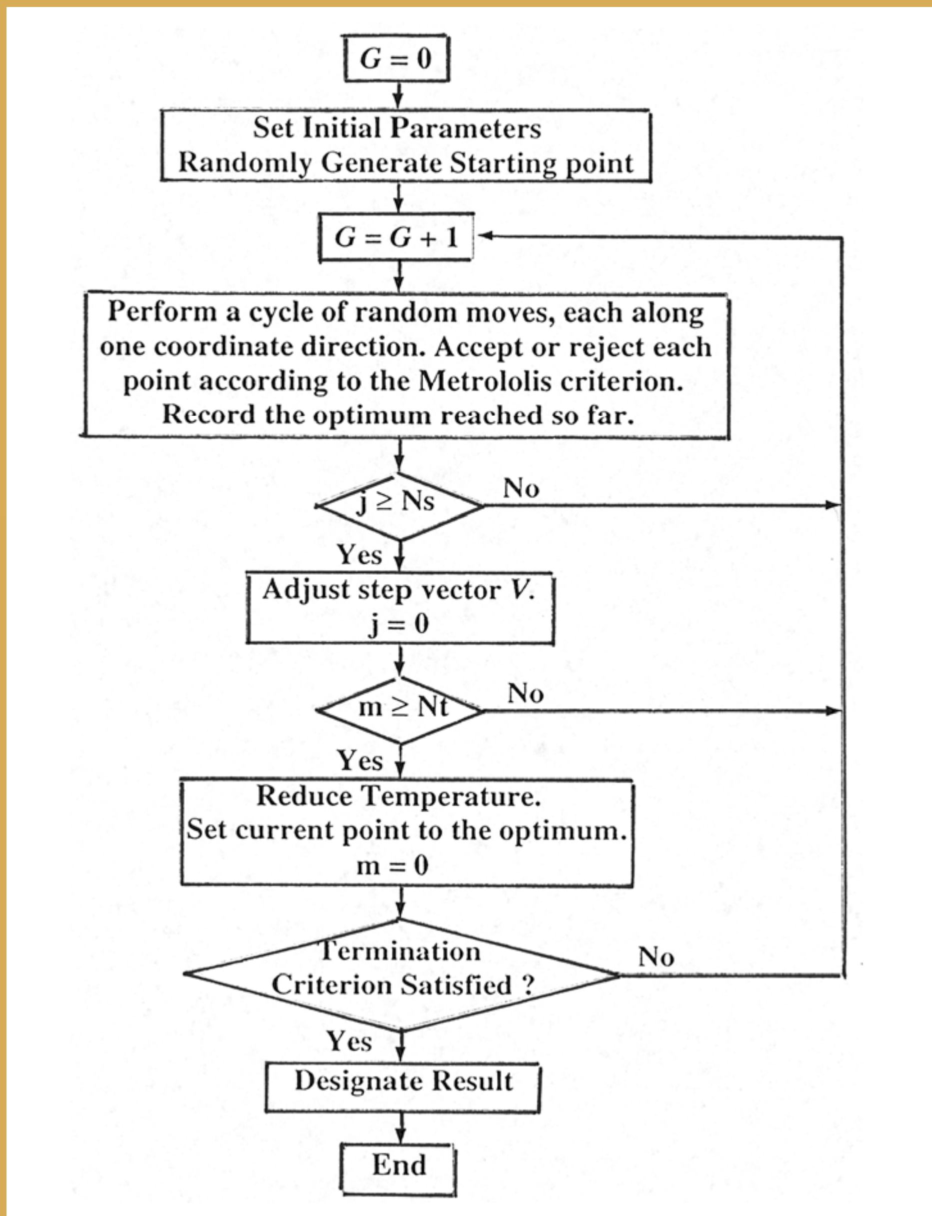
GP APPLICATION FOR HX 2 WITH DRY SURFACES, cont.

Prediction	RMS Errors (%)	Prediction	RMS Errors (%)
McQuiston	14.74	Gray & Webb	11.62
GP1	6.32	GP2	6.24
GP (MQ form)	6.21	GP3	6.18

SIMUALTED ANNEALING (SA)

- A generalized Monte Carlo stochastic methodology
- Simulation of slow cooling to avoid getting trapped in a local minima
- Sufficient slow cooling resulting in crystal with minimum energy, corresponding to global minimum
- A local optimum corresponding to quenching
- Possibility to move out of this state with a probability in accordance with the Boltzmann probability distribution by reducing the liquid temperature according to a preselected reduction schedule

SIMUALTED ANNEALING (SA), cont.



INTERVAL METHOD

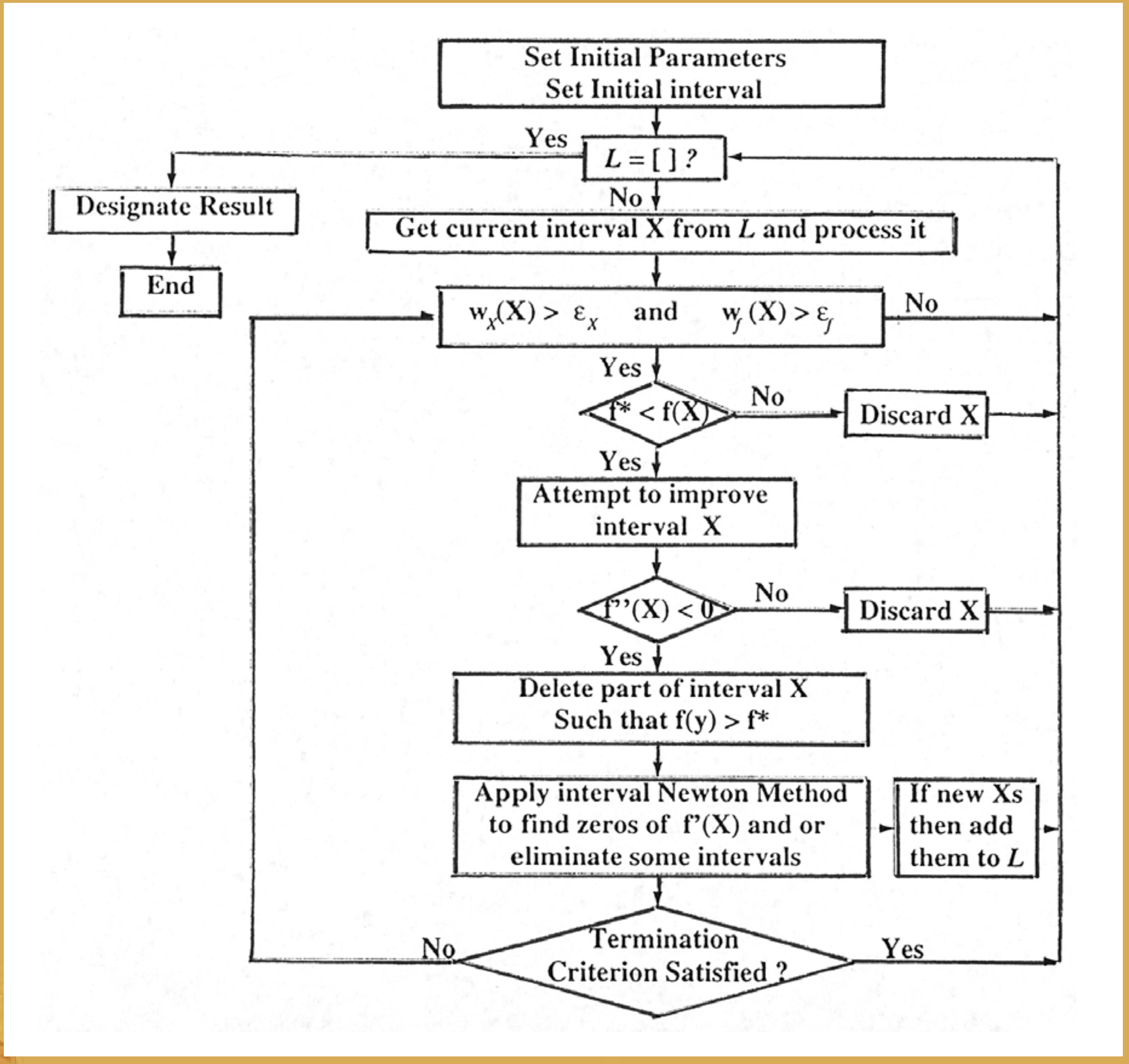
- A completely deterministic algorithm to achieve global optima with computational certainty

- All real number analysis reduced to interval counter parts based on truncated Taylor's series

- The interval Newton method based on the mean-value theorem used to find all the roots of the gradient of the objective function within each interval containing the global optimum, which is then narrowed by driving the region into subregions, and the search is continued until the final solution is reached

- Limitations of the method including the objective function to be at least twice differentiable and the method is generally intensive computationally

INTERVAL METHOD, cont.



FUZZY LOGIC (FL) AND CONTROL (FLC)

- **General Background**

FL is now well-established mathematics and computation based on linguistic, common sense, inexact and uncertain rules, very different from probability computations

Fuzziness measures the degree to which some conditions exist

FL represents a computational methodology that allows us to obtain solutions from vague, ambiguous or uncertain information

FL can be used to model any continuous system accurately, and the models are more useful in practice

The only logical constraint on FL is that the degrees of an object’s membership in complementary groups must sum to unity

FLC performs better than conventional controllers because of (a) simpler and faster, (b) simplistic design paradigm,

FUZZY LOGIC (FL) AND CONTROL (FLC), cont.

- **Applications in TSE Problems**

  Only robust area of TSE application is in HVAC systems due to fuzzy requirements for human comfort

  In most other areas of TSE, performance and parameters are specifically crisp sets

  Potential applications may include industrial thermal processes

FUZZY LOGIC CONTROL DEFINITIONS

- FLC steps consist of input fuzzy set, fuzzy rule base, output fuzzy set, defuzzification, and crisp control action

- Fuzzy sets include input and output sets defined by memberships and their respective fuzzy values, where the input set contains fuzzified controlling variables, while the output set contains the fuzzified controlled variables

- Membership functions are the assigned and quantified membership values in a fuzzy set, described by triangles, trapezoids, and others

- Rule base refers to a set of IF-THEN statements defining the fuzzy outcome of control actions. Each fuzzy rule defines a fuzzy patch

- Defuzzification refers to the way a crisp value is extracted from the output fuzzy set as a representative value, most commonly based on the centroid method

- An adaptive operation to tune or modify the rule base may be needed to improve the controller performance

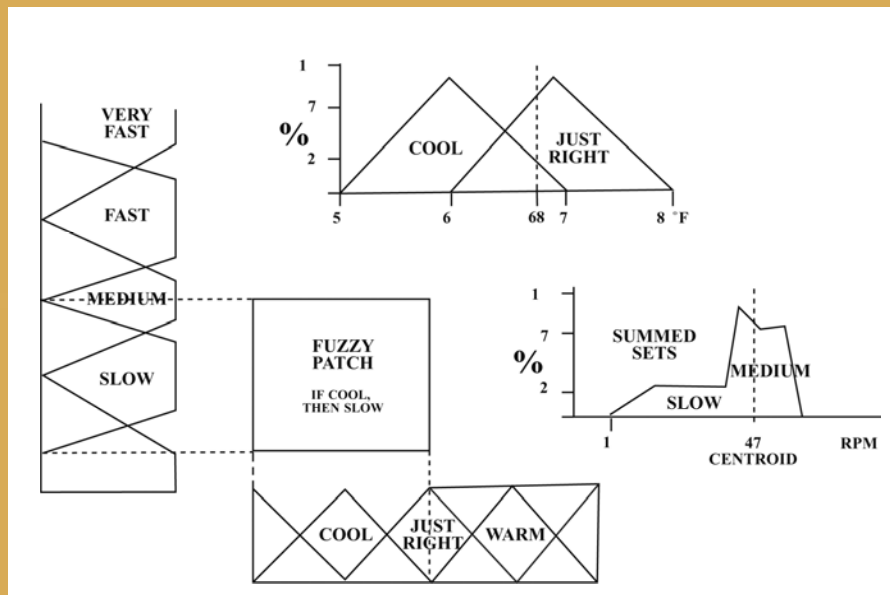
- Free choices in FLC are often based on expert systems (yet another AI methodology) and past experience

AN EXAMPLE OF FLC FUZZY TEMPERATURE CONTROL BY CHANGING AIR-CONDITIONER MOTOR SPEED

Input fuzzy set (cold, cool, just right, warm, hot)

5 fuzzy rule base (if cool, then slow, if just right, then medium …)

Output fuzzy set (very slow, slow, medium, fast, very fast)



Empirical data (68 deg. F requires 20% cool and 70% just right). According to the two rules, slow and medium speed heights would also be reduced accordingly, resulting in the output set and giving a crisp speed of 47 rpm for the motor speed, based on the centroid method

HYBRID AI ALGORITHMS

Rational for Hybrid Algorithms

- **Algorithms not competing, but complementary**
- **Increased flexibility to improve AI performance**
- **Functional and component optimization**
- **Enhancement by better learning**
- **Addressing the problem of free parameters**

Examples of Hybrid Algorithms

- **Automatic generation of ANN architecture using GA**
- **Adaptive dynamic ANN training using GA to optimize energy consumption**
- **Neural-fuzzy systems utilizing ANN as tools in fuzzy models**
- **Fuzzification of ANN in fuzzy-neural networks**
- **Fuzzy-neural hybrid system of effectively combining two separate systems into one**
- **Use of expert systems and ANN to define initial membership functions for FLC**

Recent Development

- **Concentrated in FLC for HVAC applications**

PROSPECTS OF AI METHODOLOGIES

FOR TSE APPLICATIONS

- **AI applications, with the exception of HVAC FLC studies, are still relatively new in the field of TSE. More exposure to the AI methodologies and good results from them will undoubtedly encourage others to follow**

- **In the meantime, TSE problems become increasingly more complex and problems that are very difficult to solve by traditional analysis are also increasing. It is possible that approaches by AI analysis may become the "only game in town"**

- **The migration of problems from single phenomena to systems is a good example where dynamic modeling and robust, adaptive, and optimal control are badly needed, and such problems are "natural" for the AI approaches**

PROSPECTS OF AI METHODOLOGIES FOR TSE APPLICATIONS, cont.

- **Also, there are on-going exciting theoretical and computational studies on the further development of the basic AI methodologies and new hybrid methods, which will benefit all AI application areas including TSE**
- **Another critical and exciting area of research based on AI methods and dynamic system theory deals with scalable control systems based on agent control, so that robust, real time, and optimal control can be developed independent of system complexities**

CONCLUSION

- Despite the recent development in ANN, their applications in TSE are still rather limited

- The purpose of this talk is to call attention to the exciting prospect of applying this class of methodologies to increasingly more difficult problems in TSE facing our community

- I have tried to give very brief ingredients of some of the ANN and touched on the very promising results that have been obtained by our own studies and those from others

- Just to be fair, I have also tried to point out some of the limitations and shortcomings

- Finally, I would like to take this opportunity to recognize the invaluable contribution of my collaborator and colleague, Professor Mihir Sen, in all our studies on AI

- Thank you for coming

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FOR KEEPING IN TOUCH

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