

Master of Technology in Knowledge Engineering

Unit 7:

Developing Intelligent Systems for Performing Business Analytics

Hybrid Architectures

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Hybrid Intelligent Systems

- **Hybrid Intelligent systems are intelligent systems which combine two or more techniques**
 - » e.g. neural networks, fuzzy systems, genetic algorithms, etc
- **Another common term for hybrid intelligent systems is “Hybrid Soft Computing Systems” .**

Categories of Hybrid Architectures

- **We will examine 4 broad types of hybrid system architecture**
 1. Independent sub-problems
 2. Competing Experts
 3. Self-Tuning
 4. Cooperating Experts

Independent Sub-Problems

- Sub-divide problem into independent parts each solved by an appropriate solution technique
- No cooperation is required, e.g. a decision support system has several sub-systems

Business
Strategy

Rule-Based
System

Production
Forecast

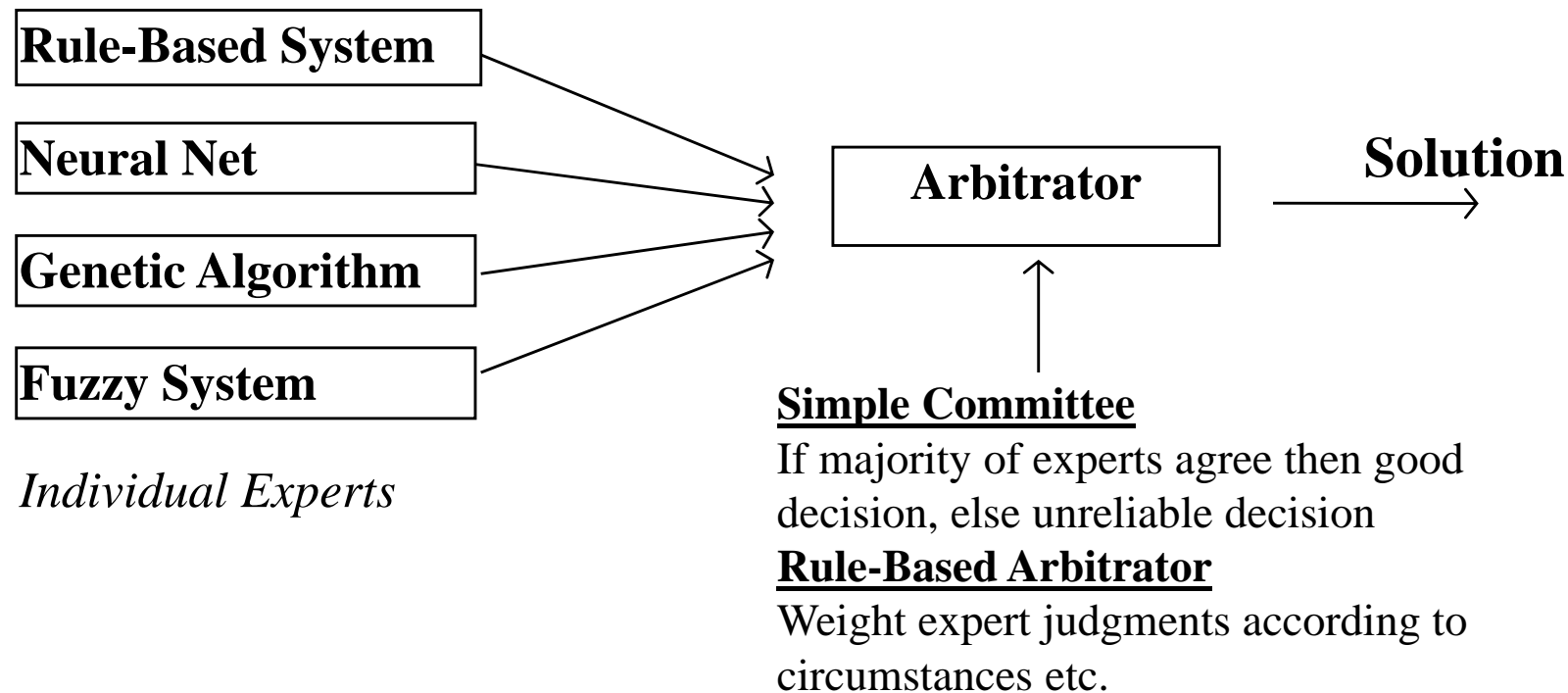
Neural
Net

Production
Scheduling

Const. Prog/
Genetic Algorithm

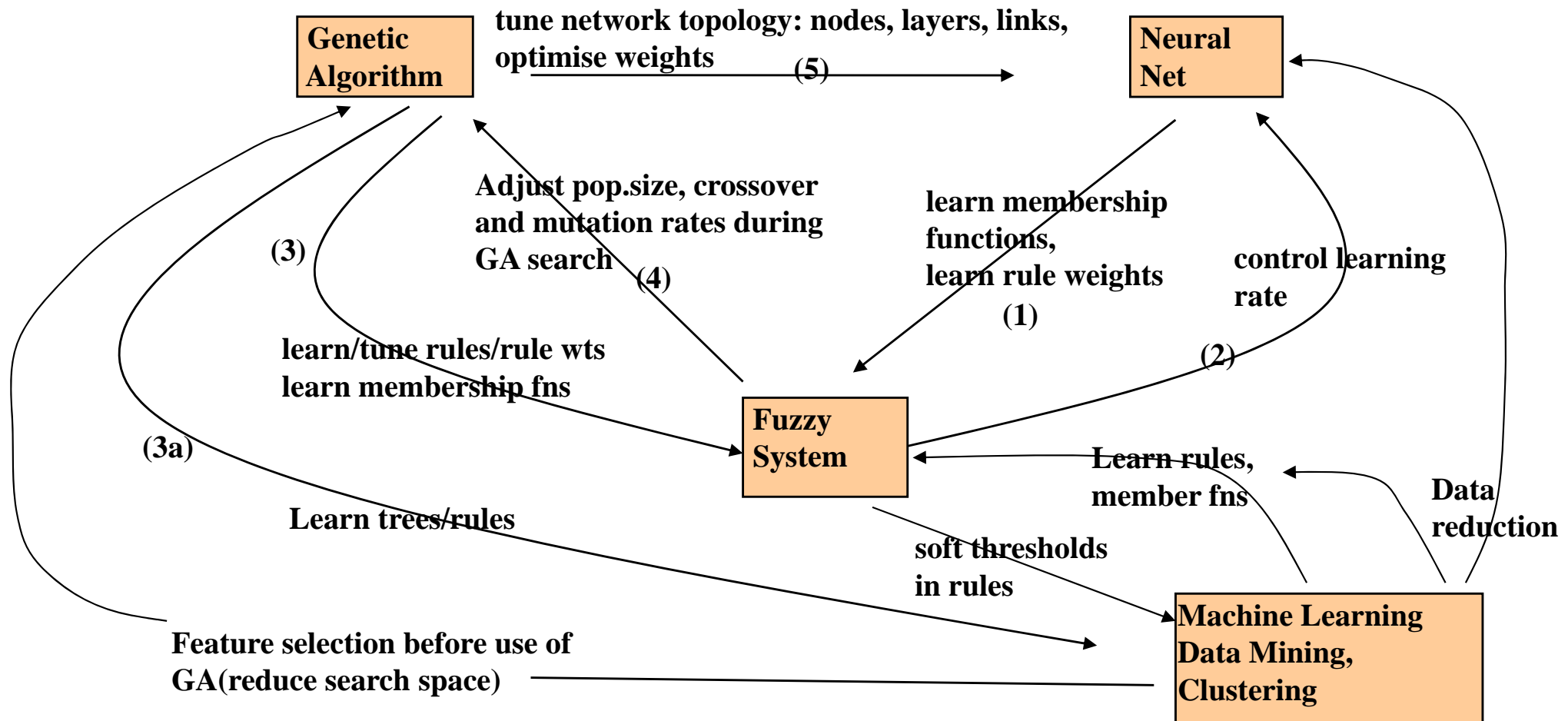
Competing Experts

- Different solution strategies (experts) offer alternative solutions. Another process decides which solution to accept or how to combine the solutions, e.g. majority vote algorithm or a rule-based system



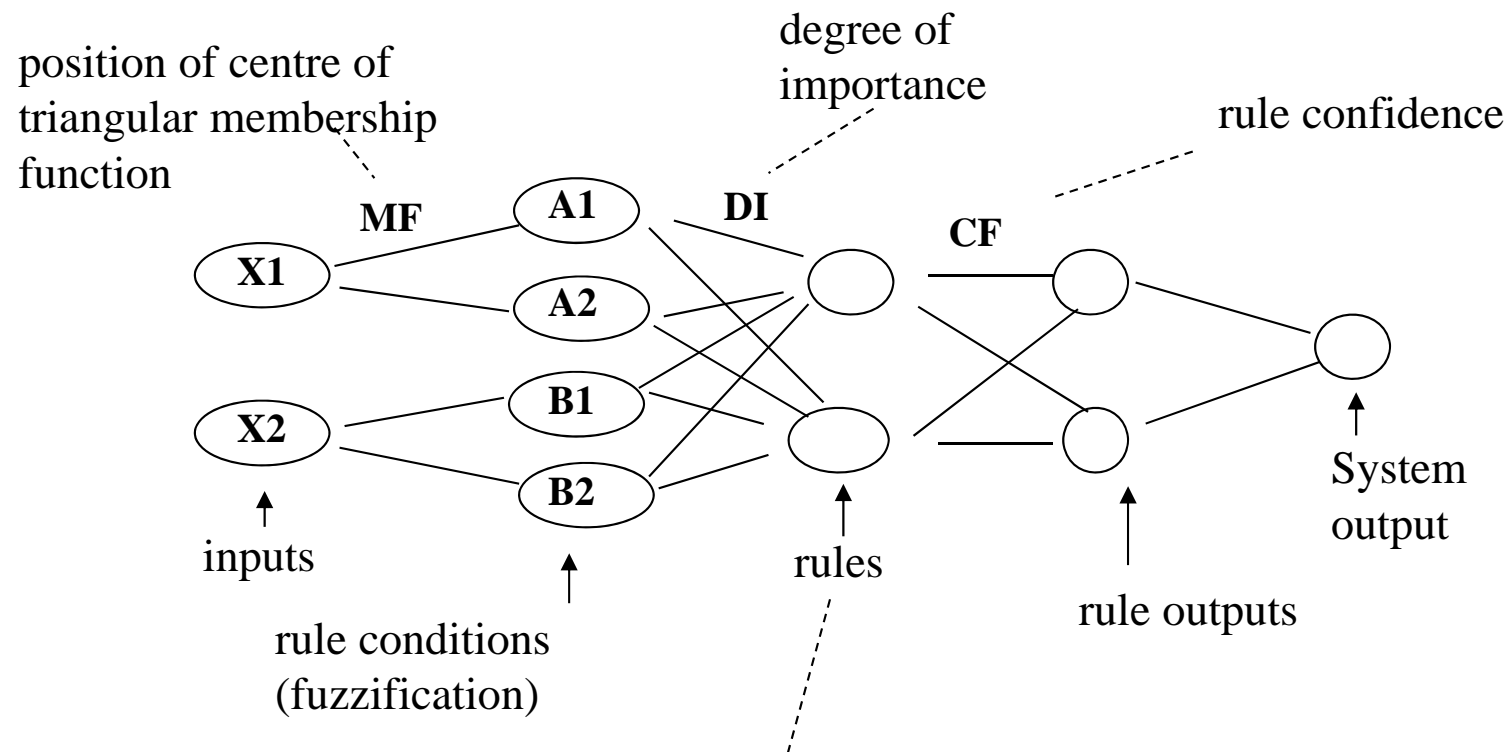
Self-Tuning Systems

- One technique is used to tune or learn the architecture for another, e.g: NN used to learn a Fuzzy System , GA used to optimise an NN



Self-Tuning Systems: (1) Neuro-Fuzzy

- **Neural Network is used to represent and “learn” a Fuzzy System**
- **Nodes represent rule inputs, conditions, actions etc**
- **Special training algorithm required**



Taking only the strongest connection to each condition element yields rules like (other schemes exist):-

e.g. If X1 is A1 (DI1) And X2 is B1 (DI2) Then output = C (CF1)

Self-Tuning Systems: (2) Fuzzy-Neuro

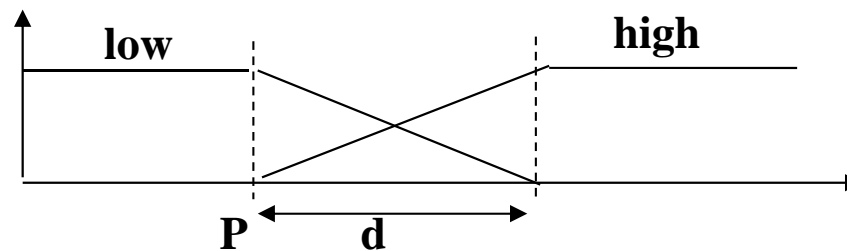
- **Fuzzy controllers have been used to control the learning rate η and momentum coefficient α of Neural Networks.**
 - » In general, large η and α result in fast error convergence, but poor accuracy. Small η and α lead to better accuracy but slow training. However, the selections are mainly ad hoc, i.e. based on empirical results or trial and error.
- **E.g. fuzzy rule table for $\Delta\eta$ and $\Delta\alpha$**

VS—Very Small S—Small M—Medium L—Large

Change of Err	Training Err		
	Small	Medium	Big
Negative	VS Increase	VS Increase	S Increase
Zero	No change	No change	S Increase
Positive	S Decrease	M Decrease	L Decrease

Self-Tuning Systems: (3) GA-Fuzzy

- GA tunes membership functions and/or learns fuzzy rules
- E.g. Each GA chromosome represents a set of fuzzy rules and input variable membership functions*
- Inputs have two fuzzy values: *high* and *low*. Membership fns are represented using parameters P & d :



- Rule conditions are represented by 0 (none), 1 (var = low), 2 (var = high). Boolean output, assumed true.
- Consider three inputs and two rules to be learned. One chromosome could be:

v1	v2	v3	rule1	rule2
P, d	P, d	P, d	v1, v2, v3	v1, v2, v3
4, 3	1, 5	2, 7	0, 2, 1	2, 0, 0

* *Designing Breast Cancer Diagnosis Systems via a Hybrid Fuzzy-Genetic Methodology*, Pena-Reyes, Sipper, 1999

Self-Tuning (3) : GA-Fuzzy

- **The fitness function measures the error of the rule set**
 - » e.g difference between training data and actual output from the fuzzy system
- **E.g. In the breast cancer example (previous page), fitness is similar to**

$$\text{Fitness} = F_c - \alpha F_v$$

where

F_c = percentage of examples classified correctly

F_v = average number of variables per rule

Self-Tuning (3a): GA-ML

- **Learning non-fuzzy rules**
- **Example: learning rules to predict type of object**

» Let F1 and F2 be the input variables with
 F1 taking values {small, medium large}
 F2 taking values {sphere, cube, brick, tube}
 Let Class take values {widgets, gadgets}

» Then the chromosome

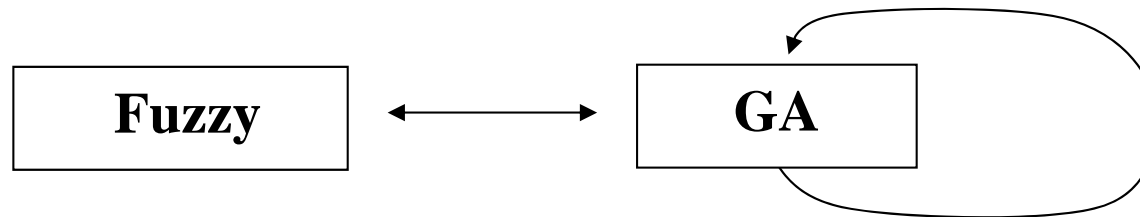
F1	F2	Class
110	0001	0

Represents the rule

If F1 = small or medium and F2 = tube then widget

Self-Tuning (4): Fuzzy-GA

- **Fuzzy rules are used to adjust the GA parameters during the operation of the GA**



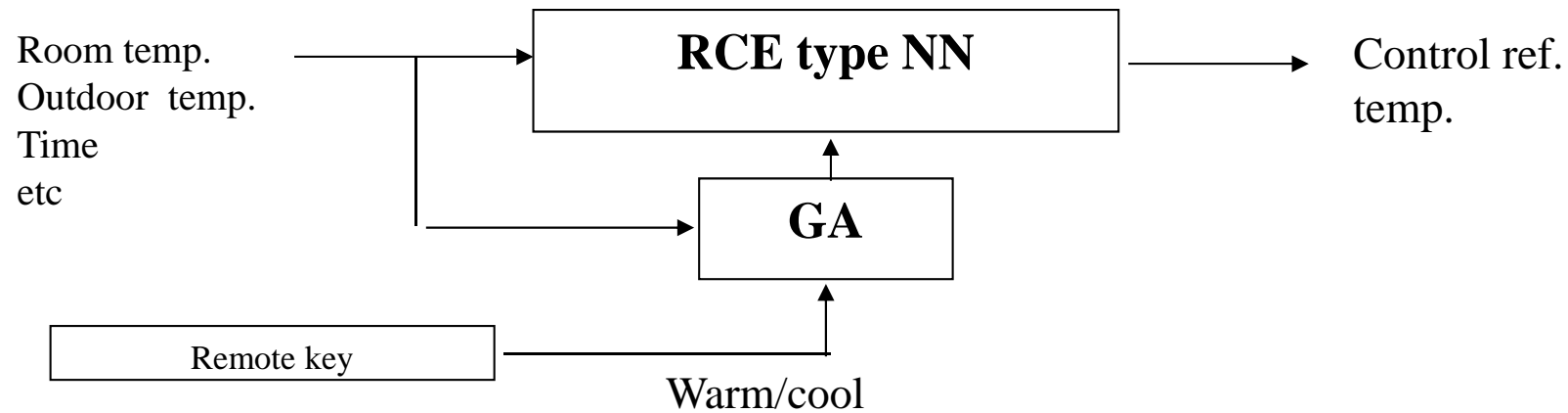
- **E.g. The Fuzzy rules take the following three inputs (Lee & Takagi 1993):**
 - » Average Fitness/Best Fitness
 - » Worst Fitness/Average Fitness
 - » Δ Best Fitness
- **And produce three outputs:**
 - » Δ Population size
 - » Δ Crossover rate
 - » Δ Mutation rate

Self-Tuning (5): GA-Neural

- **NNs are generated/tuned by GAs**
- **GA chromosome represents NN topology**
 - » number of hidden layers, hidden nodes and number of links and/or weights
- **Pros: GA can avoid local minima more than back-prop**
- **Cons: size of chromosome gets prohibitively large if topology is being learned**

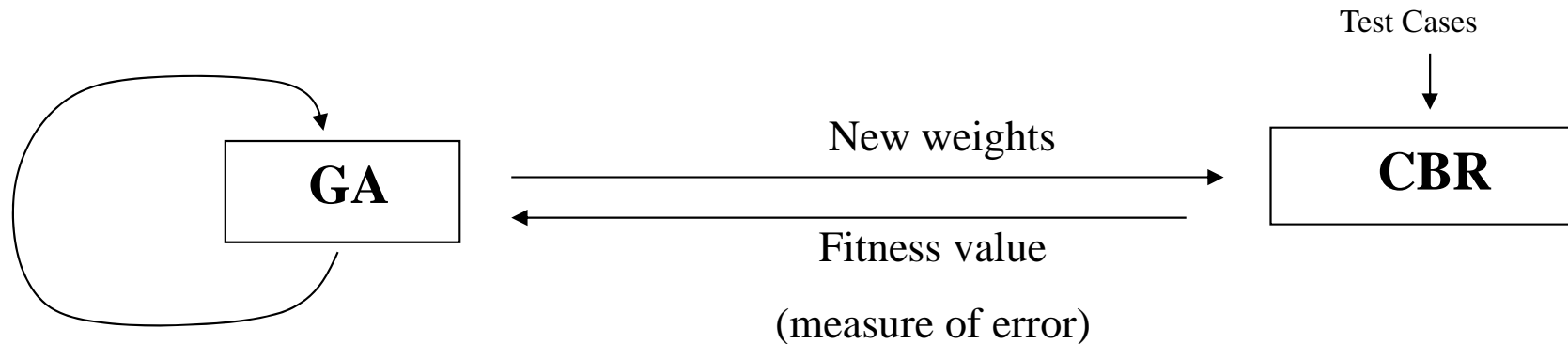
Self-Tuning (5): GA-Neural

- LG Electric developed an air-con controlled by an NN
- If the user wants the air-con to adapt to their preferences then a GA is used to change the number of neurons and weights



Self-Tuning (6): GA-CBR

- GA tunes the weights of CBR Systems



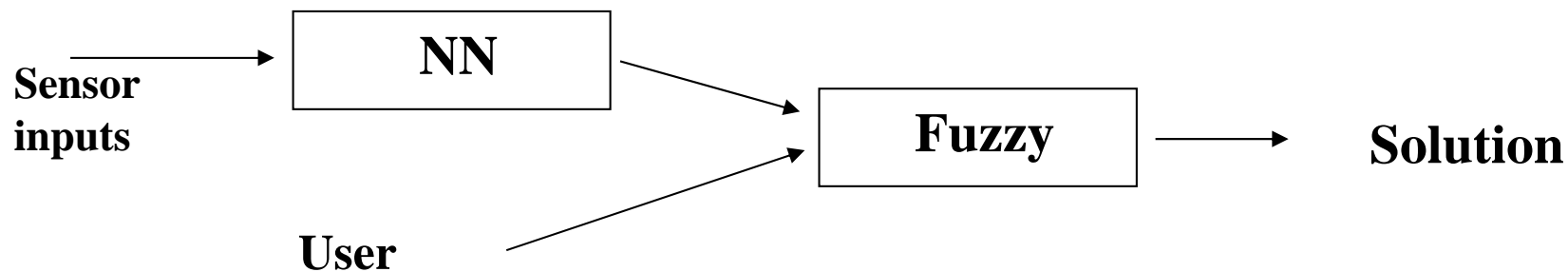
- Cancer Recurrence Support System (CARES System)

- » ISS project with Singapore General Hospital
- » Predict the recurrence of Colorectal Cancer using CBR
- » Applied GA to data sets to search for / fine-tune the weights used in the CBR system
- » In the preliminary trials conducted, the GA weights performed “better” than the intuitive weights given by the doctors

Co-operating Experts

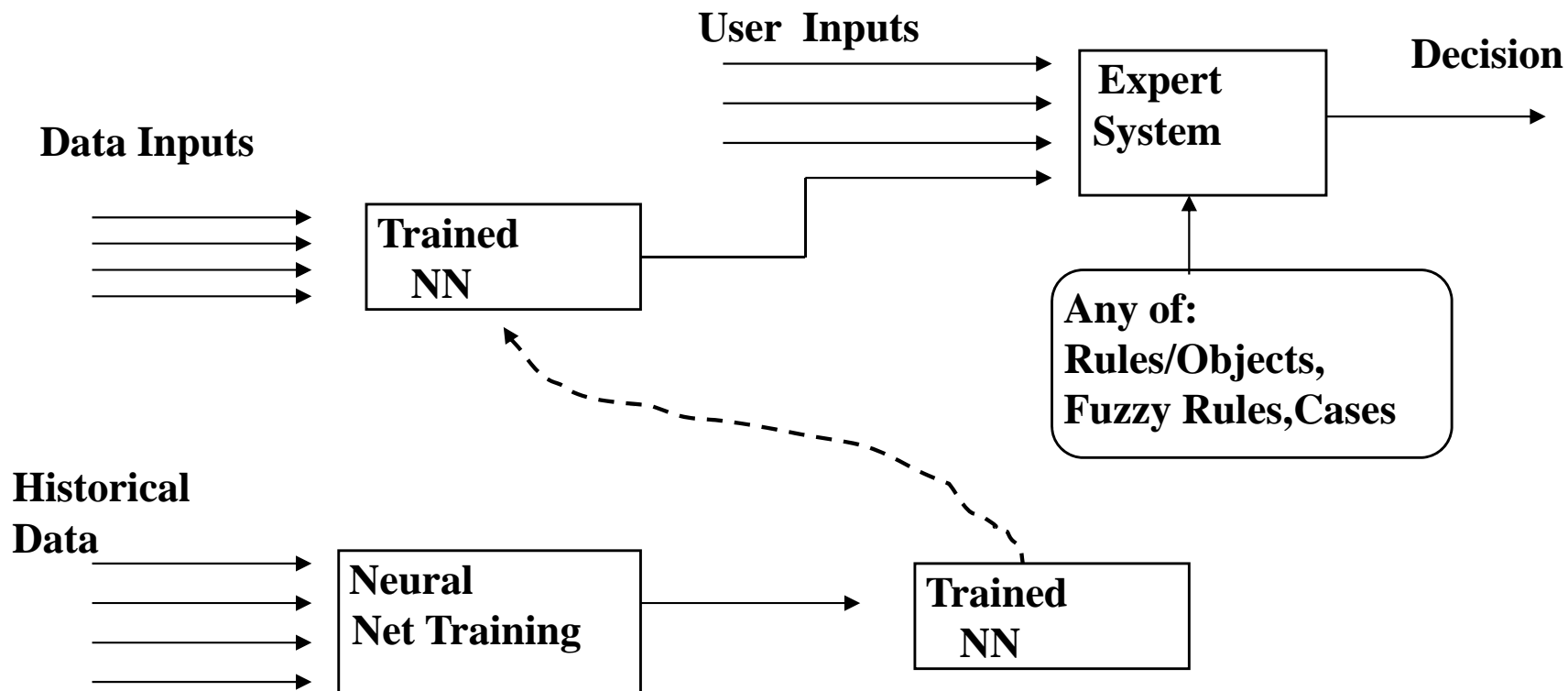
“Pooled Expertise”

- Different KE techniques work together as a team to produce a single solution, no single technique/expert is sufficient alone
- E.g, NN provides input to Fuzzy System



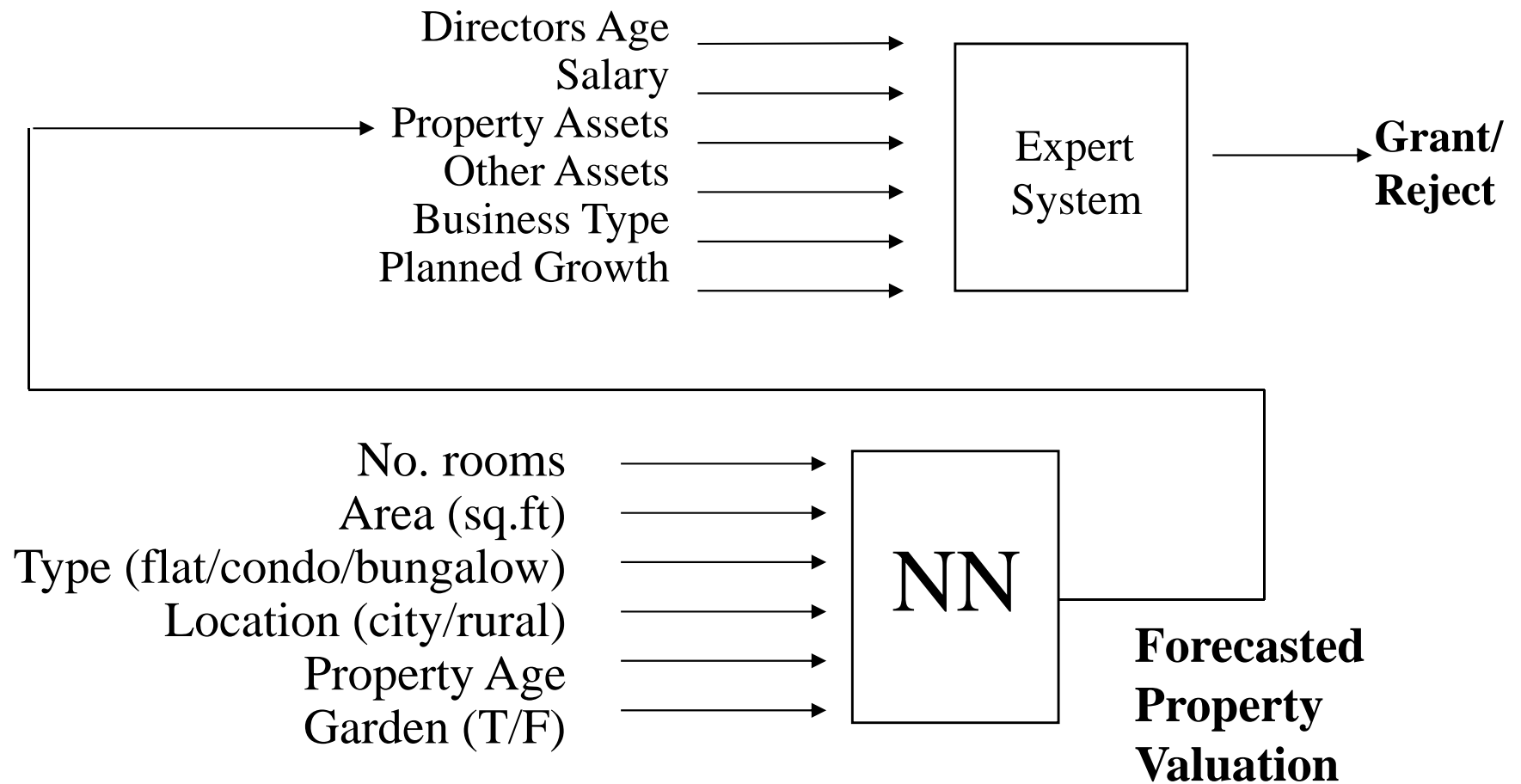
Team Pattern 1

- An expert system has an input that cannot be measured directly or inferred by the system
- NN/machine learning/regression etc. can be used to generate the input from data (if available)



Team Pattern 1: Example 1

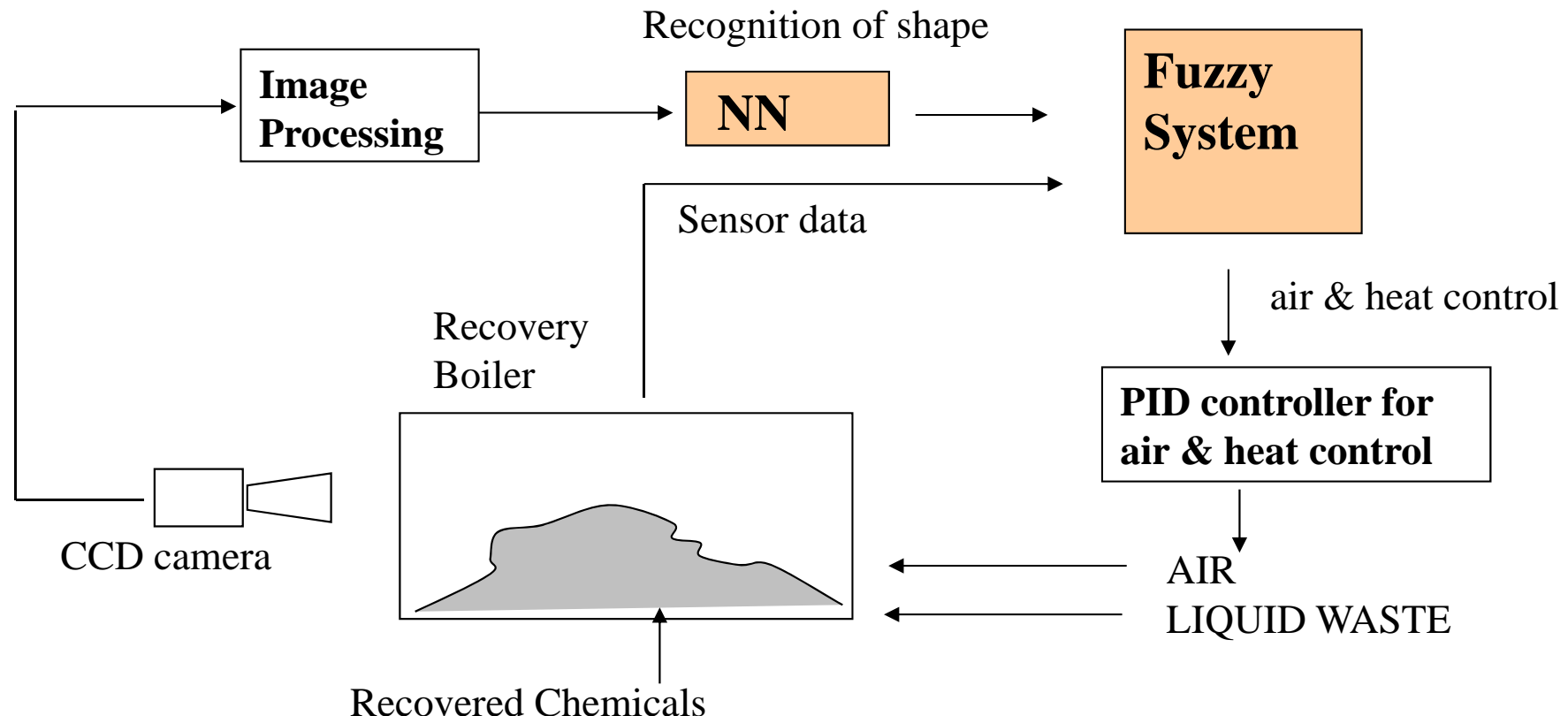
- Approving business loan to a small company



Team Pattern 1: Example 2

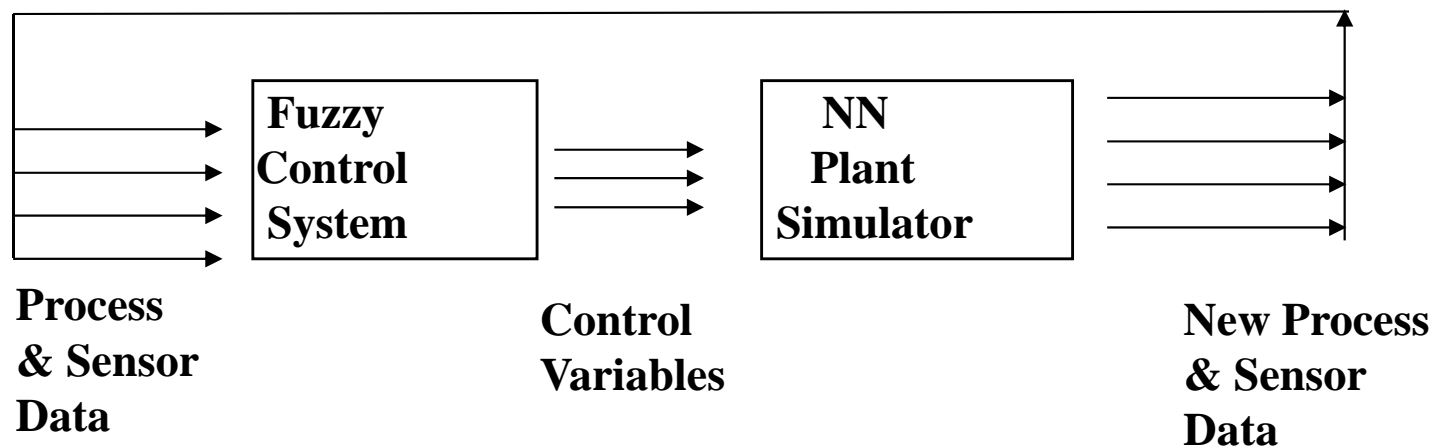
- Toshiba: Recovery of expensive chemicals at a pulp factory**

- » Fuzzy system controls the temp. of liquid waste and air before input to recovery boiler
- » Shape of pile in boiler influences the efficiency of the recovery process (deoxidisation).
NN recognises the shape of the pile from (edge) image and passes to the Fuzzy system.



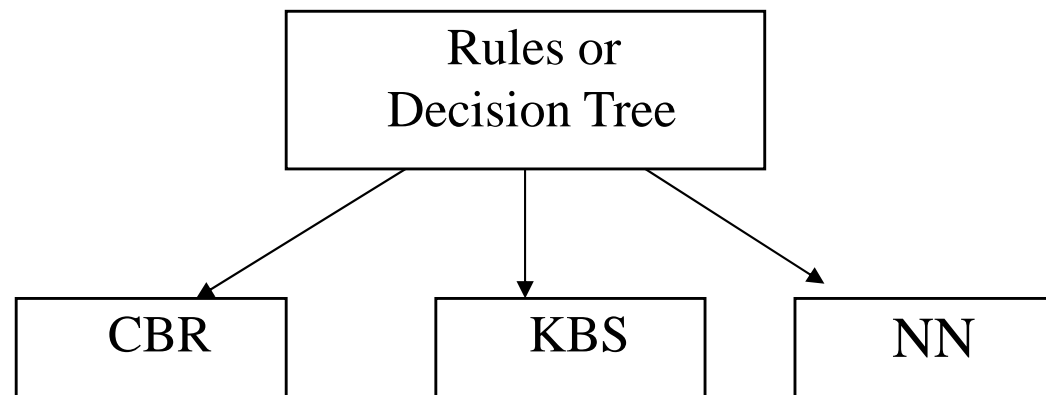
Team Pattern 1: Example 3

- In the process control industry, many of the processes are too complex to derive mathematical models for. Instead NNs can be used to build process control simulation models (e.g a plant model) based on recorded process data. The model can then be used in conjunction with the process control system – whether conventional (e.g. PID) or Fuzzy for evaluating the Control System's performance, undertaking what-if analysis, fault diagnosis etc.

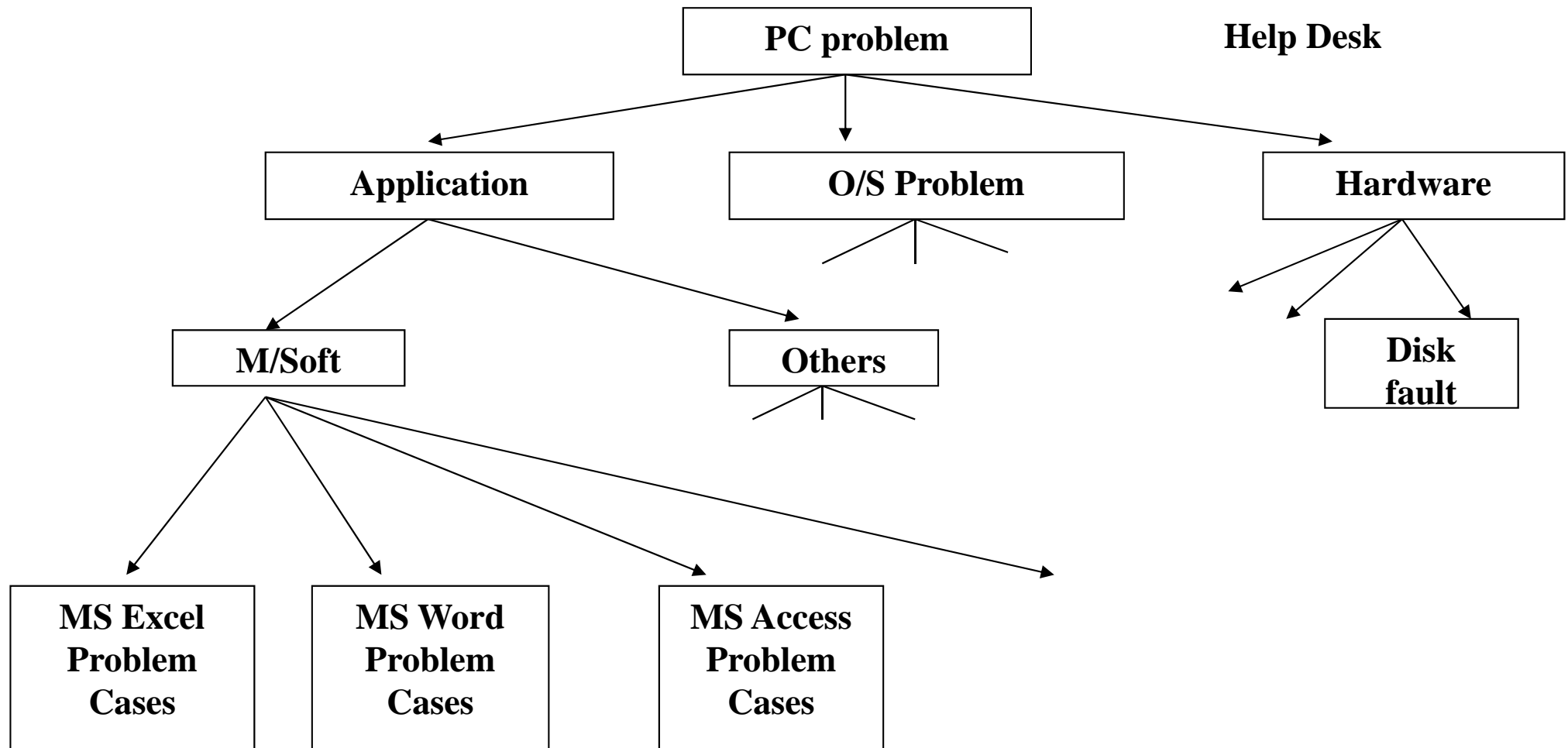


Team Pattern 2

- High-level rules are used to categorise the problem into a more specific category, this is then solved using an alternative KE technique, e.g. CBR

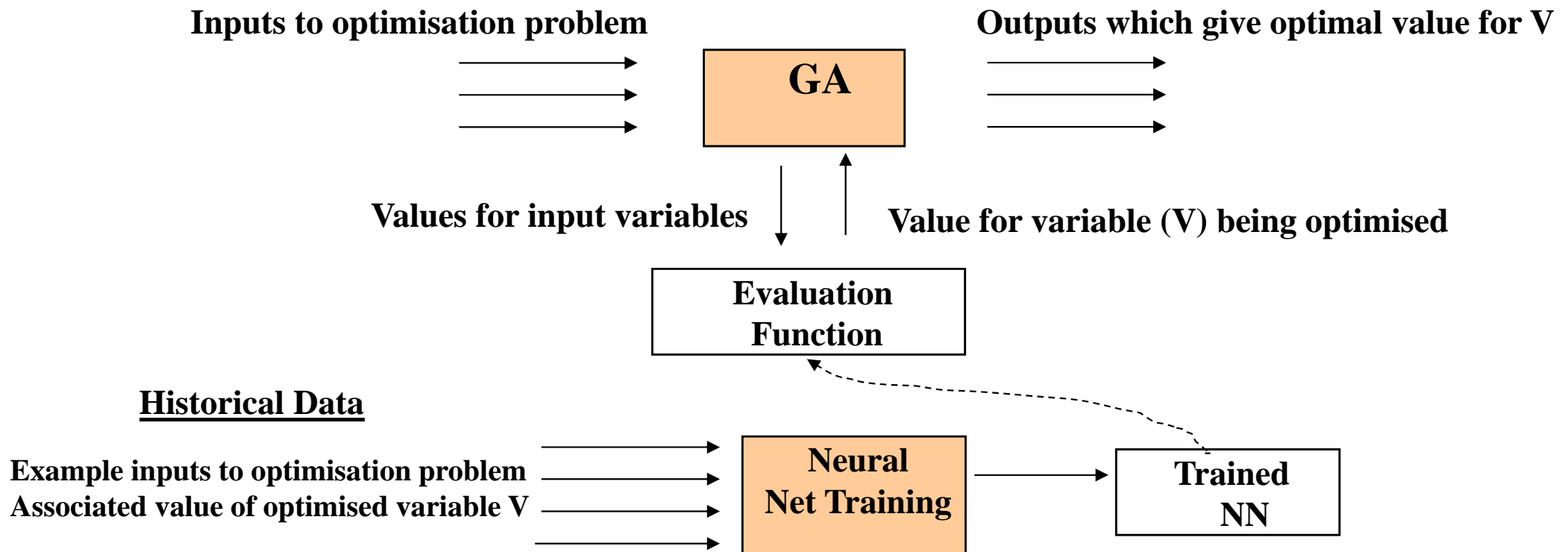


Team Pattern 2: Example 1



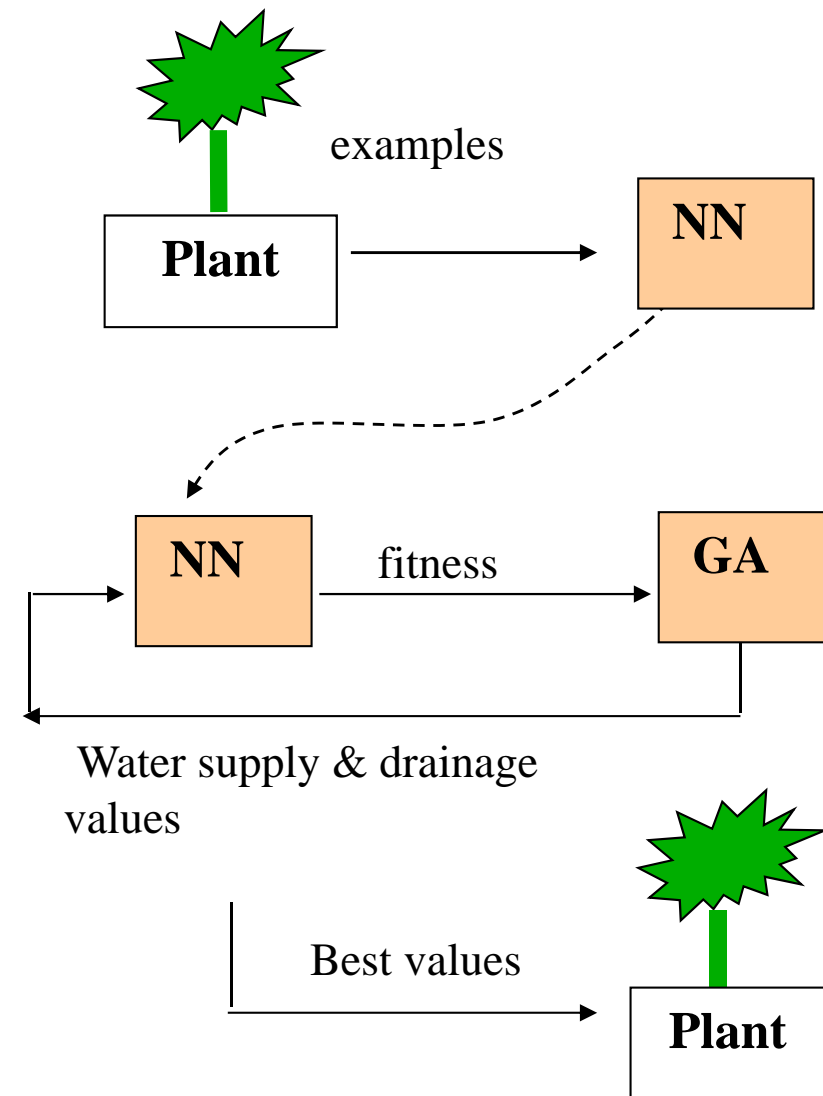
Team Pattern 3

- An optimisation problem but the evaluation function is not known, i.e. the relationship between the inputs and the variable being optimised is unknown
- Use NN or other machine learning technique to build a model of the variable (V) to be optimised



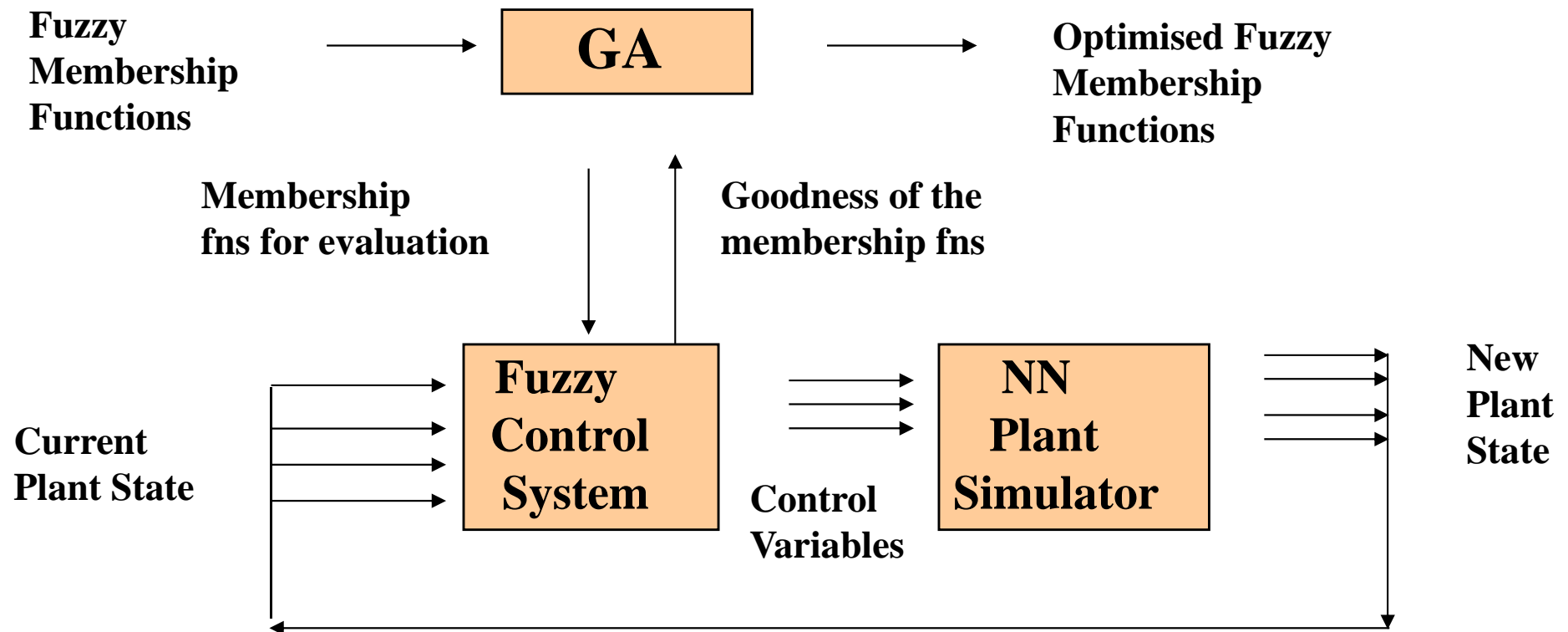
Team Pattern 3: Example 1

- **Optimal control of a hydroponics system**
- **Hydroponics system controls the water supply and water drainage of the target plant to maximise the plant's rate of photosynthesis**
- **GA is used to search for the combination of supply and drainage which maximises photosynthesis (measured using CO₂ absorbed)**
- **Using the real plant as the GA fitness function is impossible. Instead train a NN to model the plant's photosynthesis by giving it examples of supply & drainage with corresponding CO₂**



Team Pattern 3: Example 2

- The previous Process Control Example can be extended if we try to optimise the Fuzzy Control System using a GA. The evaluation function will measure the success of the Fuzzy Control system at maintaining the plant at a fixed point.



Summary

- **Hybrid Systems offer solutions to a greater range of problems**
 - » “the sum is greater than the parts”
- **Four categories of Hybrid System have been identified, each with different examples & typical (pattern) architectures. These are not intended to be exhaustive - other patterns are possible.**
- **Software integration issues can be problematic – but are becoming easier**
- **System modelling is the most important task.**
- **Agent technology offers more flexibility and possibility to build hybrid distributed intelligent systems, which may be proactive, and responsive in real-time.**

Hybrid Systems Exercise

- A soup manufacturer plans to produce a new type of canned soup. The new soup will contain up to 27 ingredients, namely 10 types of meat/fish, 7 types of vegetables, 5 flavour enhancers, 3 types of preservative, salt and sugar.
- To determine the relative quantities of each of the ingredients, the company conducts a market survey. Several hundred volunteers taste various prototype soups in which the 27 ingredients are mixed in different ratios, e.g. 30% chicken feet, 14% fish eyes, 15% turnips. Each taster is given 5 prototype soups to taste and asked to assign each to one of 7 categories.

Categories for describing the prototype soup:

- (a) horrible taste
- (b) would only eat if very hungry
- (c) weak taste
- (d) average taste
- (e) good taste
- (f) very good taste
- (g) heavenly taste

Class Discussion:

- Suggest a top-level design for a hybrid system that uses the results of the market survey to determine the mix of raw ingredients likely to achieve the highest consumer rating