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Modeling and Optimization of Textile Production by Learning from Measured Data and Human Knowledge

Xianyi Zeng, Ludovic Koehl

ENSAIT Textile Institute, Roubaix, France

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Modeling and optimization of textile production by learning from measured data and human knowledge

Plan of Presentation

- Modeling of textile production : industrial background, concepts and methods
- Fuzzy techniques and modeling
- Selection of relevant input/out variables
- Modeling by learning from measured data and human knowledge
- Conclusion
- References

Modeling of textile production : industrial interests, concepts and methods

Current situation in industrial world :

Economic pressures :

- customer's requirements;
- international competitions;
- diversified and variable markets;
- high labor cost and raw material cost.

Inside each enterprise :

- A great quantity of information and measured data related to human experience and production have not been well exploited.
- Uncertainty and imprecision in all levels of production systems.

Modeling of textile production : industrial interests, concepts and methods

Strategies of enterprises :

- Optimizing production by exploiting relevant information and data.
- Increasing product quality by minimizing production cost.
- Integrating marketing factors or consumer's behaviors into product design criteria.
- A "just in time" production and a quick reactivity.
- Shortening the duration of product design.

↓

Development of a powerful and adaptive information system (EDI, production simulation, virtual production, infodesign, …)

Modeling problems in textile industry :

Input variables → **Système complexe** → Output variables

Textile process modeling :

Input variables : process parameters

Output variables : features of product quality

Textile design modeling :

input variables : design criteria

output variables : market features

Textile materials modeling :

input variables : material structural parameters

output variables : physical properties

Modeling of textile production : industrial interests, concepts and methods

Classical methods for modeling and optimization :

- statistics
- differential equations
- transfer functions
- frequency analysis
- linear and nonlinear programming

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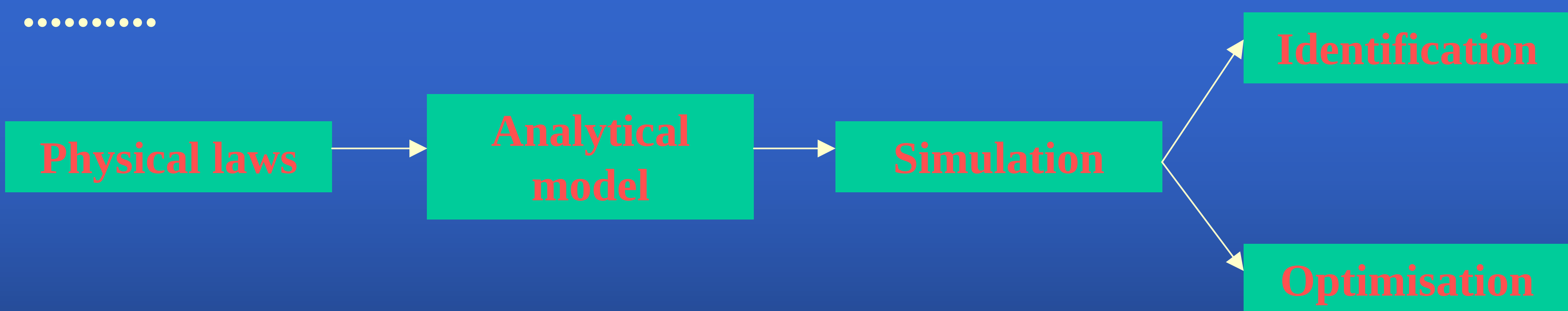


"Hard Computing" :

The system of interest and the criteria are certain and precise

Modeling of textile production : industrial interests, concepts and methods

Uncertainty and imprecision in textile modeling :

- Physical laws are not available in most of textile problems
- Complex relations between input and output variables
- Values of input and output variables are often uncertain
- Imprecise qualitative information related to human experience
- Sensory data for evaluation of product quality
- Random structure in textile materials (e.g. nonwoven)
- Experiment data are limited due to production cost and time

Basic requirements for modeling techniques :

- Data based modeling
- Qualitative human knowledge based modeling,
- Integration of measured data and human knowledge
- Selection of relevant parameters and features
- Formalization of linguistic variables
- Learning from a few number of data

Zadeh's Soft Computing (1997)

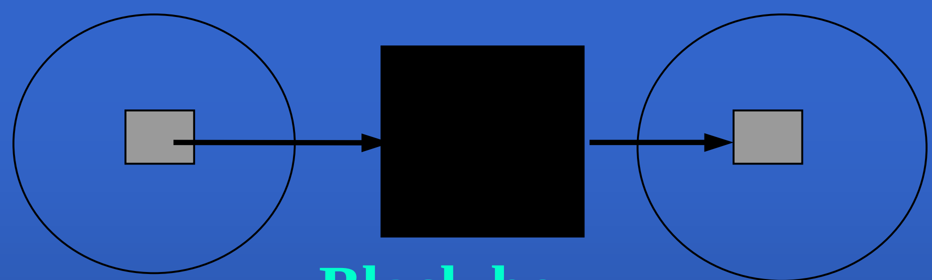
- Soft computing (SC) is an association of computing methodologies centering on fuzzy logic (FL), neurocomputing (NC), genetic computing (GC), and probabilistic computing (PC)
- The methodologies comprising soft computing are for the most part complementary and synergistic rather than competitive

Fuzzy logic :

a powerful tool formalizing human knowledge and characterizing the correlation between input and output spaces with uncertainty and imprecision

One example : the service in a restaurant

Input space (all possible qualities of service)



Black box

Output space (all possible tips)

Fuzzy rules :

1) If the service is good, then the tip is high

2) If the service is bad, then the tip is low

- values of the input variable : good, rather good, bad, ...

- values of the output variable : low, moderate, high

Fuzzy techniques and modeling

Advantages of fuzzy logic :

1) easy to understand (capacity of interpretation)
2) flexible
3) processing uncertain and imprecise data
4) processing numerical and linguistic data
5) approximate modeling complex systems
6) experiment based modeling
7) human experience based modeling

Main concepts of fuzzy logic :

set A <====> individual x $x \in A$ or $x \notin A$

fuzzy set A <====> individual x

membership function $\mu_A : X \rightarrow [0, 1]$

Fuzzy techniques and modeling

- **Fuzzy set :**

If the universe X is discrete ($X=\{x_1, x_2, ..., x_n\}$),
then $A=\mu_A(x_1)/x_1+\mu_A(x_2)/x_2+ ... +\mu_A(x_n)/x_n$

If X is continuous, then A= $\int_X \mu_A(x)/x$

- **α-cut : a set of level α of the fuzzy set A :**

$[A]^\alpha = \{t\in X \mid A(t)\geq\}$ if $\alpha>0$

$= supp(A)$ si $\alpha<0$

- **Fuzzy number :** a continuous fuzzy set with normal and convex membership function

- Operations on fuzzy sets :

Fuzzy intersection : t-norm

$A \cap B \rightarrow t(A, B) : [0, 1] \times [0, 1] \rightarrow [0, 1]$

standard intersection : $t(a, b)=\min(a, b)$

Fuzzy union : t-conorm

$A \cup B \rightarrow u(A, B) : [0, 1] \times [0, 1] \rightarrow [0, 1]$

standard union : $u(a, b)=\max(a, b)$

- Construction of a fuzzy variable :

=> definition of a number of fuzzy sets or fuzzy values

simple variables :

price : {cheap, expensive, very expensive};

temperature : {high, middle, low};

complexes variables :

beautiful : {less beautiful, middle, beautiful, very beautiful}

soft : {hard, a little soft, very soft}

Number of fuzzy sets for a fuzzy variable : 3, 5, 7, 9

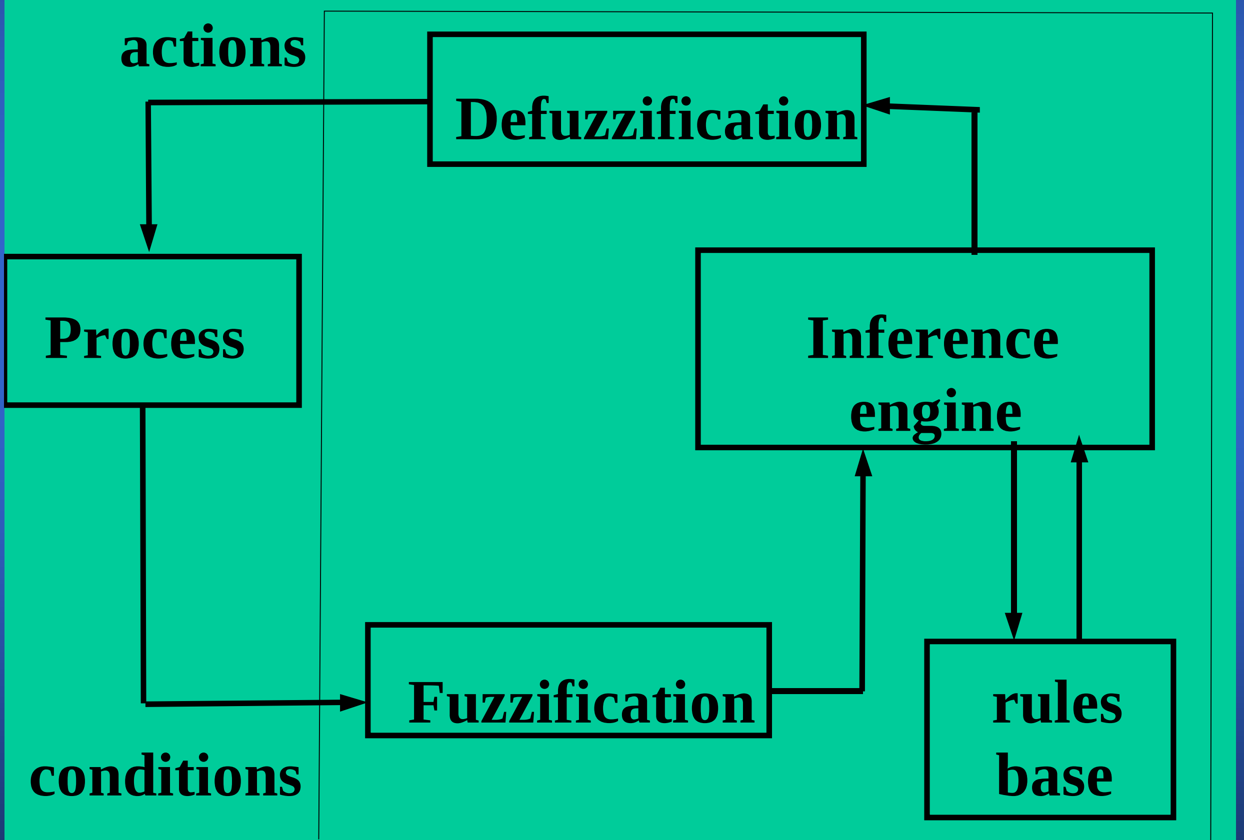
Shapes of membership degrees :

triangular, trapezoidal, Gaussian, ...

Modeling with Fuzzy Logic Controller :

- structure of a FLC :

1) fuzzy rule base
2) inference engine
3) fuzzification
4) defuzzification



A scheme of FLC

Design of a FLC :

1) Building fuzzy rules from human knowledge
2) Building fuzzy rules from experimental data

Working steps for modeling with FLC :

Step 0 : identifying input and output variables (e.g. v=f(x,y))

Step 1 : selecting linguistic values for each variable and defining fuzzy sets

Step 2 : fuzzfication (interpreting data of input variables)
For given input values (x_0,y_0), computing their membership functions for all fuzzy sets

Step 3 : building fuzzy rules

If x is A_1 and y is B_1, then v is C_1
If x is A_2 and y is B_2, then v is C_2
……………………………………………
If x is A_n and y is B_n, then v is C_n

A_1, ..., A_n, B_1, ..., B_n, C_1, ..., C_n : the fuzzy sets of x, y and v

Step 4 : computing the fuzzy set for the output variable for

$\alpha_i=t(\mu_{Ai}(x_0), \mu_{Bi}(y_0))$ ----- t-norm (fuzzy AND)
the membership degree of (x_0, y_0) related to rule i

$\mu_C(v)=u(t(\alpha_1, \mu_{C1}(v)), t(\alpha_2, \mu_{C2}(v)), ..., t(\alpha_n, \mu_{Cn}(v)))$
----- t-conorm (fuzzy OR)

Step 5 : defuzzification

- Mandani method : C_i=fuzzy set

$$v_0 = \frac{\int z \cdot \mu_C(z) dz}{\int \mu_C(z) dz}$$ **(gravity center)**

- One example : two fuzzy rules, two input variables

$\Re^1$: if x is A_1 and y is B_1 then w is C_1

$\Re^2$: if x is A_2 and y is B_2 then w is C_2

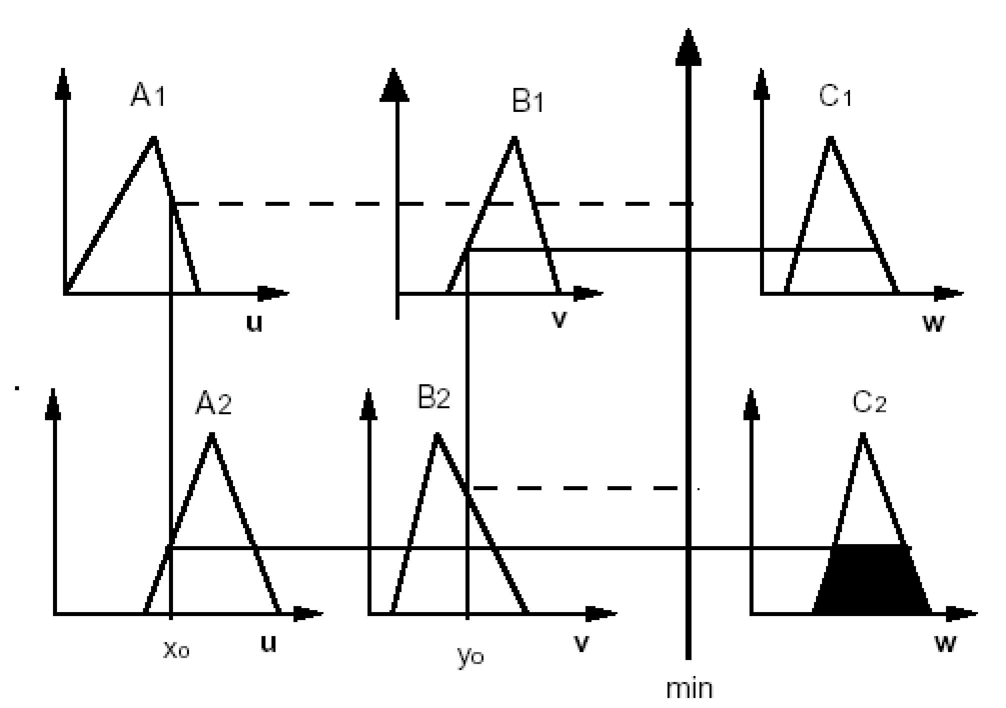
fact : x is x_0 and y is y_0 consequence : w is C

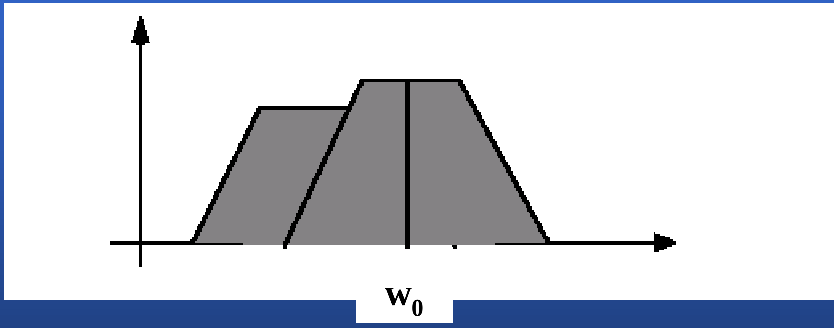
Fuzzy techniques and modeling

t-norm : min   t-conorm : max

For the rule $\Re^1$, $\alpha_1 = t(\mu_{A1}(x_0), \mu_{B1}(y_0)) = \min\{\mu_{A1}(x_0), \mu_{B1}(y_0)\}$
For the rule $\Re^2$, $\alpha_2 = t(\mu_{A2}(x_0), \mu_{B2}(y_0)) = \min\{\mu_{A2}(x_0), \mu_{B2}(y_0)\}$

$\mu_C(z) = u(t(\alpha_1, \mu_{C1}(z)), t(\alpha_2, \mu_{C2}(z)))$
$\quad = \max(\min\{\alpha_1, \mu_{C1}(v)\}, \min\{\alpha_2, \mu_{C2}(v)\})$





Fuzzy techniques and modeling

- Sugeno method (general form)
C_i = linear combination of all rules (weighted average)

n rules : $R^1, R^2, \ldots, R^n$

R^i : if x_1 is A_1^i and … and x_k est A_k^i **then** $y = p_0^i + p_1^i x_1 + \ldots + p_k^i x_k$

A new input data $X^0 = (x_1^0 \; x_2^0 \; \ldots \; x_k^0)$ =====>

for each rule R^i, $y^i = p_0^i + p_1^i x_1^0 + \ldots + p_k^i x_k^0$

$(y=y^i)$ = $(x_1^0$ is $A_1^i)$ and …… and $(x_k^0$ is $A_k^i)$

$\mu(y=y^i) = t(\mu_{A_1^i}(x_1^0), \ldots, \mu_{A_k^i}(x_k^0))$ t-norm

$$y = \frac{\sum \mu(y = y^i) \times y^i}{\sum \mu(y = y^i)}$$

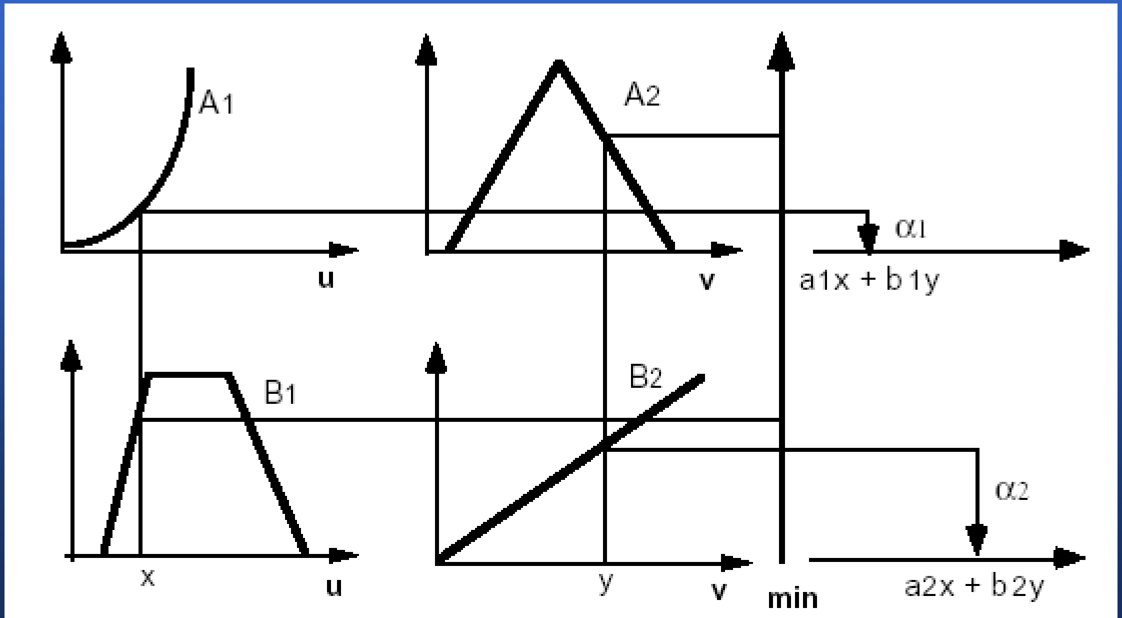
Fuzzy techniques and modeling

- One example : two fuzzy rules, two input variables

$\Re^1$: if x is A_1 and y is B_1 then $z_1=a_1x+b_1y$
$\Re^2$: if x is A_2 and y is B_2 then $z_2=a_2x+b_2y$
fact : x is x_0 and y is y_0 consequence : z_0

For the rule $\Re^1$, $\alpha_1=t(\mu_{A1}(x_0), \mu_{B1}(y_0))= \min\{\mu_{A1}(x_0), \mu_{B1}(y_0)\}$
For the rule $\Re^2$, $\alpha_2=t(\mu_{A2}(x_0), \mu_{B2}(y_0))=\min\{\mu_{A2}(x_0), \mu_{B2}(y_0)\}$
computing $z_{10}=a_1x_0+b_1y_0$ $z_{20}=a_2x_0+b_2y_0$

$$z_0 = \frac{\alpha_1 z_{10} + \alpha_2 z_{20}}{\alpha_1 + \alpha_2}$$



Selection of relevant input/output variables

Aims of variables selection :

- Reducing the complexity of the model
- Making the model more significant and more interpretable
- In practice, only a small number of the most relevant variables are available

Criteria of selection :

- Sensitivity of input (output) variables to output (input) variables
- Conformity of variables to human knowledge
- Others (according to specific problems)

Selection of relevant input/output variables

Principles for the criterion of sensitivity S_k :

(selection of input variables)

- IF a small variation of an input variable x_k corresponds to a big variation of the output variable y, THEN this input is considered as a sensitive variable.
- If a big variation of an input variable x_k corresponds to a small variation of the output variable y, THEN this input is considered as an insensitive variable.

Formalization of the criterion of sensitivity :

$$S_k = \frac{1}{2} - \frac{1}{\pi} \arctan\left(\sum_{\substack{i \neq l \\ 1}}^{z} \frac{d(y_{ij}, y_{lj})}{d_k^{'}(X_i, X_l)} \right)$$

$$d_k^{'}(X_i, X_l) = \sqrt{d^2(X_i, X_l) - d_k^2(X_i, X_l)}$$

- A big value of S_k means that x_k is sensitive to y
- A small value of S_k means that x_k is insensitive to y

Principles for the criterion of conformity H_k :

- If a variable x_k has the same variation trend in the learning data set as in the human knowledge, it is considered as conform to the human knowledge.
- Otherwise, x_k is considered as non conform to the human knowledge.

General criterion of relevancy F_k :

a linear combination of the sensitivity and the conformity

$$F_k = g_1 \, . \, H(x_k, y_j) + g_2 \, . \, S_k$$

- A big value of F_k means that x_k is relevant
- A small value of F_k means that x_k is irrelevant

Modeling by learning from measured data and human knowledge

Modeling by extracting fuzzy rules from measured data :

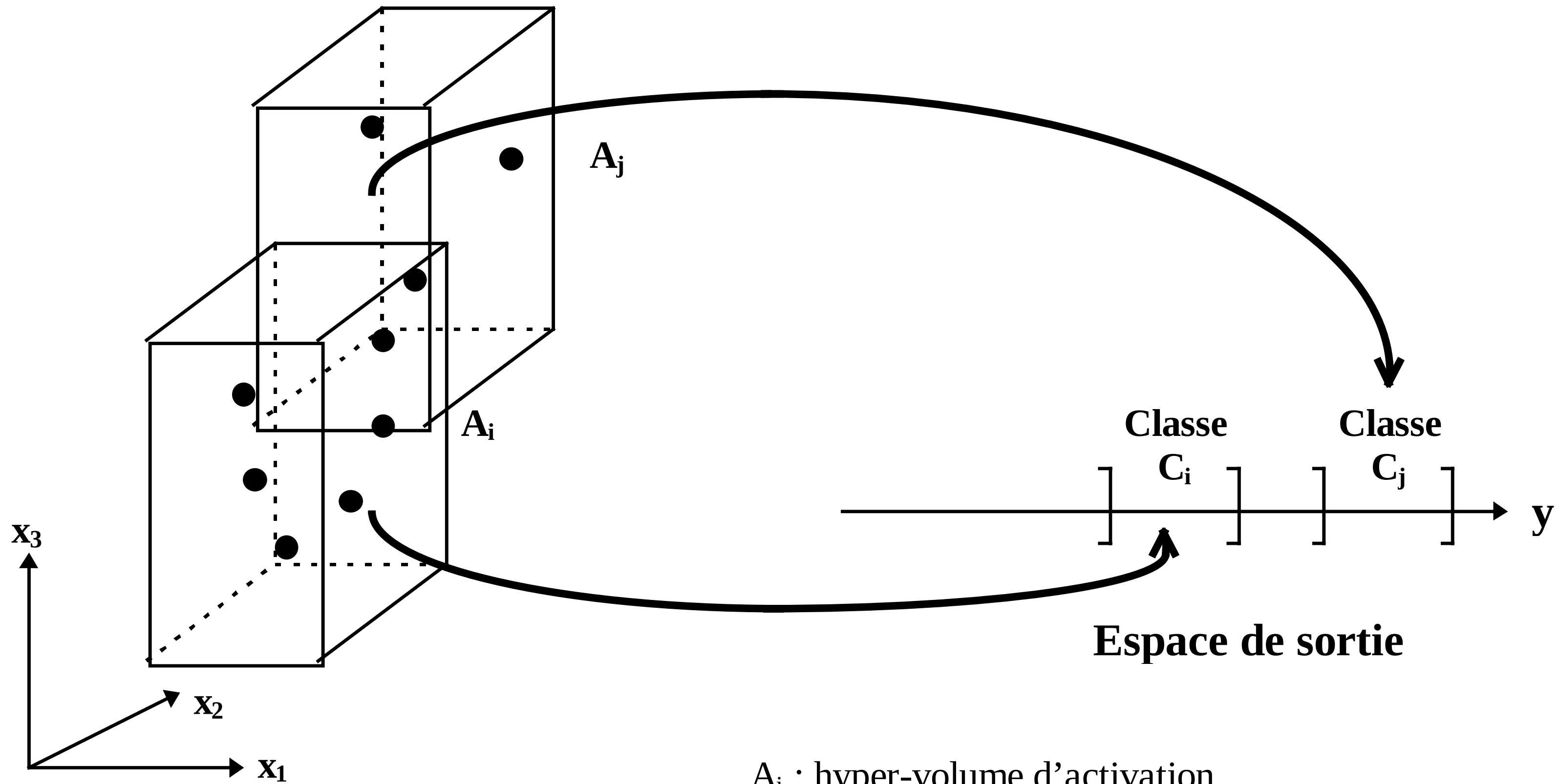
- Collection of input/output numerical data
- Partition of input and output spaces using classification methods
- Building correspondence between partitioned input subspaces and output subspaces
- Determining parameters of membership functions
- Determining parameters of defuzzification
- typical methods: fuzzy c-means, ANFIS (fuzzy-neural), Mandel-Wang method, Abe method

One example (Abe method) : modeling the relation between objective evaluation and subjective evaluation of fabric hand :

- 11 input variables, 1 output variable for each term
- 45 learning data collected from instruments and human evaluators

Modeling by learning from measured data and human knowledge

Principle of Abe method :



Espace des entrées

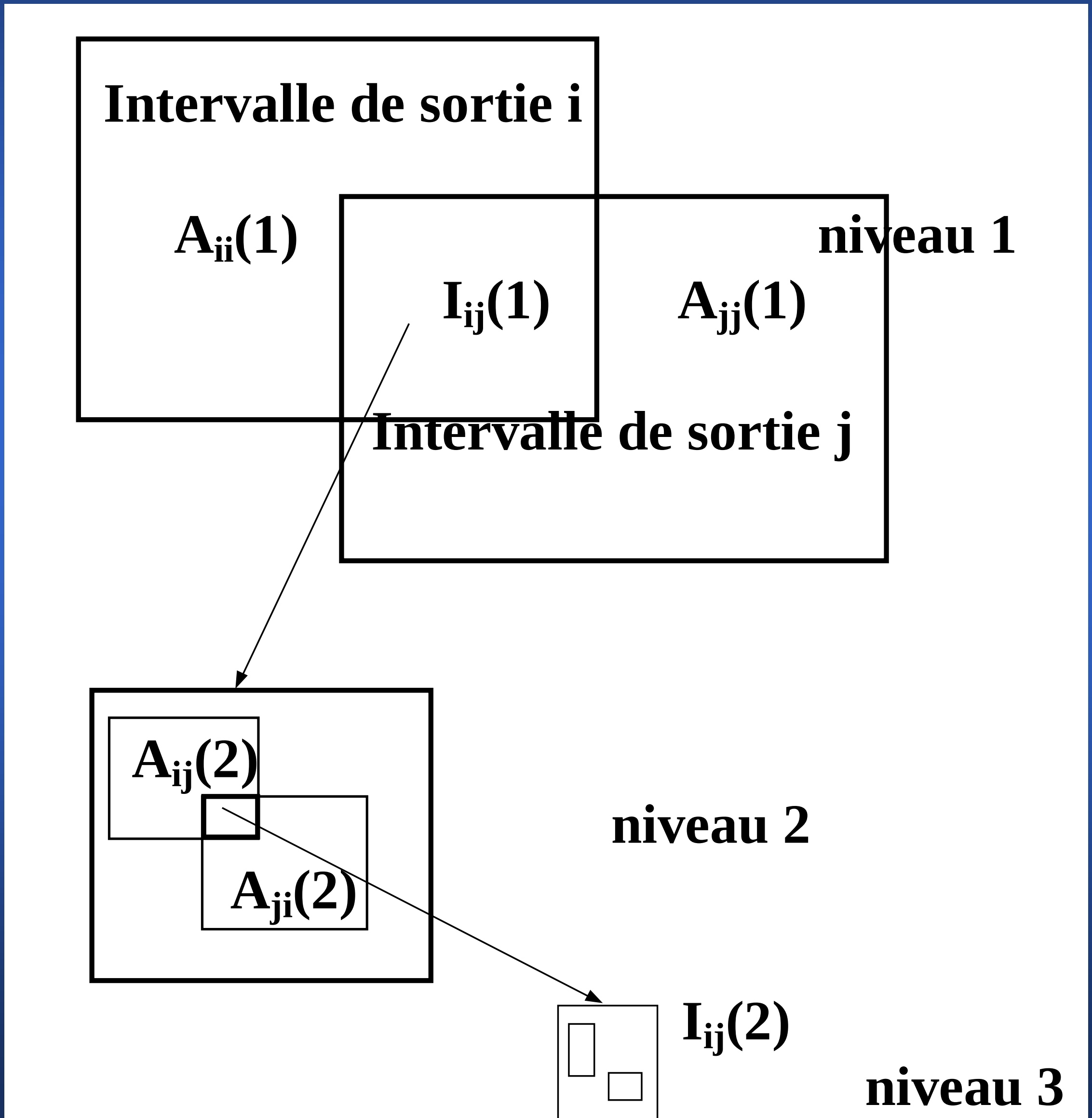
● Echantillons de Ω

A_i : hyper-volume d'activation associé à la classe de sortie i

I_{ij} : hyper-volume d'inhibition associé ni à la classe i, ni à la classe j

$$I_{ij} = A_i \cap A_j$$

Modeling by learning from measured data and human knowledge



Definition of hyper-volumes

Modeling by learning from measured data and human knowledge

Input space

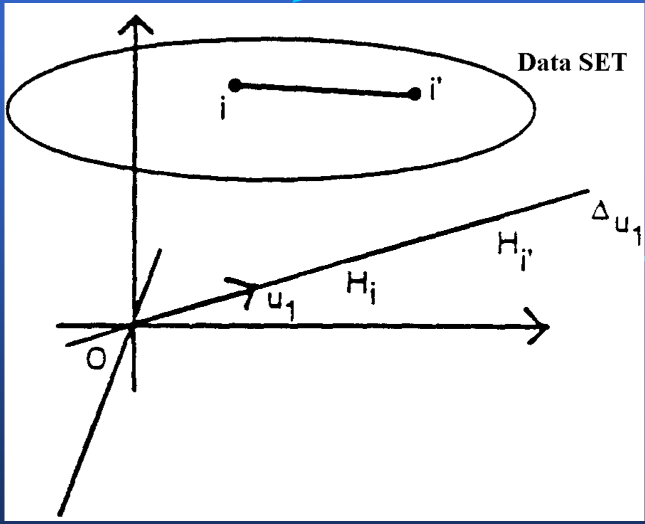
$\Re^{11}$ $\qquad \Re^2 = (O, \vec{u}_1, \vec{u}_2)$

$$Y_j = \begin{pmatrix} y_{j1} \\ \vdots \\ y_{j11} \end{pmatrix} \rightarrow \boxed{\text{PCA}} \rightarrow Y_j' = \begin{pmatrix} y_{j1}' \\ y'_{j2} \end{pmatrix} \rightarrow \boxed{\Sigma} \rightarrow C_1 \; C_2 \; C_3 \; C_4 \; C_5 \; C_6 \; C_7$$

Fuzzy Rules Base

Output space

subjective term: 'Soft'

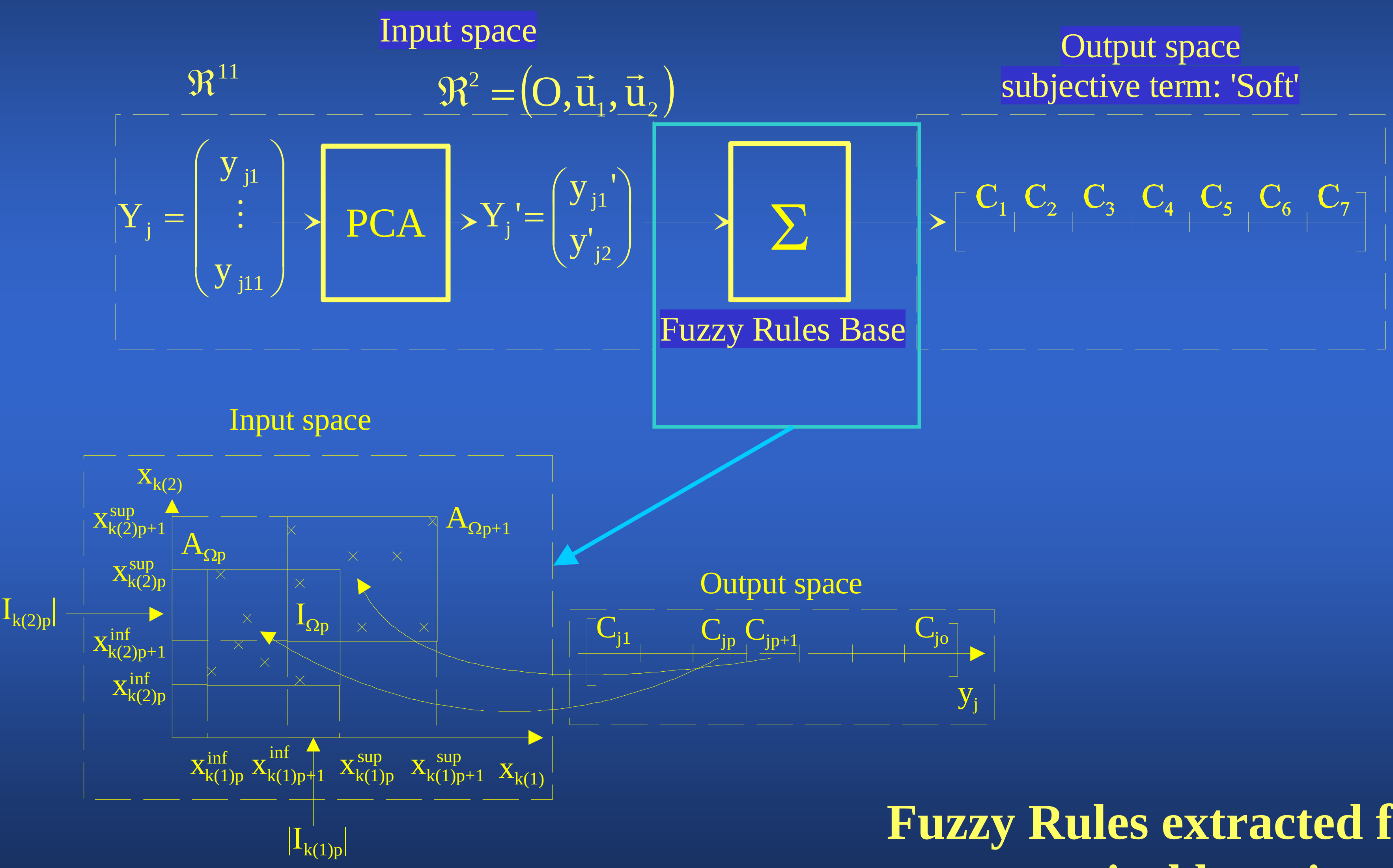


Input vector X' / Output

Samples	x'_1	x'_2	Soft
4_1	-1.196	-0.197	7
10_1	-0.978	-0.168	7
14_1	-0.287	0.111	6
14_2	-0.380	-0.187	4
16_1	-0.164	0.093	6
16_2	-0.201	0.401	4
22_1	-0.190	-0.126	6
22_2	-0.150	0.251	4
24_1	0.139	0.233	5
24_2	0.157	0.132	4
26_1	0.217	-0.012	3
26_2	0.170	0.098	3
28_1	0.194	0.189	3
28_2	0.388	0.469	2
31_1	0.489	-0.115	2
31_2	0.401	-0.905	2
34_1	0.622	-0.056	1
34_2	0.768	-0.211	1

Projections on the first 2 principal axis (PCA)

Modeling by learning from measured data and human knowledge



Fuzzy Rules extracted from numerical learning data

Modeling by learning from measured data and human knowledge

Some Results

Removed Sample	# rules	# level(s)	Real Output	Estimated Output	error
4_1	8	2	7	5.83	1
10_1	8	2	7	4.95	2
14_1	8	2	6	3.50	2
14_2	7	1	4	4.50	1
16_1	8	2	6	4.25	2
16_2	8	2	4	3.74	0
22_1	8	2	6	3.50	2
22_2	8	2	4	4.02	0
24_1	7	2	5	3.27	2
24_2	8	2	4	3.51	0
26_1	8	2	3	3.44	0
26_2	8	2	3	3.71	1
28_1	8	2	3	3.85	1
28_2	8	2	2	2.89	1
31_1	8	2	2	2.49	0
31_2	8	2	2	2.71	1
34_1	8	2	1	1.65	1
34_2	8	2	1	1.20	0

average: 0.94

Fabric Evaluation Model Outputs&Features - term ‘ SOFT ’

Modeling by learning from measured data and human knowledge

Modeling by extracting fuzzy rules from human knowledge :

- Definition of input and output variables
- Determination of fuzzy sets for each variable from human knowledge
- Transformation of human knowledge into “if-then” rules
- Determination of membership functions from human knowledge
- Human knowledge in production : operator’s experience on production and products, expert evaluation on product quality, information from marketing and sales departments, ...
- Acquisition of human knowledge : sensory evaluation, questionnaires, dialog with operators, production records, ...

Modeling by learning from measured data and human knowledge

Modeling by combining measured data and human knowledge :

example: modeling the relation between fabric process parameters and selected physical features

- **input variables : 5 process parameters**

  2 linguistic variables (quality, process type)

  3 numerical variables (count, twist, cover factor)

- **output variable : each selected physical feature**

- **principle : cross-validation and combination of numerical data and human knowledge**

1) 45 learning data $(X_i: (x_{i1}, \ldots, x_{in})^T; y_{ij})$ **with** $i \in \{1, \ldots, q\}$

2) qualitative physical knowledge on fabric production

Modeling by learning from measured data and human knowledge

- q fuzzy rules (q=45) from direct matching :

$$\textit{If } x_1=x_{i1} \textit{ and } \ldots \textit{ and } x_n=x_{in}, \textit{ then } y_j=y_{ij}\ (i\in\{1, \ldots, q\})$$

- Human knowledge :

Y \ X	quality	count	cover factor	twist
T_0	-	+	0	0+
T_M	0-	+	0	0+
EMC	+	0	-	-
W_c	-	0-	+	+
R_c	-	-	+	+
MIU	-	0-	0-	0+
MMD	-	+	-	+
SMD	-	+	-	+
E_p	+	+	-	+
P_{abs}	0	0-	+	-
σ	0	+	+	0

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Modeling by learning from measured data and human knowledge

- Validation of the human knowledge x_i-y_j related to measured data :

If y_j decreases with x_i (-) and

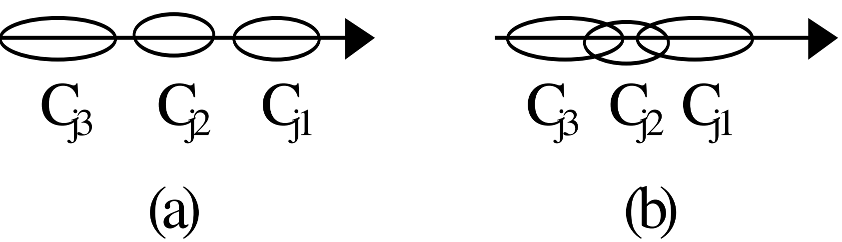
x_i is a three valued input variable: a_{i1}, a_{i2}, a_{i3} ($a_{i1}<a_{i2}<a_{i3}$),

grouping all measured data based fuzzy rules for y_j into three classes:

Class 1: If … and $x_i=a_{i1}$ and … then $y_j \in C_{j1}$

Class 2: If … and $x_i=a_{i2}$ and … then $y_j \in C_{j2}$

Class 3: If … and $x_i=a_{i3}$ and … then $y_j \in C_{j3}$



(a) strict validation, $VA(x_i,y_j)=1$

(b) weak validation, $0<VA(x_i,y_i)<1$

Adjusting the output data in the fuzzy rules for maximizing :

$$VA\_Total = \frac{1}{n}\sum_{i=1}^{n} VA(x_i, y_j) + \frac{1}{q}\sum_{d=1}^{q} VA(FR_d)$$

Modeling by learning from measured data and human knowledge

Finding the compromise between human knowledge and measured data by maximizing :

$$F = VA\_Total - h \cdot \frac{1}{q} \sum_{i=1}^{q} \sum_{j=1}^{m} \left| y_{ij}^{new} - y_{ij}^{old} \right|$$

Results of optimization of validation degrees :

	T0(old)	T0(new)	Tm(old)	Tm(new)
4-1	**0,293**	**0,600**	**0,000**	**0,400**
10-1	**0,309**	**0,600**	**0,000**	**0,200**
14-1	**0,105**	**0,500**	**0,021**	**0,167**
14-2	**0,115**	**0,670**	**0,006**	**0,167**
16-1	**0,103**	**0,500**	**0,038**	**0,333**
16-2	**0,111**	**0,500**	**0,000**	**0,167**
22-1	**0,107**	**0,670**	**0,034**	**0,500**
22-2	**0,132**	**0,670**	**0,012**	**0,333**
24-1	**0,108**	**0,670**	**0,075**	**0,333**
24-2	**0,110**	**0,670**	**0,046**	**0,500**
26-1	**0,110**	**0,600**	**0,141**	**0,000**
26-2	**0,129**	**0,600**	**0,113**	**0,000**
28-1	**0,079**	**0,600**	**0,089**	**0,000**
28-2	**0,054**	**0,600**	**0,108**	**0,000**
32-1	**0,144**	**0,200**	**0,159**	**0,400**
32-2	**0,167**	**0,400**	**0,167**	**0,200**
34-1	**0,153**	**0,400**	**0,167**	**0,200**
34-2	**0,144**	**0,400**	**0,167**	**0,200**

Modeling by learning from measured data and human knowledge

Modeling from data measured on several families of samples :

example: modeling the relation between structural parameters of nonwoven and physical properties

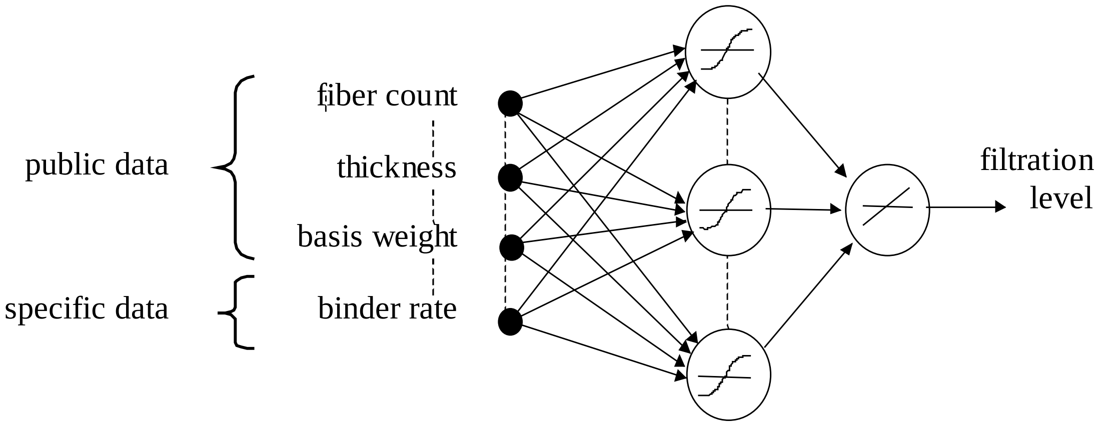
- input variables : 3 public parameters, 1 specific parameter

- principle :

1) Building a public model with public data of all families
2) For each family, adding the specific input variables and learning the concerned structure from specific data set based on the public model

Modeling by learning from measured data and human knowledge

The scheme for ANN based modeling from different families of nonwoven :



Conclusion

Comparison of modeling techniques :

- Classical techniques : analytical model, physical law driven modeling, precise model, less flexible and less robust
- Statistical techniques : statistical model, imprecise model, flexible, robust
- Intelligent techniques : data driven modeling or human knowledge driven modeling, flexible , robust, relatively precise and interpretable, capacity of learning and adaptation

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