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Short-Term Load Forecasting Algorithm in Smart Grid Operations And planning

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Outlines

- Contribution of load forecasting to smart grid
- Load forecasting with neural network
- Comparative study of load forecasting
- Generalization problem
- Proposed algorithm
- Results
- Conclusion and future work

Contribution of load forecasting to electrical grid

Operation and planning

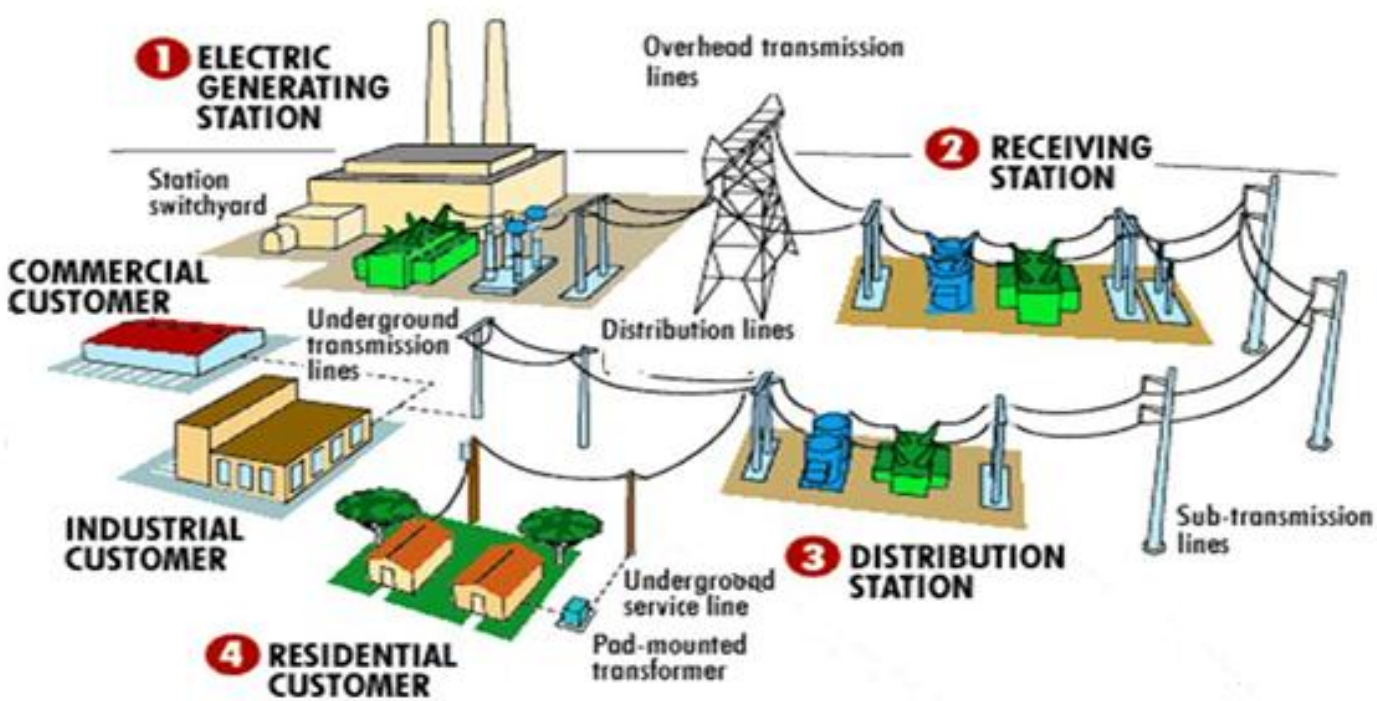


Image source : www.avalon-energy.com

Contribution of load forecasting to smart grid

Compliance with renewable energy plan

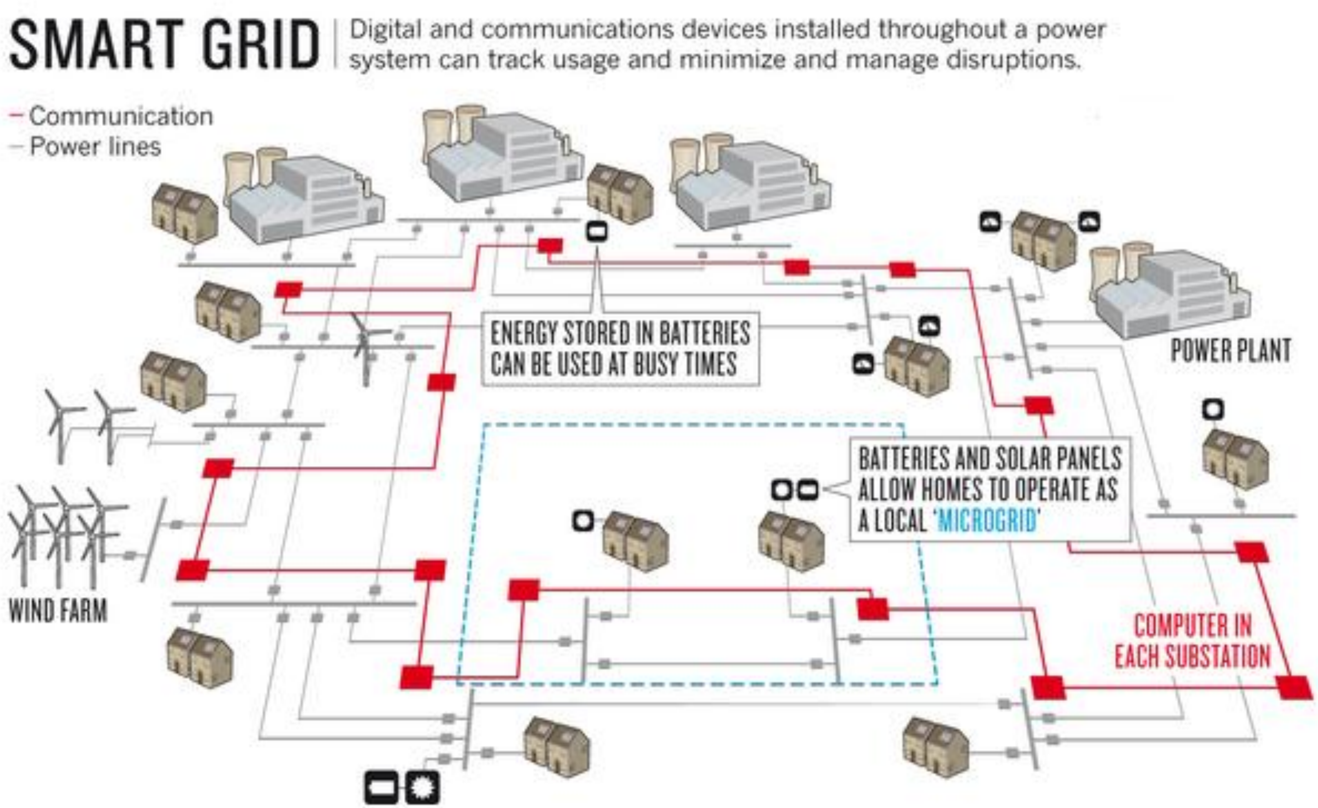


Image source : www. nature.com

Contribution of load forecasting to smart grid

Demand side management
- Load shifting
- Energy efficiency and conservation

➢ Customers reduce electricity bills

➢ Utility save costs for infrastructure

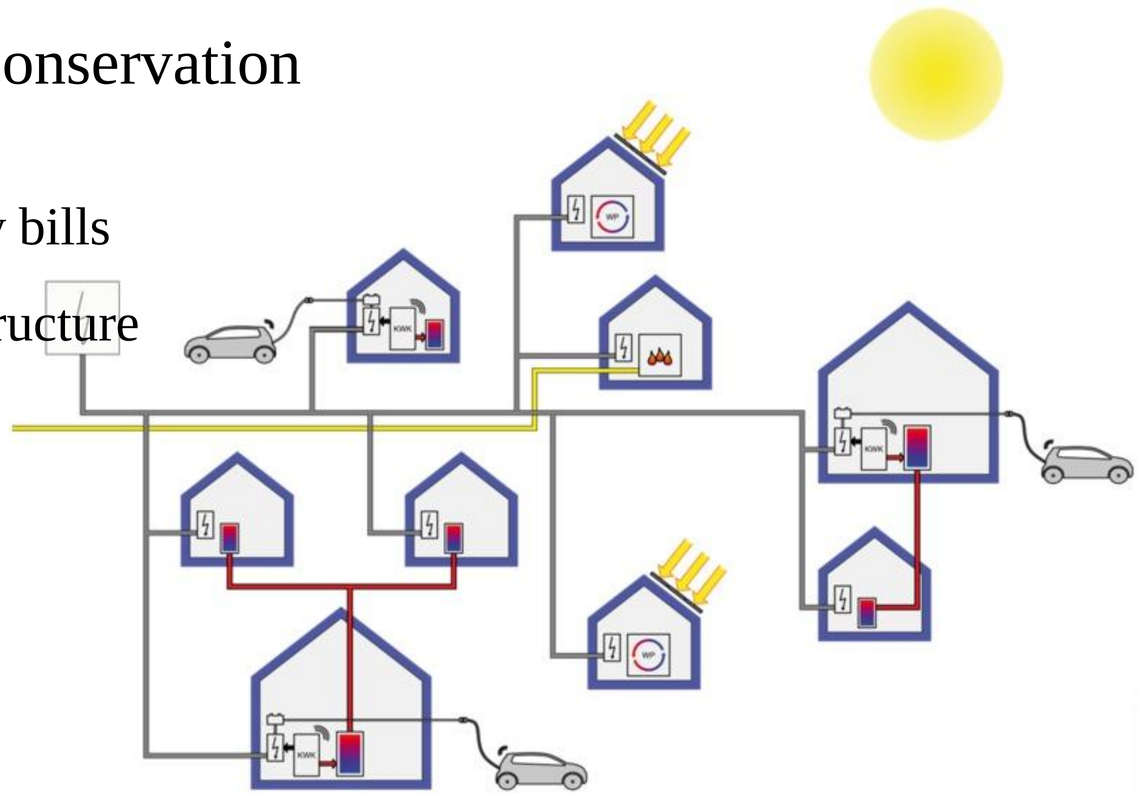
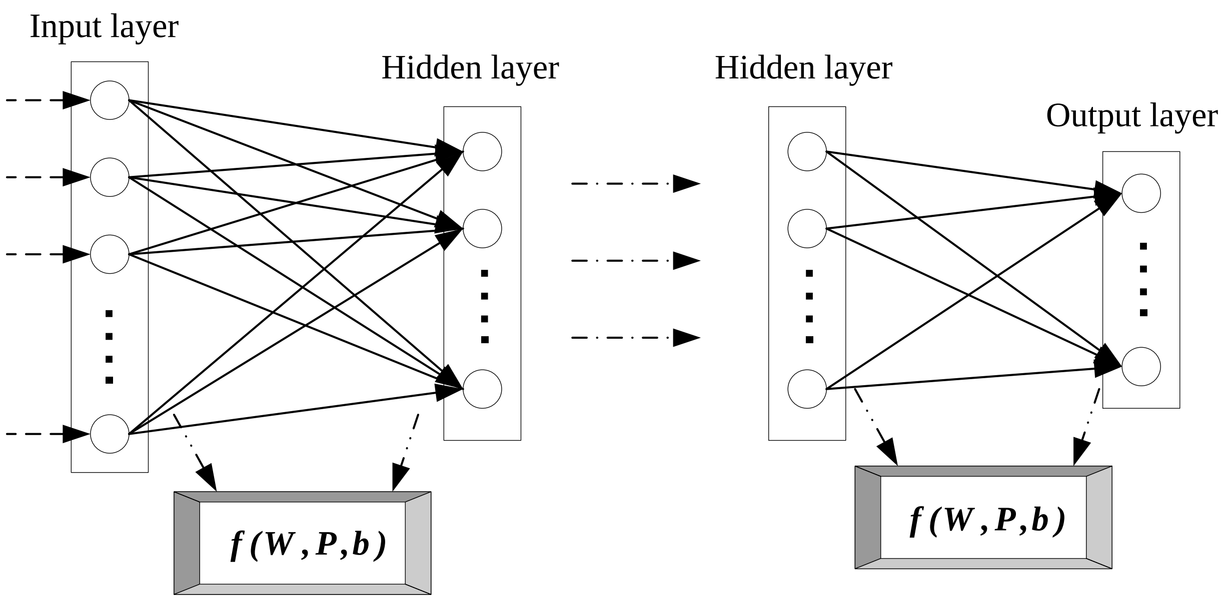


Image source: www.hannovermesse.de

Load forecasting with neural network

Artificial Neural Network (ANN) architecture

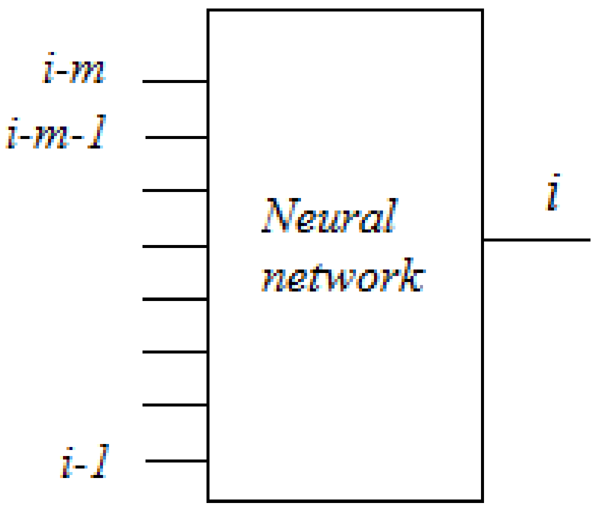


$$Y = f\,(W, P, b)$$

Y : output   W : weights,   P : inputs,   b : biases

Load forecasting with neural network

Iterative forecasting (single output)



i : predicted hour
m : historical data points

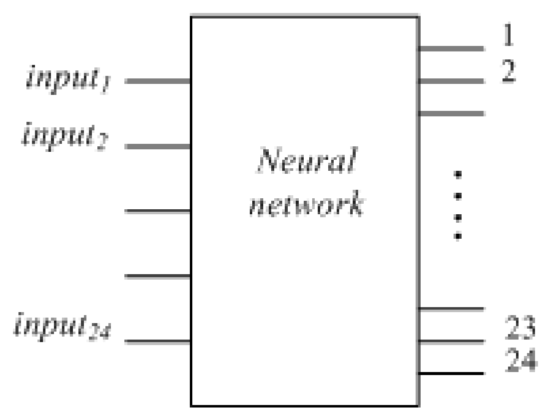
Iterative forecasting

- Forecast one hourly load at a time
- m input nodes for m input data points

Single Output advantageous

- Input data are updated
- Small model

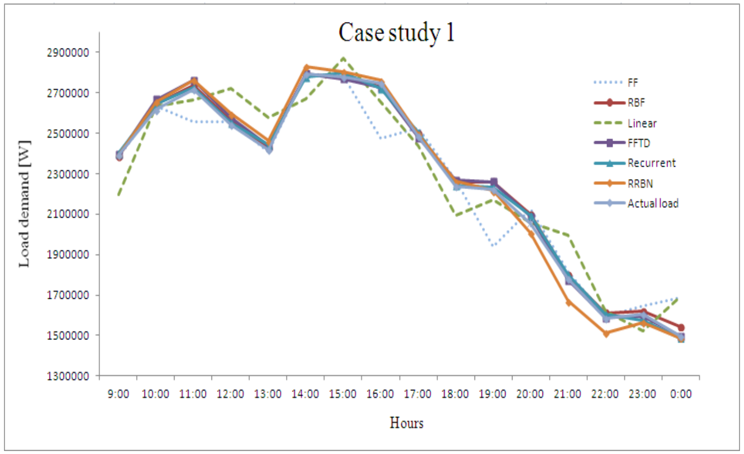
Multi-output



Comparative study of load forecasting

Case study 1 : Average-workday load profile of medium-sized businesses in winter

- Six models are selected for comparison
- 8-hour data is used to predict load at hour 9, and so on

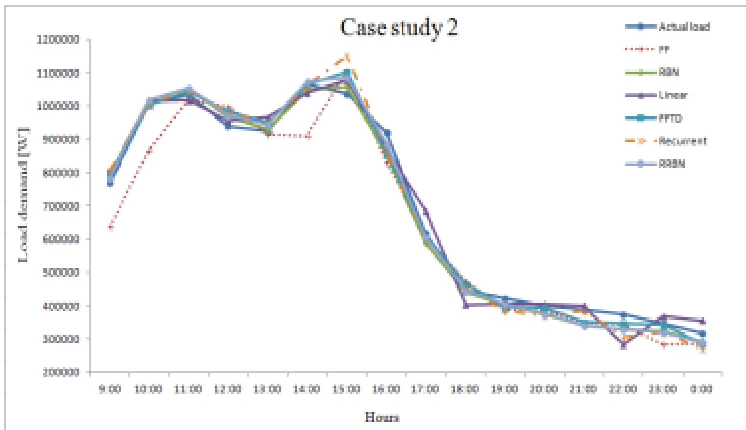


Models / MSE	Training data	Test data	Time [seconds]
FF	0.0044	0.0046	1.5812
Radial basis	2.5037e-31	7.4731e-5	0.078
Linear	0.0021	0.0020	0.4128
FFTD	1.0723e-32	1.0235e-4	0.5092
Recurrent	1.8951e-32	9.559e-5	1.2544
RRBN	4.3142e-32	2.5933e-4	0.094

FF : Feedforward
FFTD : Focused Time-Delay
RRBN : Recurrent radial basis neural network

Comparative study of load forecasting

Case study 2 : Peak-workday load demand of nonprofit businesses in summer



Models / MSE	Training data	Testing data	Time [seconds]
FF	0.0054	0.0056	1.5904
Radial basis	1.1402e-31	7.2003e-4	0.1186
Linear	9.5767e-4	0.0013	0.3910
FFTD	1.8643e-32	9.8249e-4	0.5124
Recurrent	3.1316e-32	7.2450e-004	0.9936
RRBN	5.3522e-31	6.2539e-4	0.093

Performance ranking

Ranking	Case study 1		Case study 2	
	MSE	**Time**	**MSE**	**Time**
1	Radial basis	Radial basis	RRBN	RRBN
2	Recurrent	RRBN	Radial basis	Radial basis
3	FFTD	Linear	Recurrent	Linear

- Challenge to design the architecture
- Simplest method leads to surplus hidden neurons and generalization problem

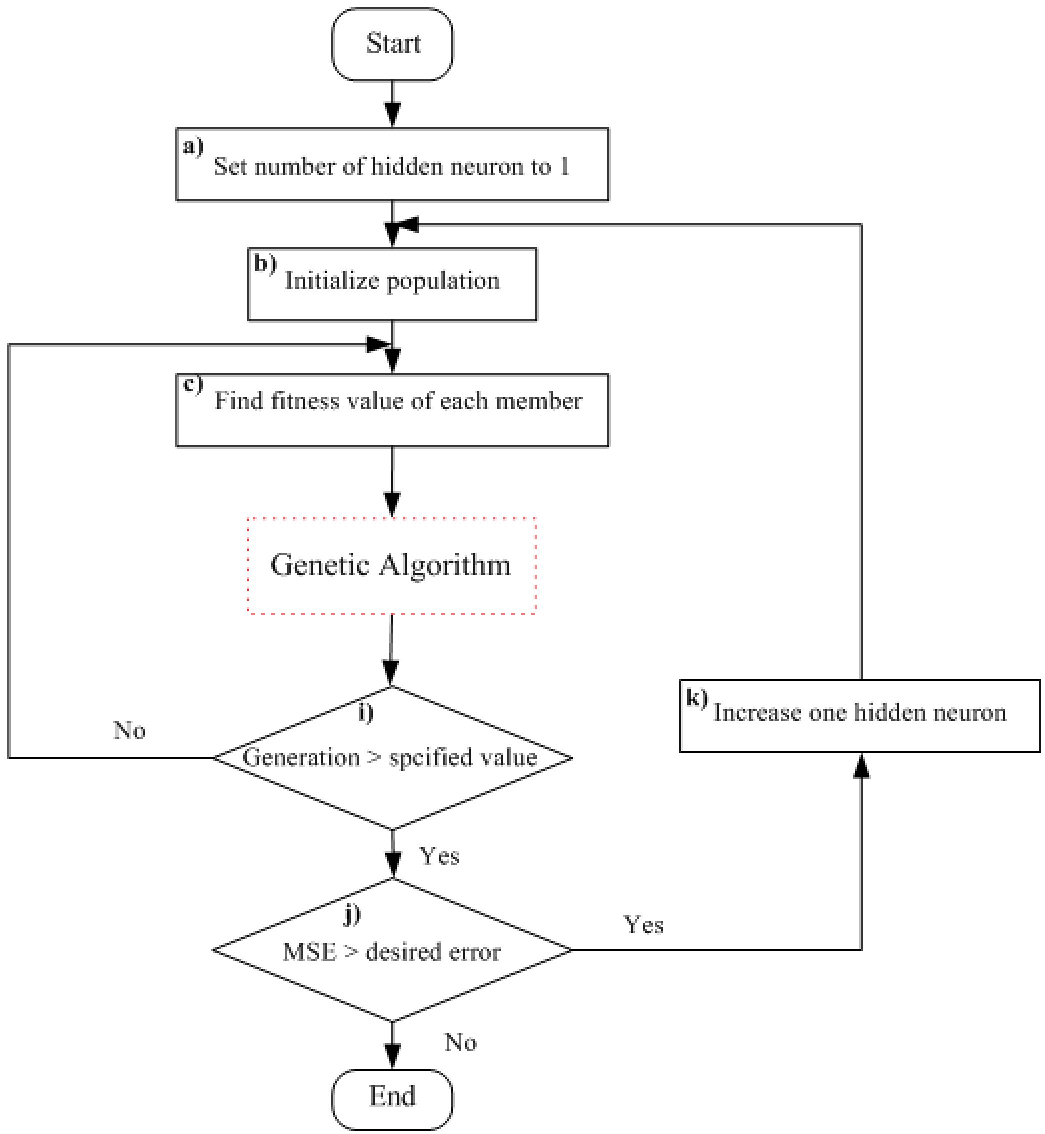
Generalization or overfitting problem

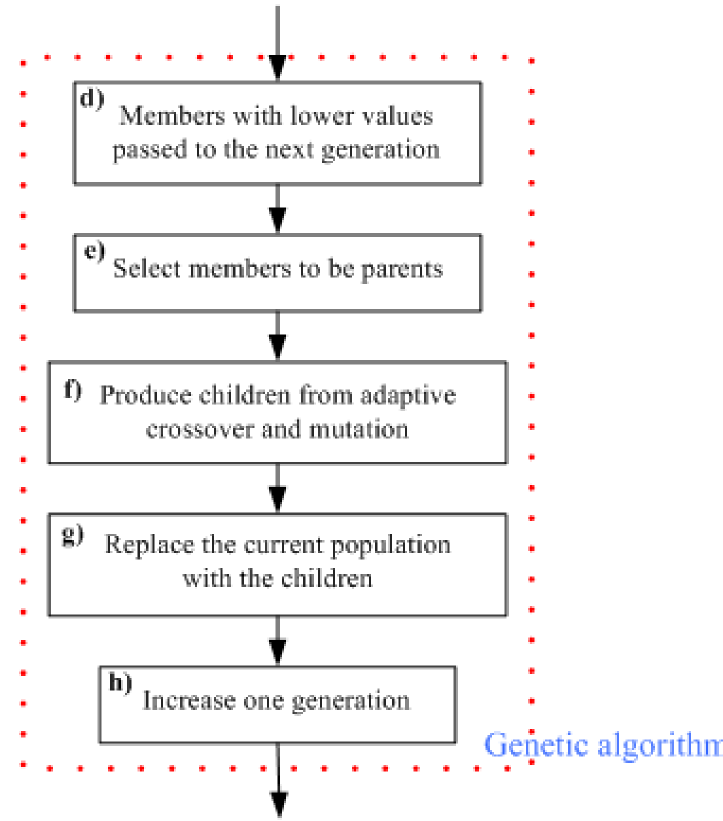
- The neural network fits well with the training data and gives small errors
- The network memorizes the pattern of the training data
- It can not adjust to the new slightly different data
- The output of the new data is poor.

Causes:

- The insufficiency of the training data
- An excessive numbers of hidden neurons

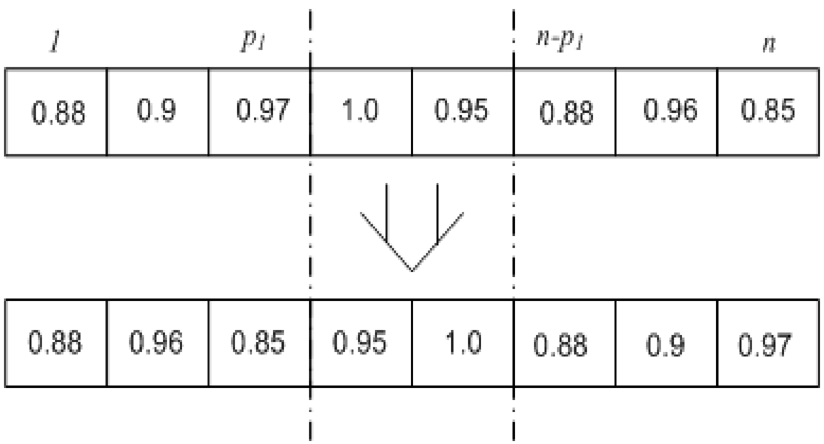
Proposed Algorithm



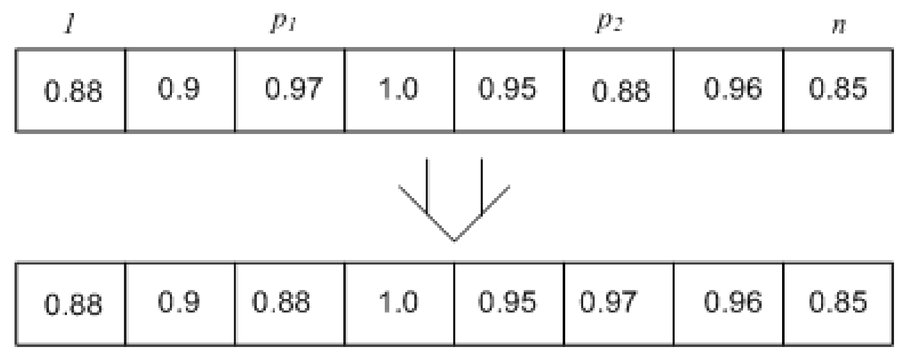


Proposed Algorithm

Crossover method

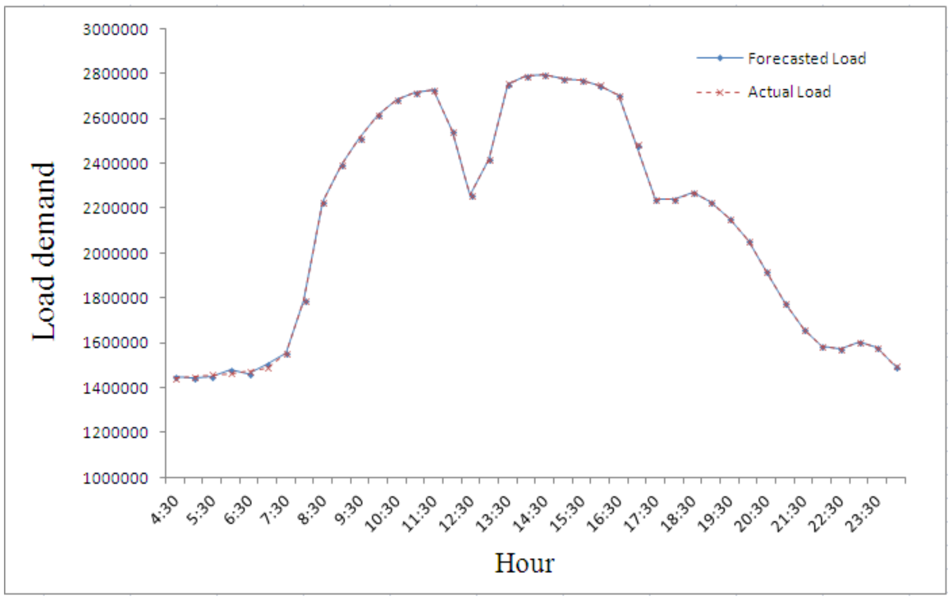


Mutation method



Simulation results

Radial basis neural network



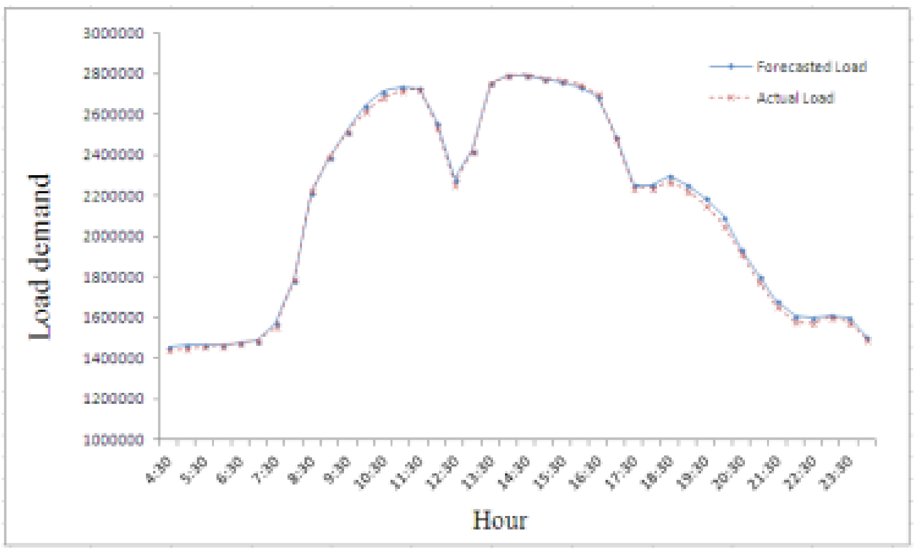
MSE is $2.4661e^{-6}$

Mean squared error

Numbers of Hidden neurons	The proposed approach	Orthogonal Least Square
1	0.0012	0.0034
2	$2.3447e^{-4}$	0.0029
3	$3.2659e^{-4}$	0.0020
4	$5.1468e^{-5}$	0.0012
5	$3.2527e^{-6}$	$6.8513e^{-4}$
6	$9.2695e^{-7}$	$6.2697e^{-4}$
7	$1.0502e^{-8}$	$2.1013e^{-4}$
8	$5.2518e\text{-}^{12}$	$1.1743e^{-4}$
9	0	$4.9304e^{-32}$

Simulation results

Recurrent radial basis neural network



MSE is $4.519e^{-5}$

Mean squared error

Numbers of Hidden neurons	The proposed approach	Orthogonal Least Square
1	$0.2266e^{-3}$	0.0037
2	$0.0175e^{-3}$	0.0032
3	$0.0219e^{-3}$	0.0020
4	$0.0052e^{-3}$	0.0013
5	$0.0003e^{-3}$	$7.9012e^{-4}$
6	$2.0664e^{-8}$	$7.8934e^{-4}$
7	$6.5128e^{-9}$	$6.3322e^{-4}$
8	$3.6095e^{-13}$	$3.2801e^{-4}$
9	$4.9304e^{-33}$	$6.1630e^{-33}$

Conclusion

Proposed approach

- The proposed algorithm uses modified genetic algorithm
- Optimize the numbers of hidden neurons
- Avoid generalization or overfitting problem
- Uses less hidden neurons compared to the OLS method

Future work

The load forecasting includes the effects of :

- Demand response
- Energy storage
- Electric vehicles
- Electricity prices

Thank you