Applied Artificial Intelligence in Energy: Challenges and Solutions

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Outline

- Biography
- Research Program
- Machine Learning Solutions in Power Systems
  - Data-Driven Load Forecasting
- Data Analysis in Nuclear Security
  - Machine Intelligence Solutions
- Future Directions

Brief Biography

University of Thessaly, Volos, Greece

Education

2012 Ph.D. Nuclear Eng.(Intelligent Systems), *Purdue University*

2010 M.S. Nuclear Eng.(Intelligent Systems), *Purdue University*

2005 Dipl.-Ing. Electrical and Computer Eng., *University of Thessaly, Greece*

2018 Power System Certificate, *Georgia Institute of Technology*

Research Experience

2014 – Present	Research Assistant Professor, *Purdue University*
March 2017	Visiting Professor, *Electrical and Computer Eng., University of Thessaly*
May 2016	Visiting Scientist, *Power and Energy Systems Group, Oak Ridge National Laboratory*
June 2015	Research Visitor, *Nevada National Security Site (LANL)*
2012-2014	Postdoctoral Research Fellow, *UNEP, The University of Utah*
2010-2012	Guest Researcher, *Detection and Diagnostics Group, Argonne National Laboratory*
2004	Summer Intern, *Greek Telecommunications Organization*

Research Program

- Artificial Intelligence in Power Systems
- Smart Power and Energy Systems
- Pattern Recognition in Cyber-Physical Systems

Alamaniotis, M., Gatsis, N., & Tsoukalas, L.H., "Virtual Budget: Integration of Electricity Load and Price Anticipation for Load Morphing in Price-Directed Energy Utilization," *Electric Power Systems Research, In press*.

Alamaniotis, M., Bargiotas, D., Bourbakis, N., & Tsoukalas, L.H., "Genetic Optimal Regression of Relevance Vector Machines for Electricity Price Forecasting in Smart Grids," *IEEE Transactions on Smart Grid*, vol. 6(6), November 2015, pp. 2997-3005.

Alamaniotis, **M**., Ikonomopoulos, A., & Tsoukalas, L.H., "Evolutionary Multiobjective Optimization of Kernel-based Very Short-Term Load Forecasting," *IEEE Transactions on Power Systems*, Institute of Electrical and Electronic Engineers, vol. 27 (3), August 2012, pp. 1477-1484.

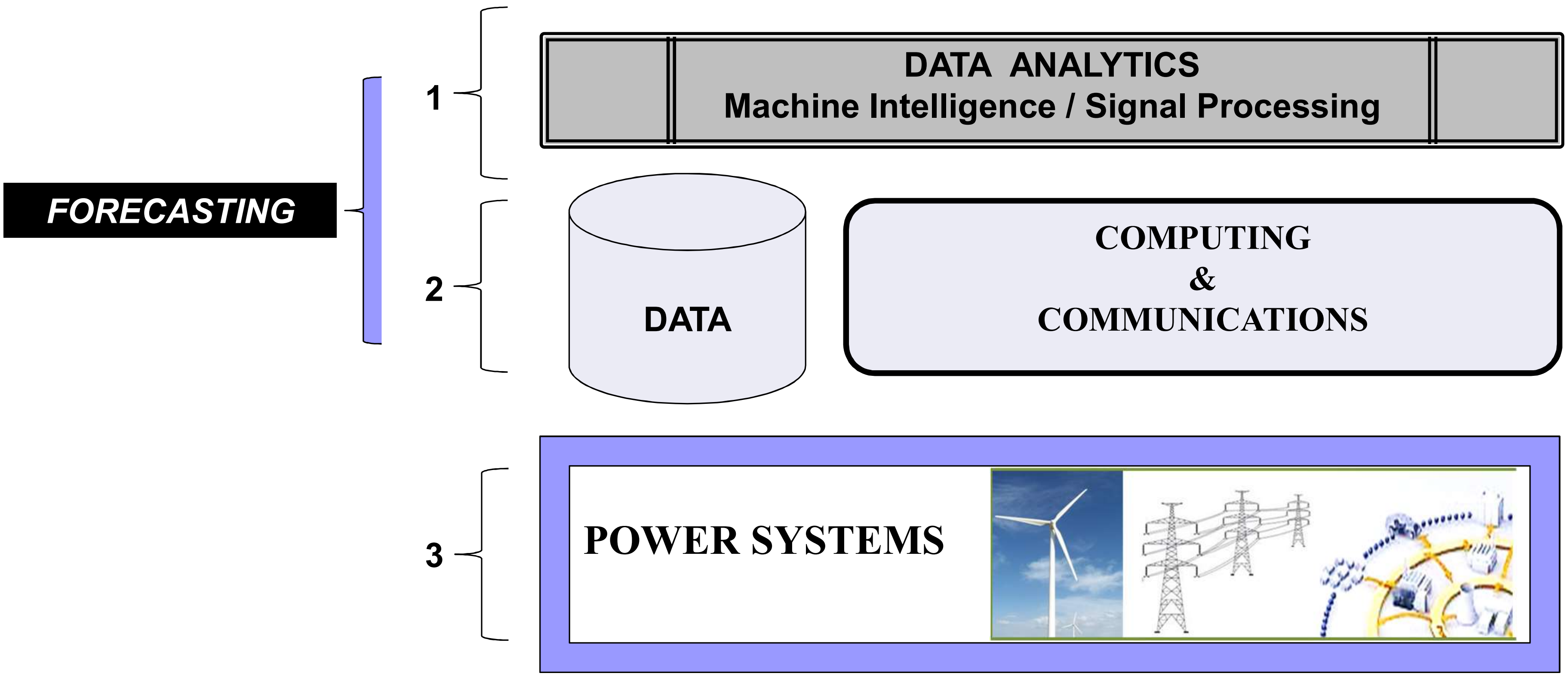
- Data Analytics and Sensor Networks
- Machine Learning in National Security and Nuclear Nonproliferation Applications

Alamaniotis, **M**., Heifetz, A., Raptis, A., & Tsoukalas, L.H, "Fuzzy-Logic Radioisotope Identifier for Gamma Spectroscopy in Source Search," *IEEE Transactions on Nuclear Science*, vol. 60 (4), August 2013, pp. 3014-3024.

Alamaniotis, M., Mattingly, J., & Tsoukalas, L.H., "Kernel-based Machine Learning for Background Estimation of NaI Low Count Gamma Ray Spectra," *IEEE Transactions on Nuclear Science*, Institute of Electrical and Electronic Engineers, vol. 60 (3), June 2013, pp. 2209-2221..

Alamaniotis, M., & Tsoukalas, L.H., "Assessment of Gamma-Ray Spectra Analysis Method Utilizing the Fireworks Algorithm for Various Error Measures," *Critical Developments and Applications of Swarm Intelligence*, Chapter 7, 2017, pp. 1-22.

Critical Energy: Applications
Smart Power Systems



Main Components

Artificial Intelligence Solutions in Power

Smart Power Systems

Ensemble Gaussian Process
Load Forecasting

Alamaniotis, M., Ikonomopoulos, A., & Tsoukalas, L.H., "Evolutionary Multiobjective Optimization of Kernel-based Very Short-Term Load Forecasting," *IEEE Transactions on Power Systems*, vol. 27 (3), August 2012, pp. 1477-1484

Learning from Loads
Cybersecurity

Alamaniotis, M., & Tsoukalas, L.H., "Learning from Loads: An Intelligent System for Decision Support in Identifying Nodal Load Disturbances of Cyber-Attacks in Smart Power Systems using Gaussian Processes and Fuzzy Inference," *Data Analytics and Decision Support for Cybersecurity – Trends, Methodologies and Applications,* Springer, 2017, Chapter 8, pp. 223-241.

Consumption Analysis
Hidden Facility Detection

Alamaniotis, M., & Tsoukalas, L.H., "Anticipatory system for detection of hidden facilities utilizing nodal load consumption information in smart grids," *IEEE Global Conference on Signal and Information Processing* (GlobalSip), Washington D.C., USA, December 2016, pp. 806-810.

RVR Kernels
Electricity Price Forecasting

Alamaniotis, M., Bargiotas, D., Bourbakis, N., & Tsoukalas, L.H., "Genetic Optimal Regression of Relevance Vector Machines for Electricity Price Forecasting in Smart Grids," *IEEE Transactions on Smart Grid*, Institute of Electrical and Electronic Engineers, vol. 6(6), November 2015, pp. 2997-3005.

Neural Networks
Line Congestion Monitoring

Fainti, R., Alamaniotis, M., & Tsoukalas, L.H., "Three-Phase Line Overloading Predictive Monitoring utilizing Artificial Neural Networks," *IEEE International Conference on Intelligent System Application to Power Systems (ISAP 2017)*, San Antonio, TX, USA, September 2017, pp. 6.

Fuzzy Driven
Distribution Grid Partition

Nasiakou, A., Alamaniotis, M., Tsoukalas, L.H., & Vavalis, E., "Dynamic Data Driven Partitioning of Smart Grid Using Learning Methods," *Selected Topics on Dynamic Data Driven Application Systems (DDDAS)*, Edited Book, Springer, 2016.

Learning Kernel Machines: *Very-Short-Term Load Forecasting*

Alamaniotis, M., & Tsoukalas, L.H., “Multi-Kernel Assimilation for Predictive Intervals in Nodal Short Term Load Forecasting,” *IEEE International Conference on Intelligent System Application to Power Systems* (ISAP 2017), San Antonio, TX, USA, September 2017, pp. 1-6.

Alamaniotis, M., Ikonomopoulos, A., & Tsoukalas, L.H., “Evolutionary Multiobjective Optimization of Kernel-based Very Short-Term Load Forecasting,” *IEEE Transactions on Power Systems*, Institute of Electrical and Electronic Engineers, vol. 27 (3), August 2012, pp. 1477-1484.

Very-Short Term Load Forecasting (VSTLF)

- VSTLF: Forecasting of Load Demand from a few minutes up to two hours ahead-of-time

USEFULENESS

- Planning of Grid Operation and Scheduling of Maintenance
- Efficient Energy Management
- Grid Reliability
  - Prevent Voltage Drop
  - Prevent Overvoltage
  - Reduce Faults and Blackouts
- Auction based Energy Markets
  - Determine Price
- Smart Cities / Optimization

CHALLENGES

- High Volatility of Data
- Dynamically Varying Factors
- Complicated Load Features
- Random Effects
- Irregular Days
- Real-Time Forecasting (Speed)

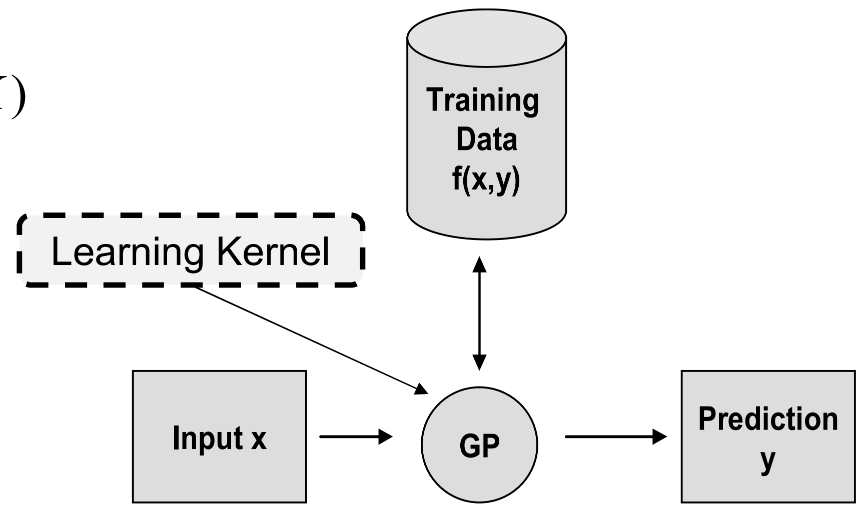
Gaussian Process for Machine Learning

- In **machine learning**:
  - Gaussian Processes (GP) are identified as **learning kernel methods**
  - Kernels: Dual Representation: $k(x_1, x_2) = \varphi(x_1)^T \varphi(x_2)$
  - Prior distribution over functions: $p(y) = N(y \mid 0, K)$
  - Predictive distribution (Rasmussen 2006):

$$\left.\begin{aligned} m\left(x_{N+1}\right) &= k^T K_*^{-1} t \\ \sigma^2\left(x_{N+1}\right) &= k_* - k^T K_{*N}^{-1} k \end{aligned}\right\} \boxed{\text{Normal distr. of y for input: } x_{N+1}}$$

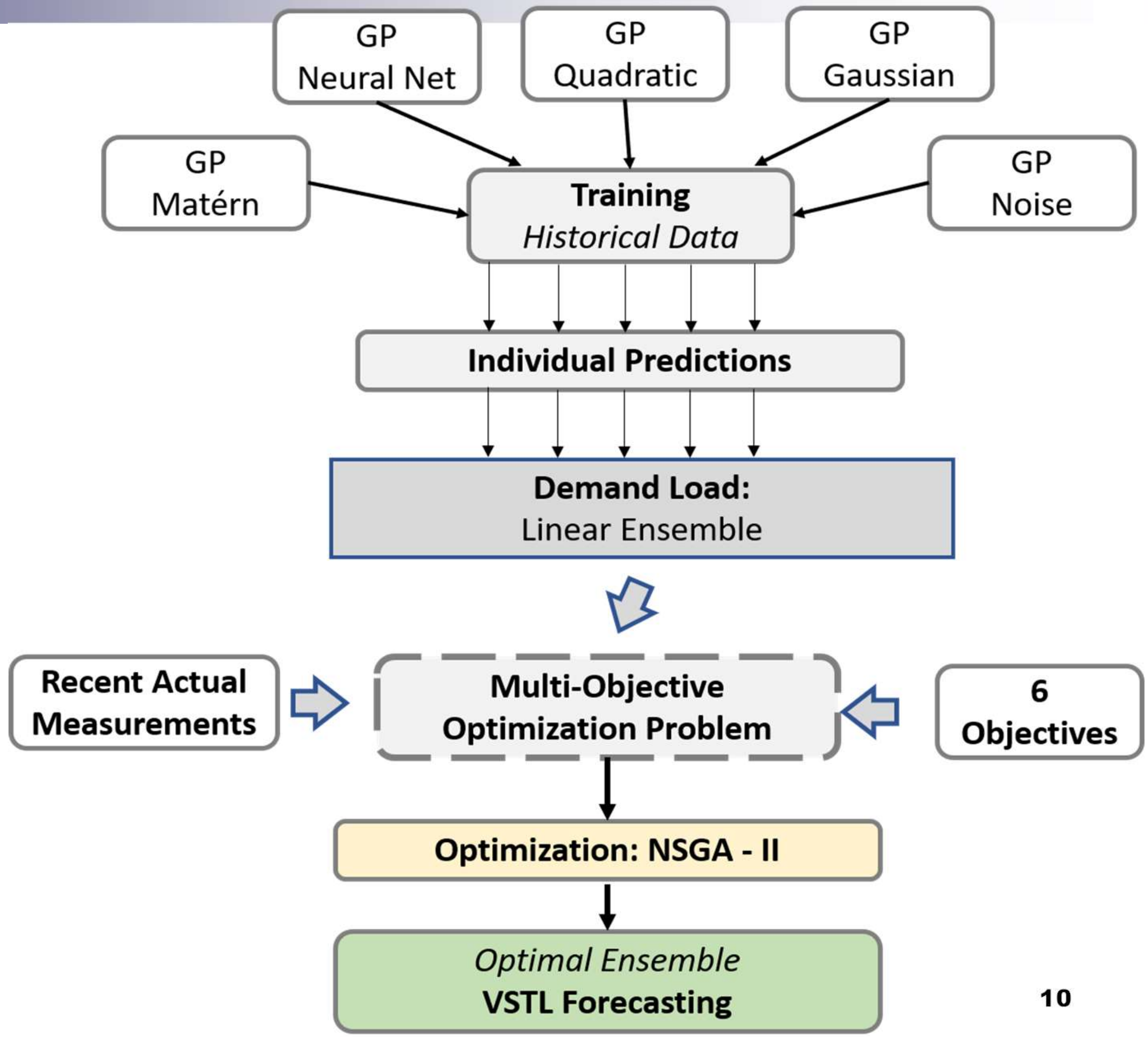
  - With K being the Gram Matrix:

$$K_*(x_i, x_j) = k(x_i, x_j) + \sigma_n^2 \delta_{ij}$$



Methodology

- Analysis of Demand Data
  - Family of GP
  - Different kernels
- Formulating Multi-Objective Problem
- Use of Evolutionary Computing
- 2 Stages of Learning



Load Analysis: **Linear Ensemble**

Matérn *Neural Net* *Quadratic* *Gaussian* *Noise*

$$\boldsymbol{Load} = \alpha_M * P_M + \alpha_{NN} * P_{NN} + \alpha_Q * P_Q + \alpha_G * P_G + \alpha_N * P_N$$

<u>Approach</u>

- Different *Data Properties* modeled by various *kernels*
- Weights of GP Predictions (P_M,P_{NN},P_Q,P_G,P_N)
  - Contribution of Data Properties

Unknown

- Approximation of Load Dynamics via Data Properties of Predictions

Kernel Formulas

Gaussian Kernel

$$k(\mathbf{x}_1, \mathbf{x}_2) = \exp\left(-\frac{\left\|\mathbf{x}_1 - \mathbf{x}_2\right\|^2}{2\sigma^2} \right)$$

Matérn Kernel

$$k(\mathbf{x}_1, \mathbf{x}_2) = \left(\frac{2^{1-\theta_1}}{\Gamma(\theta_1)} \right) \left[\frac{\sqrt{2\theta_1} |\mathbf{x}_1 - \mathbf{x}_2|}{\theta_2} \right]^{\theta_1} K_{\theta_1} \left(\frac{\sqrt{2\theta_1} |\mathbf{x}_1 - \mathbf{x}_2|}{\theta_2} \right)$$

Rational Quadratic Kernel

$$k(\mathbf{x}_1, \mathbf{x}_2) = \left(1 + \frac{|\ \mathbf{x}_1 - \mathbf{x}_2\ |^2}{2a\theta_1^2} \right)^{-a}$$

Neural Network Kernel

$$k(\mathbf{x}_1, \mathbf{x}_2) = \theta_0 \sin^{-1} \left(\frac{2\tilde{\mathbf{x}}_1^T \Sigma \tilde{\mathbf{x}}_2}{\sqrt{\left(1 + 2\tilde{\mathbf{x}}_1^T \Sigma \tilde{\mathbf{x}}_1\right)\left(1 + 2\tilde{\mathbf{x}}_2^T \Sigma \tilde{\mathbf{x}}_2\right)}} \right)$$

Noise Kernel

$$k(\mathbf{x}_1, \mathbf{x}_2) = \theta_1 \delta_{x_1 x_2}$$

Objective Functions

Mean Square Error

$$MSE = \frac{1}{N} \sum_{t=1}^{N} (R_t - P_t)^2$$

Mean Absolute Error

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |R_t - P_t|$$

Maximum Absolute Percentage Error

$$MAP = \max\left(100 \times \left|\frac{R_t - P_t}{R_t}\right|\right)$$

Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (R_t - P_t)^2}{N}}$$

Mean Absolute Percentage Error

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \left|\frac{R_t - P_t}{R_t}\right|$$

Theil Coefficient

$$Theil = \frac{\sqrt{\frac{\sum_{t=1}^{N} (R_t - P_t)^2}{N}}}{\sqrt{\frac{\sum_{t=1}^{N} (R_t)^2}{N}}}$$

R_t: Actual Value at time t P_t: Forecasted Value at time t

Multi-Objective Optimization Problem

$$\underset{\boldsymbol{\alpha}}{\text{minimize}}\ [\mathbf{M}(\boldsymbol{a})]$$

$$\textbf{\textit{subject to}}\ \left\{Load_F^{(t)}(\boldsymbol{\alpha}) \geq 0\right\}$$

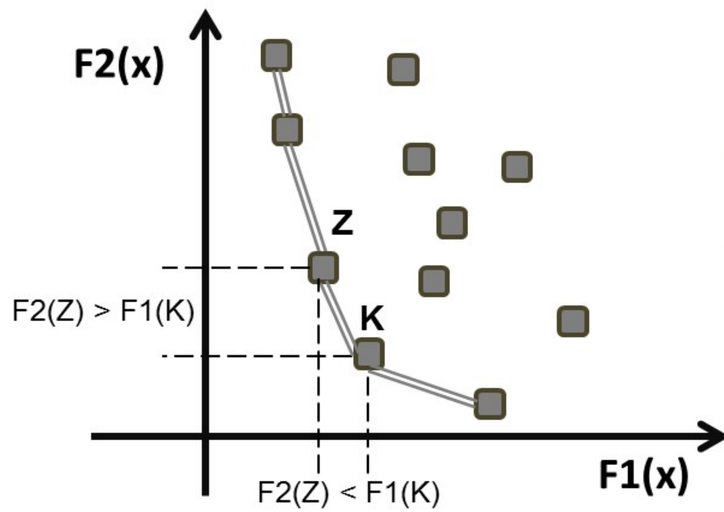
$$\textbf{\textit{where}}\ t = 1, \ldots, t_n$$

$$\mathrm{M}(\boldsymbol{a}) = [MSE(\boldsymbol{\alpha}), RMSE(\boldsymbol{\alpha}), MAE(\boldsymbol{\alpha}), MAPE(\boldsymbol{\alpha}), MAP(\boldsymbol{\alpha}), Theil(\boldsymbol{\alpha})]$$

$$\boldsymbol{\alpha} = [a_M, a_{NN}, a_Q, a_G, a_N]$$

$n = 6$ ⟶ *6 most recent measurement (last 30 min)*

Solution: Pareto Theory



•A Pareto frontier illustration where each box represents a feasible solution.

•Boxes Z and K are part of Pareto Frontier

<u>Multiobjective Optimization Problems</u>

$$\min_{\mathbf{x}} \mathbf{C}(\mathbf{x}) = \left[C_1(\mathbf{x}), C_2(\mathbf{x}), \ldots, C_N(\mathbf{x})\right]$$

$$s.t. \quad \mathrm{f}_i(\mathbf{x}) \le 0, \qquad i = 1,\ldots,k$$

$$\mathrm{g}_j(\mathbf{x}) = 0, \qquad j = 1,\ldots,m$$

A point, $\mathbf{x}^* \in \mathbf{X}$, *is Pareto Optimal iff there does not exist another point,* $\mathbf{x} \in \mathbf{X}$, *such that* $\mathbf{C}(\mathbf{x}) \le \mathbf{C}(\mathbf{x}^*)$, *and* $C_i(\mathbf{x}) \le C_i(\mathbf{x}^*)$ *for at least one function .*

SOLUTION FINDING Using Evolutionary Computing

- Non-dominated Sorting Genetic Algorithm – II (NSGA-II)
  - Uses Pareto Theory to identify a solution

Testing Setup

- Datasets from Chicago Metropolitan Area
- Training Datasets
  - Measurements from Previous Day
  - Measurements from respective Day a Week ago
  - Measurements from respective Day a Year ago
- Forecasts of Load at 5min Intervals
- Benchmark against:
  - Support Vector Regression using Gaussian Kernel
  - Autoregressive Moving Average (ARMA)
    - Determined by Akaike Information Criterion (AIC)

Regular Week Results

FALL WEEK (September)

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Monday - Friday			Saturday - Sunday		
MSE	0.066	2.4377	0.691	0.0553	4.4798	0.7915
RMSE	0.2366	1.2433	0.7999	0.2201	1.7876	0.8579
MAE	0.1974	1.2052	0.6276	0.1872	1.7643	0.6596
MAPE	1.1756	6.6554	4.021	1.5877	14.0696	6.4998
MAP	0.0237	0.0872	0.2014	0.0316	0.1716	0.3198
Theil	0.0009	0.0044	0.0022	0.0017	0.0118	0.0071

WINTER WEEK (January)

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Monday - Friday			Saturday - Sunday		
MSE	0.3686	9.0534	7.9835	0.4042	4.4035	0.5689
RMSE	0.5173	2.5245	2.0011	0.5092	1.6485	0.6964
MAE	0.4552	2.4932	1.4666	0.4428	1.6055	0.5197
MAPE	1.8561	9.5868	7.4123	2.04	7.1642	2.4531
MAP	0.0331	0.1108	0.4912	0.0374	0.089	0.1297
Theil	0.0009	0.0039	0.0041	0.0011	0.0033	0.0015

SPRING WEEK (April)

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Monday - Friday			Saturday - Sunday		
MSE	0.2973	1.956	7.8579	0.0669	8.6265	0.4441
RMSE	0.4404	1.2115	1.9918	0.233	2.6345	0.6067
MAE	0.3899	1.1675	1.7528	0.1979	2.6201	0.47
MAPE	1.9895	5.5971	7.8527	1.5036	19.8321	3.8302
MAP	0.0343	0.0742	0.2815	0.0296	0.2278	0.2183
Theil	0.0012	0.003	0.0036	0.0014	0.0154	0.0034

SUMMER WEEK (Jun-Jul)

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Monday - Friday			Saturday - Sunday		
MSE	0.071	3.5728	0.6375	0.0535	6.9237	0.4078
RMSE	0.2403	1.4586	0.7569	0.2048	2.4092	0.6326
MAE	0.2007	1.422	0.5868	0.1716	2.3927	0.5031
MAPE	0.987	6.1254	3.0301	1.302	18.8903	4.0509
MAP	0.0203	0.079	0.1487	0.0268	0.2138	0.1692
Theil	0.0006	0.003	0.0016	0.0012	0.0156	0.0038

Special Days Results

Thanksgiving – Black Friday

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Thanksgiving Day			Black Friday Day		
MSE	0.0749	16.2865	0.2872	0.0596	2.4747	0.2369
RMSE	0.2437	3.2479	0.5359	0.2236	1.3958	0.4867
MAE	0.2062	3.2338	0.4356	0.1860	1.3658	0.3891
MAPE	1.6424	25.7547	3.6461	1.1672	7.5482	2.5714
MAP	0.0326	0.2819	0.1327	0.0237	0.0943	0.1160
Theil	0.0015	0.0206	0.0036	0.0009	0.0045	0.0016

M. Luther King – New Year

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Martin Luther King Day			New Year Day		
MSE	0.1000	12.8354	0.4483	0.0624	8.6289	0.3585
RMSE	0.2834	3.3455	0.6696	0.2333	2.7821	0.5987
MAE	0.2399	3.3245	0.5312	0.2007	2.7705	0.4621
MAPE	1.0342	13.3860	2.3684	1.3063	18.6138	3.2285
MAP	0.0203	0.1494	0.1107	0.0251	0.2081	0.1902
Theil	0.0005	0.0056	0.0011	0.0010	0.0126	0.0026

Independence - Labor

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Independence Day			Labor Day		
MSE	0.0580	35.3353	3.1954	0.0453	17.8265	0.2657
RMSE	0.2196	5.2498	1.7875	0.2015	4.0581	0.5154
MAE	0.1878	5.2441	1.4326	0.1687	4.0526	0.4218
MAPE	1.5770	42.8576	15.4015	1.3505	32.3218	3.5359
MAP	0.0307	0.4624	0.6398	0.0272	0.3484	0.1479
Theil	0.0015	0.0351	0.0156	0.0013	0.0261	0.0033

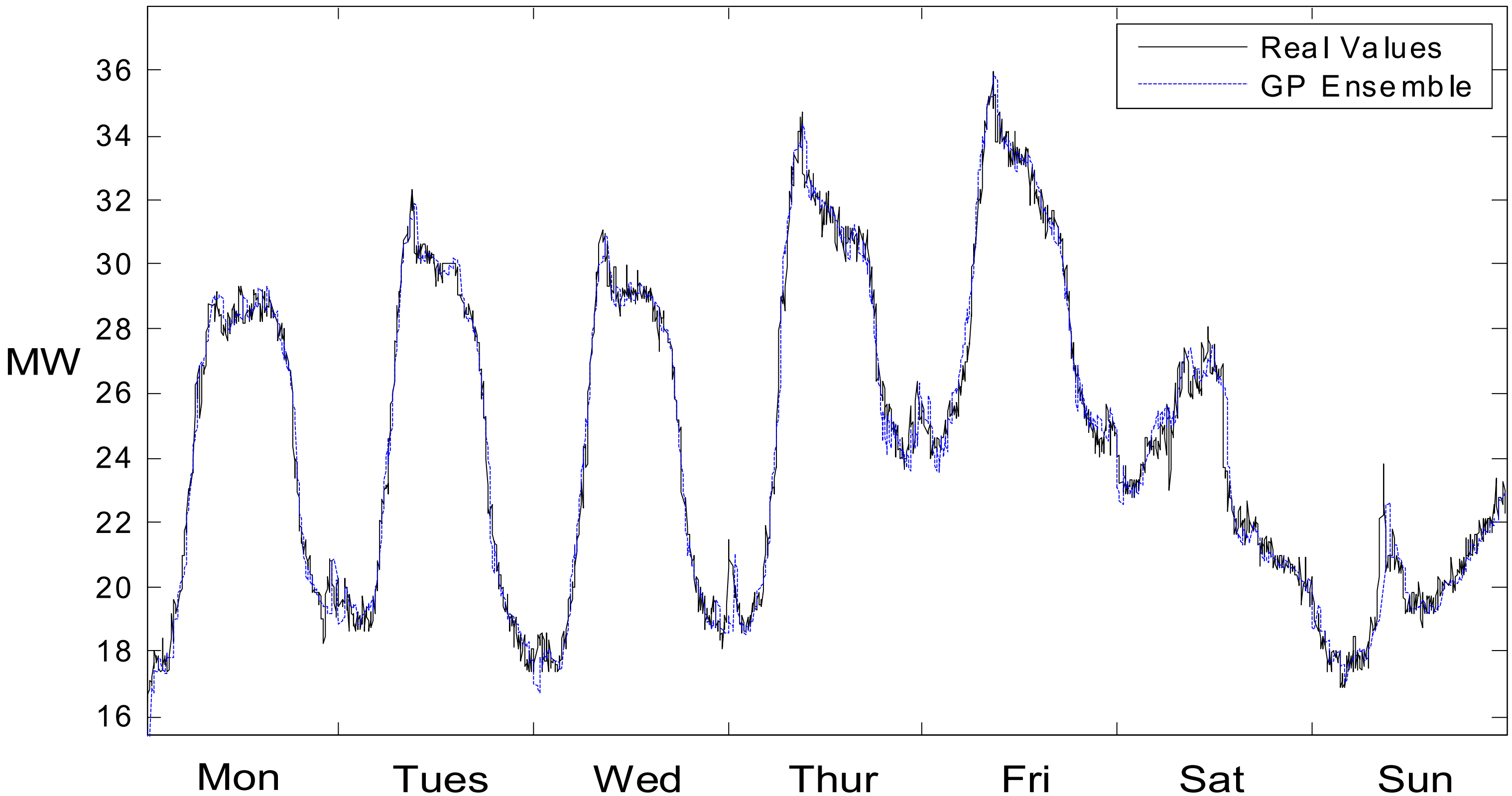
Good Friday - Memorial

Objective	GP Ensemble	SVR Gaussian	ARMA (AIC)	GP Ensemble	SVR Gaussian	ARMA (AIC)
	Good Friday Day			Memorial Day		
MSE	0.0800	3.1283	0.5346	0.0450	76.0419	0.0723
RMSE	0.2602	1.6171	0.7311	0.1976	8.0137	0.2689
MAE	0.2198	1.5874	0.5931	0.1631	8.0113	0.1980
MAPE	1.1963	8.6589	3.4616	1.3843	67.6102	1.6731
MAP	0.0241	0.1056	0.1445	0.0295	0.7090	0.0868
Theil	0.0008	0.0050	0.0020	0.0014	0.0574	0.0019

Main Conclusions from VSTLF

- **Analysis of Demand Load**
  - Linear Ensemble of GP
  - Set of 5 different Kernels
- **Two stage Learning**
  - Individual GP
  - Optimization of GP Ensemble
- **Multi-objective Problem**
  - 6 different Objective (error measures)
- **Testing**
  - High Accuracy
    - ARMA (AIC)
    - SVR with Gaussian Kernel

Winter (January) Week Visualization



	Weekday	Weekend
MSE	0.3686	0.4042
RMSE	0.5173	0.5092
MAE	0.4552	0.4428
MAPE	1.8561	2.04
MAP	0.0331	0.0374
Theil	0.0009	0.0011

Critical Energy Applications:

National Security and Nuclear Nonproliferation

Nuclear Security and Nonproliferation Challenges

- Identify the Origins of Nuclear Materials (e.g., Forensics)
- Monitor Global Fissile Material Production and Accountability
- Monitor Nonproliferation Activities (e.g., Hidden Facilities)
- Counter Nuclear Smuggling
- Enhance International Safeguards
- Enhance Public Safety from Terrorist Attacks

Border Inspection

Artif. Intelligence: Challenges

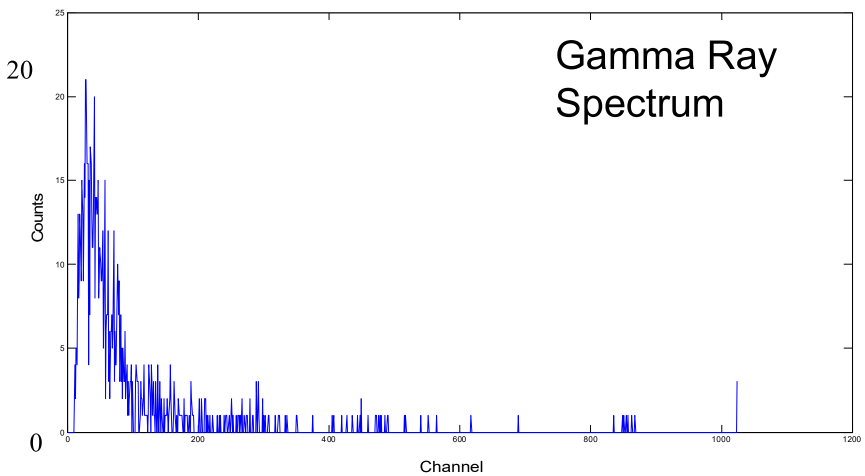
- Data Analysis from Radiation Sensors
  - Patterns of Interest
- Data Analysis of Sensor Networks
  - Mobile sensors / Static Sensors
- Data Fusion and Decision Making
- Threat Identification
  - Support Decision Making

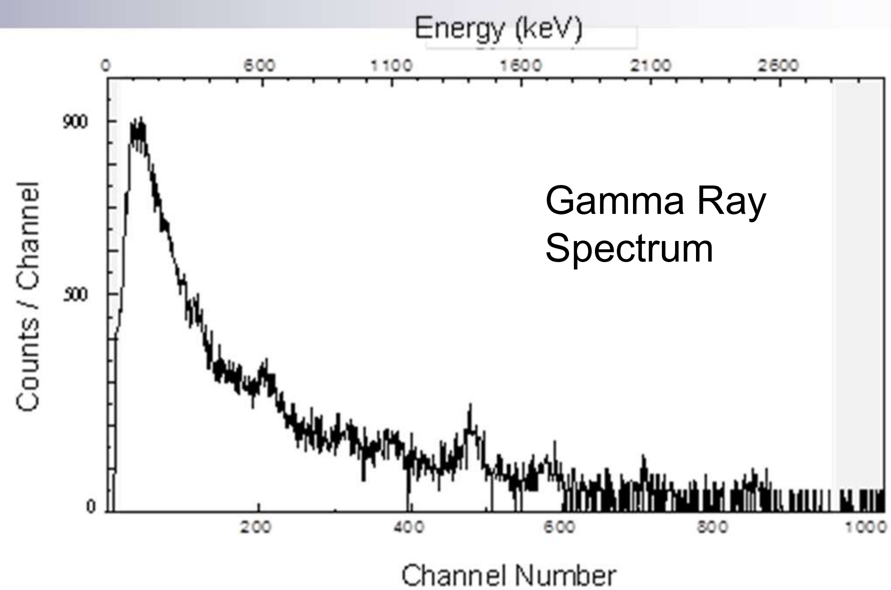
NYPD Officer with Rad Detector

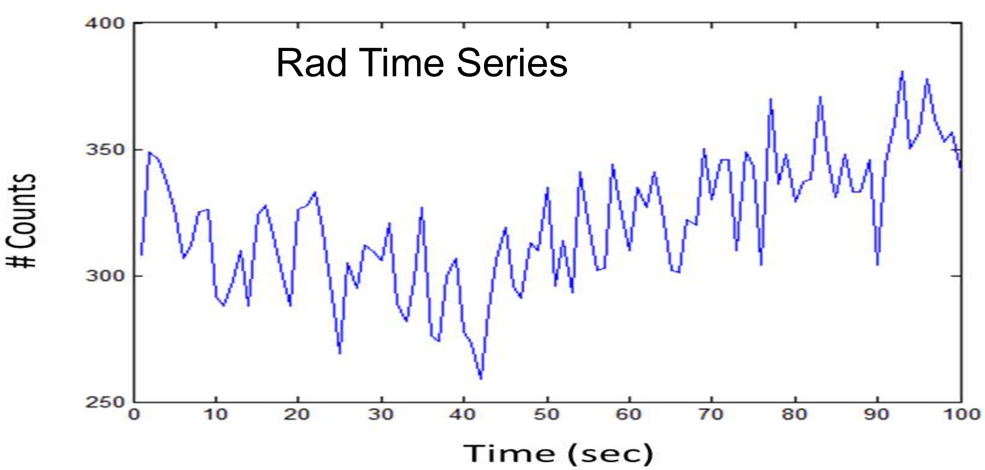
Monitoring for Radioactive Threats

AI Solutions:
Expertise not needed
Minimum Attention (less Fatigue)

Sensor Data







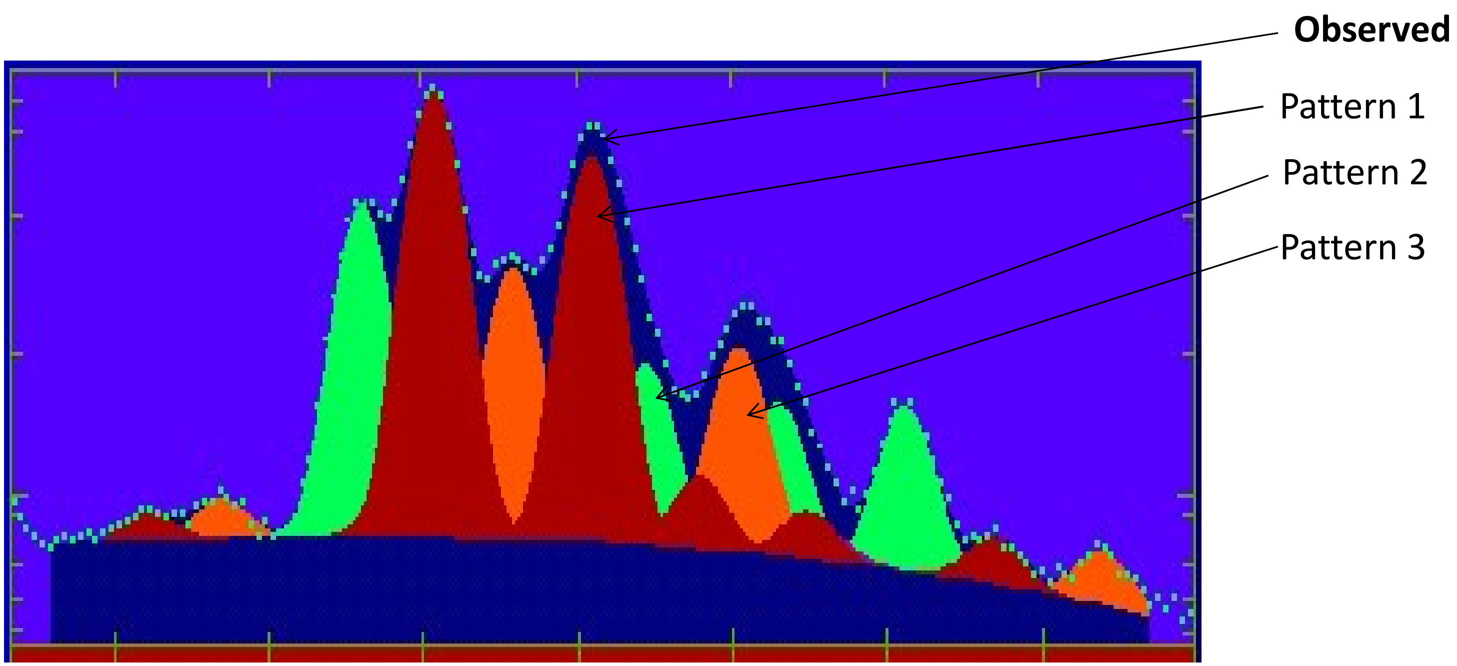
1) Measured Spectrum
= Aggregation of Patterns

2) Pattern -> Source Pattern
-> Background Pattern

BIG DATA PROBLEM

Analysis of a Spectrum

- **Signal analysis methodology principles**
  - Spectrum Stripping/ Synthesis



Analysis of Gamma Ray Signals
Fuzzy Logic Isotope Identifier

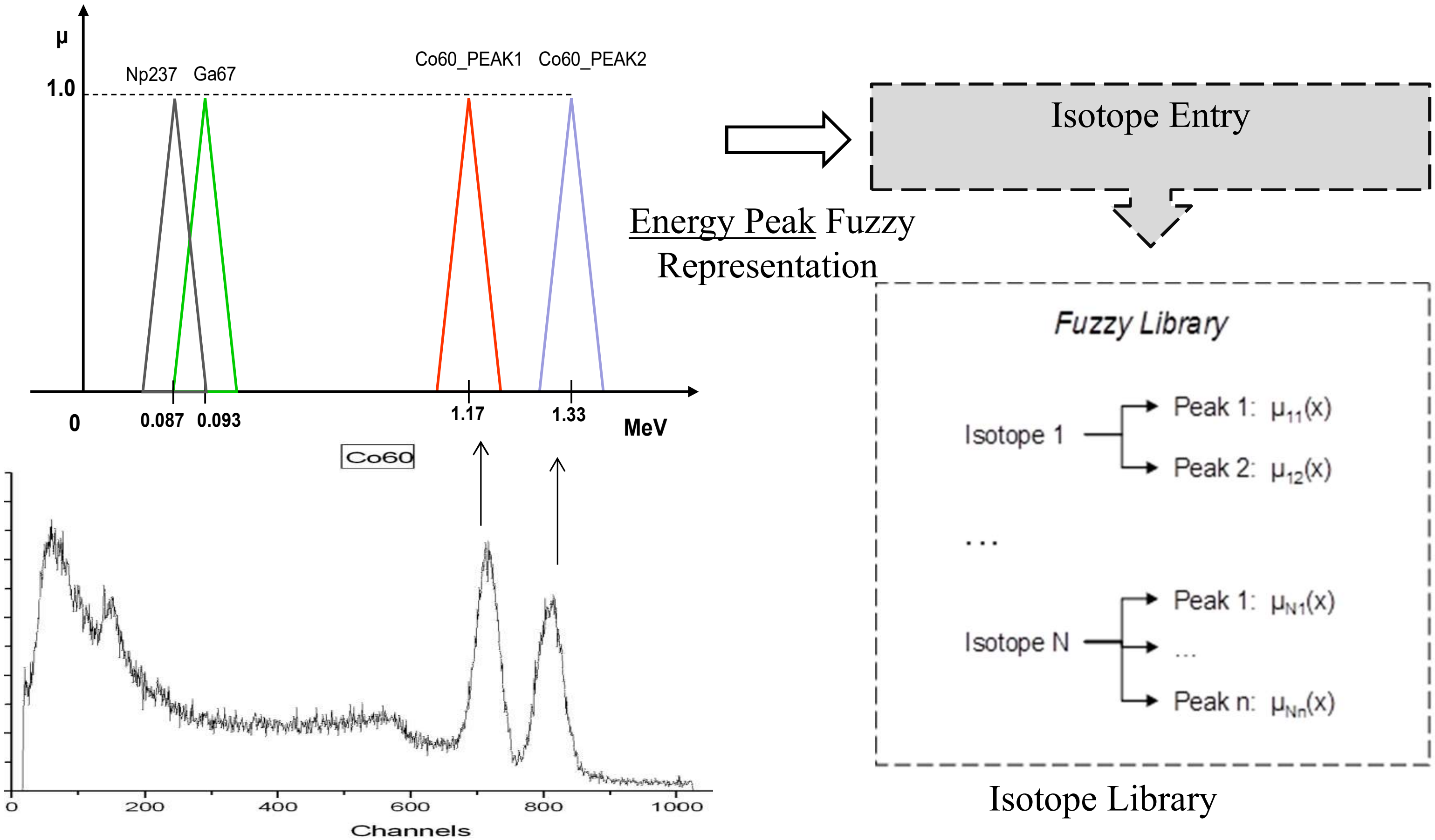
Alamaniotis, M., "Data Interpretation and Algorithms," *Active Interrogation in Nuclear Security-Science, Technology, and Systems*, Book edited by I. Jovanovic and A. Erickson, Springer Nature, 2017, pp. 1-30.

Alamaniotis, M., Heifetz, A., Raptis, A., & Tsoukalas, L.H, "Fuzzy-Logic Radioisotope Identifier for Gamma Spectroscopy in Source Search," *IEEE Transactions on Nuclear Science*, Institute of Electrical and Electronic Engineers, vol. 60 (4), August 2013, pp. 3014-3024.

Machine Intelligence Solution: Fuzzy Representation

Use of Quantum Mechanics:

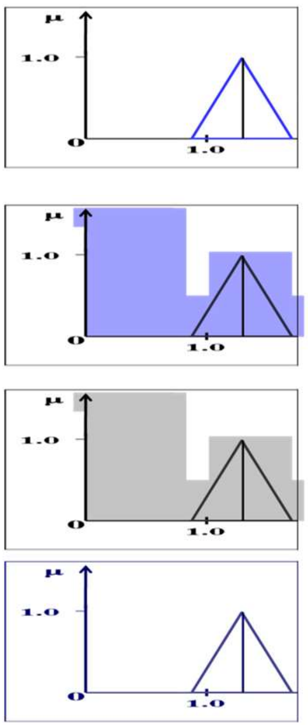
Feature Extraction (Emission Energies)



Machine Intelligence Solution: Fuzzy Inference

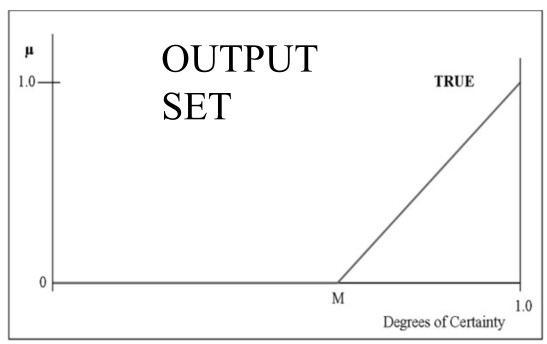
Feature Extraction from Measured Data

INPUTS



RULES

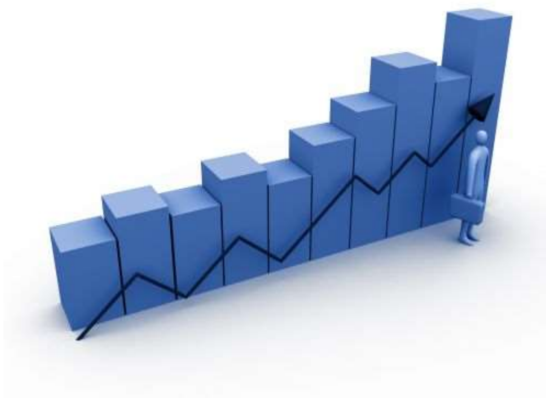
IF Candidate is Plutonium1, THEN Detection is TRUE
IF Candidate is COBALT1, THEN Detection is TRUE
……..
……….
IF Candidate is U235_1, THEN Detection is TRUE



Detection Confidence for each Library Isotope

$$DC_I = \frac{\sum_{j=1}^{n} w_{Ij} c_{Ij}}{\sum_{j=1}^{n} w_{Ij}}$$

Future Research Directions



Smart Energy Systems

Machine Intelligence in

- Forecasting
- Integration of Renewables
- Intelligent Management of Power Grid
- Integration of Electricity with other forms of Energy
- Modeling/Predicting Consumer Behavior
- Smart Energy for Smart Cities

Nuclear Security

Intelligence in

- Smart Rad Sensor Networks
- Threat Identification
- Modeling of Background Radiation
- Data Interpretation
- Data Visualization
- Cybersecurity and Physical Impact

***Taxis*: Sensor Network in Urban Environments**

Power Systems and Nuclear Security

Machine Intelligence

- Analysis of Power Grid Data
  - Enhancing Nuclear Security
  - Consumption Profiles of Nuclear Sites

- Analysis of Grid Contextual Environments
  - Detection of Hidden Facilities

Summary and Conclusion

- Brief Bio
- Machine Learning in Critical Energy Applications
  - Power Systems
    - Learning Kernels for VSTLF
  - Nuclear Security
    - Fuzzy Analysis of Spectra
- Future Directions

Thank you for your Attention

Questions?

Discussion