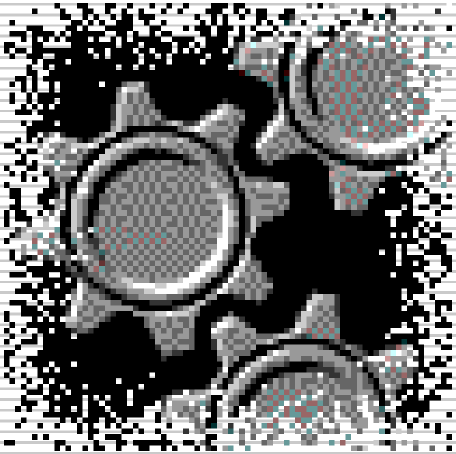

A Multi-Scale Crowd Behavior Modeling Framework: Emergency Evacuation and Normal Scenarios

Sponsors:
AFOSR MURI F49620-03-1-0377
NSF SOD 0725336
NIST SB1341-05-W-0852
DTFH61-10-C-00009 (via IIT)

THE UNIVERSITY OF ARIZONA
TUCSON ARIZONA

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Systems and Industrial Engineering
The University of Arizona
Collaborators: X. Zhao, K. Vasudevan, S. Lee

INFORMS Sim. Society Research Workshop, July 18th, 2011

Synthetic Human Decision Behavior Model

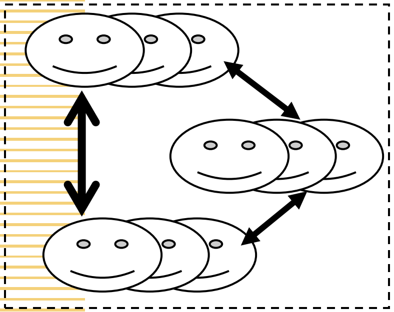
Research Goal:
Synthetic human decision behavior model for complex and dynamic scenarios

- Bayesian belief network (subjective evaluation of environment)
- Extended Decision Field Theory (Busemeyer & Townsend (1993))
- Planning involving (random depth first search)
- Reinforcement-learning
- CAVE-based VR system And PC game
- Distributed Computing (Web services) -- integration of Software modules

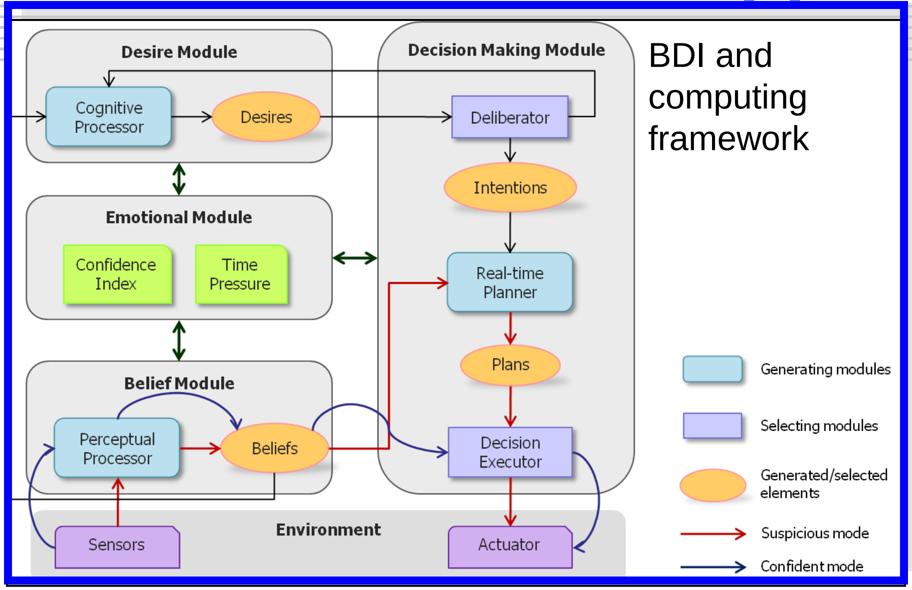
Conceptual architecture: Extended belief-desire-intention (BDI) framework
Enabling methodologies and technologies

- **Requirements of model**
- Coherent and comprehensive framework for various applications
- Human subjective evaluation of environment via deductive inference
- Psychological (human like) rather than AI-only agent
- Generating a probabilistic plan in real-time with a varying horizon
- Reinforcement learning for model update
- Reverse-engineering and validation of model via HIL experiment
- Integration of software modules to improve model accuracy

Extended BDI for Various Applications

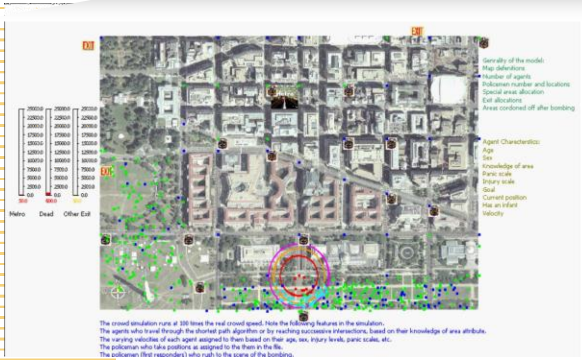


Network of stake holders in an enterprise (Sponsor: NSF)

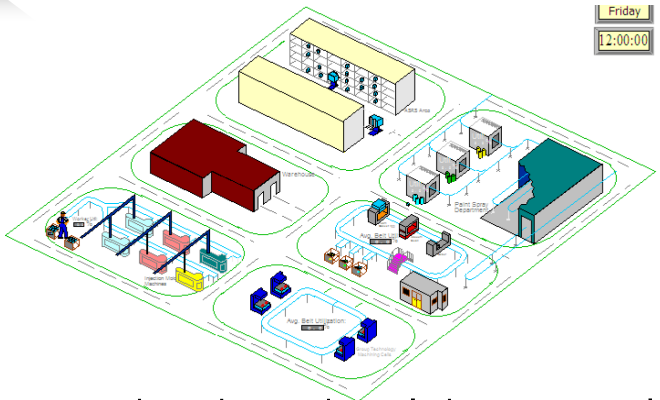


BDI and computing framework

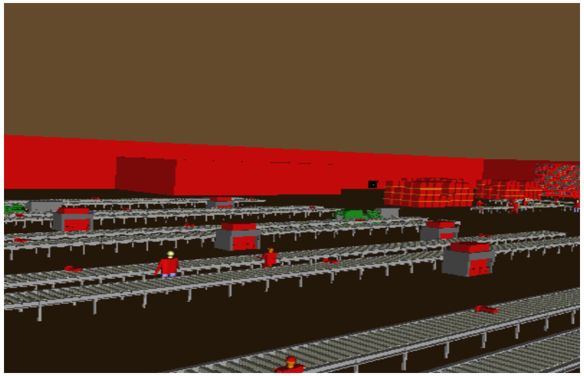
Traffic simulation (pedestrian /vehicle interaction; driver's behavior) (Sponsor: FHWA)



Evacuation behaviors under a terrorist bomb attack (Sponsor: AFOSR, NIST)



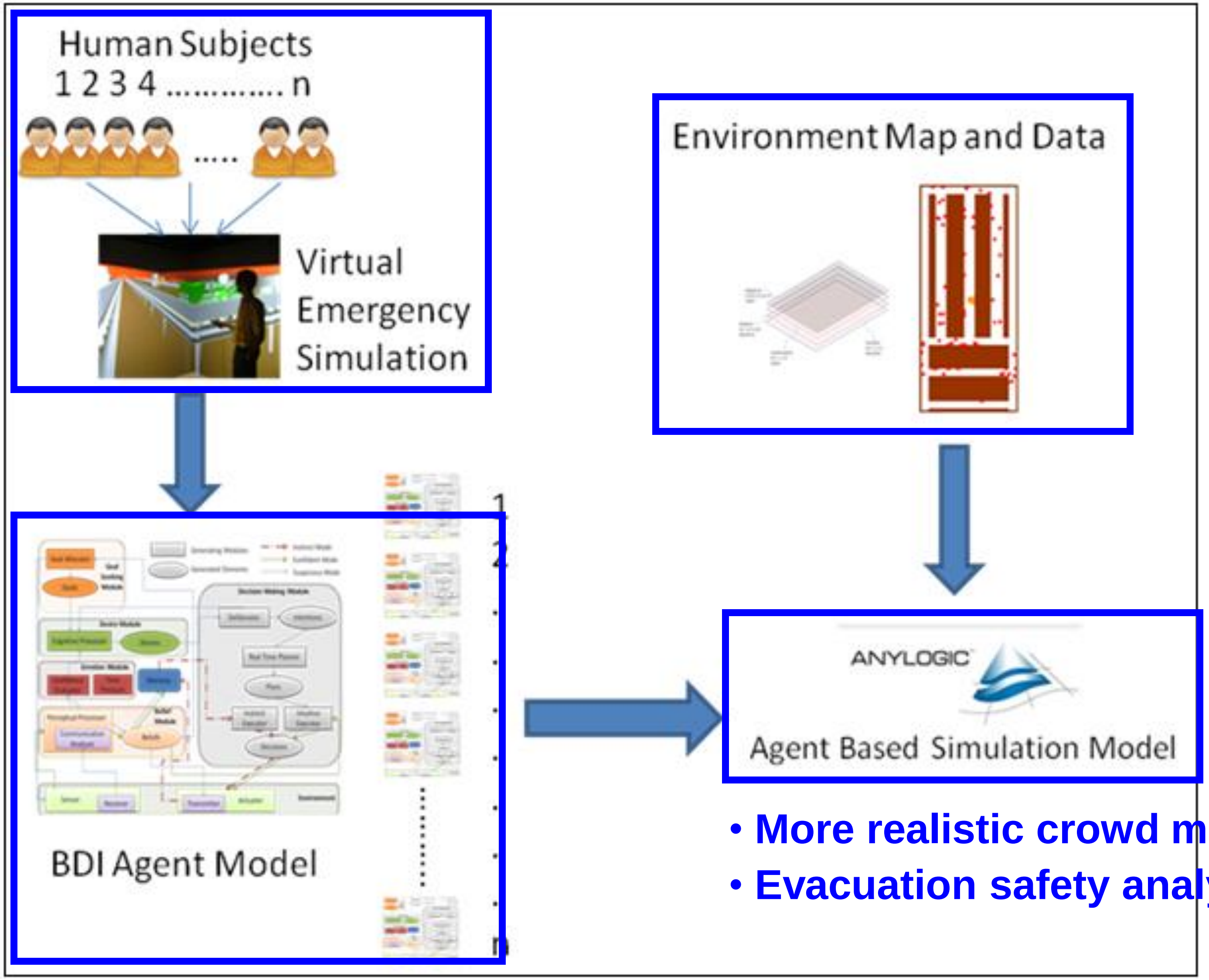
Error detection and resolution personnel in complex mfg (Sponsor: AFOSR);



Evacuation behaviors under fire in a factory (Sponsor: UA)

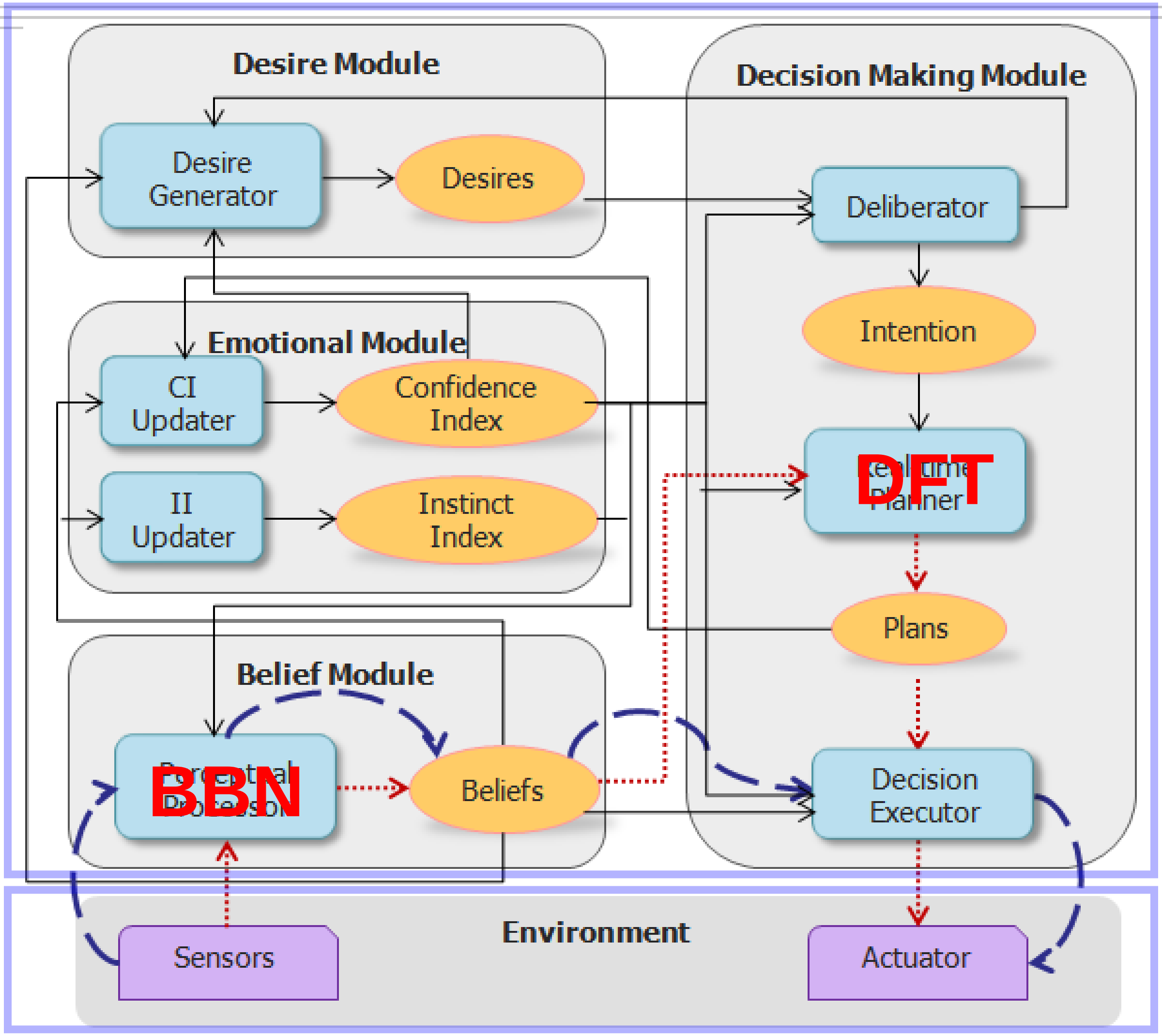
[illegible]

Crowd Simulation Model Development Process

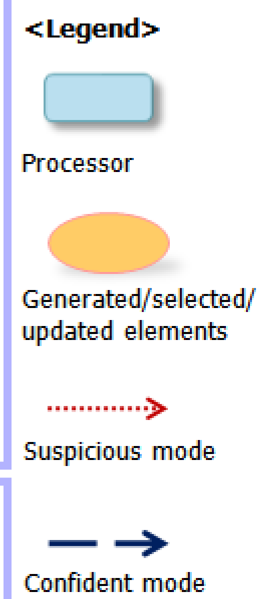


- More realistic crowd model
- Evacuation safety analysis

Extended Belief-Desire-Intention Framework



Bratman, 1987
Rao and Georgeff, 1998
Zhao and Son, 2008



Lee, S., Y.-J. Son, and J. Jin (2010), Integrated human decision making and planning model under extended belief-desire-intention framework, *ACM Transactions on Modeling and Computer Simulation*, 20(4), 23(1)~23(24).

Motivation in Application (Evacuation from Fire)

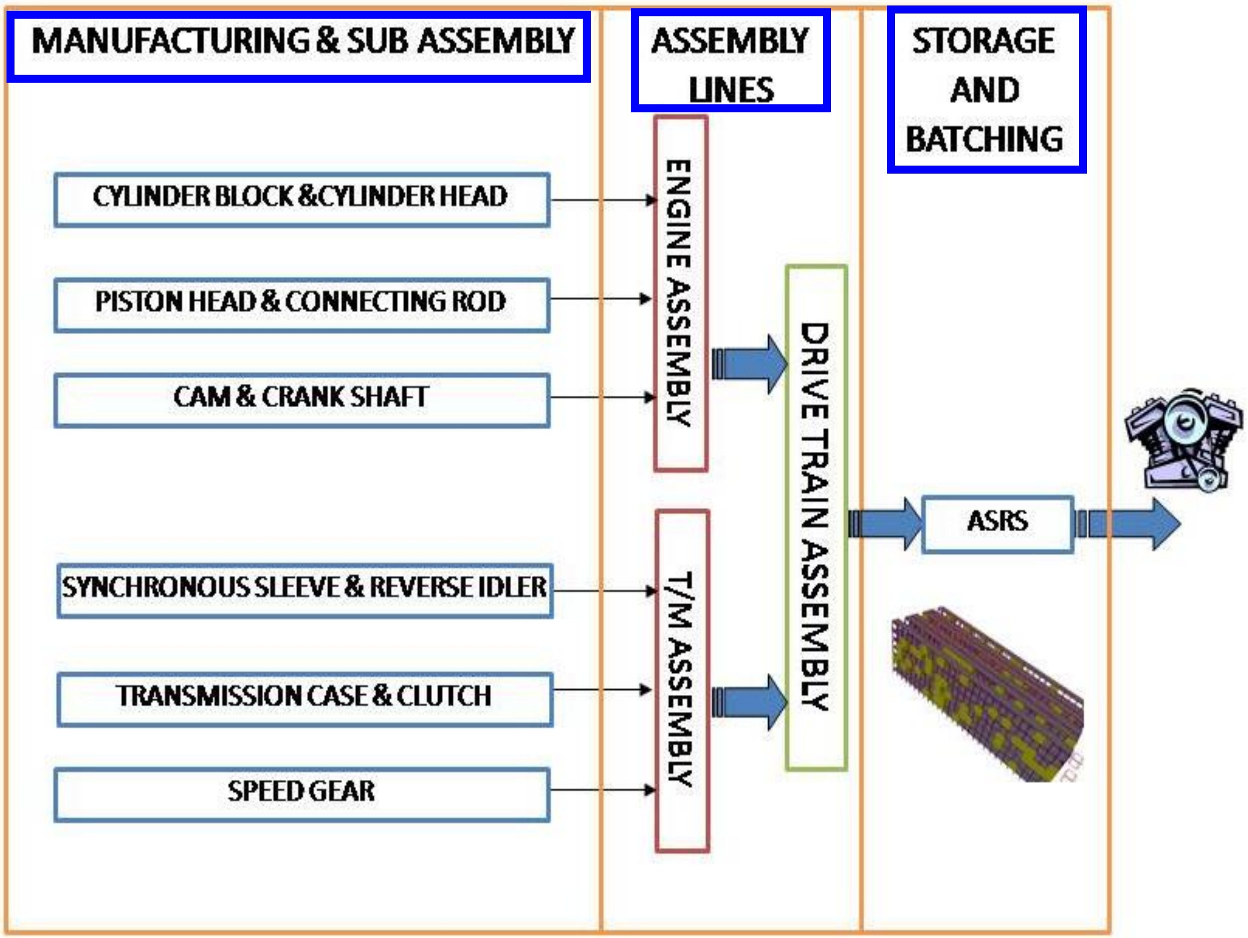
- Motivation 1: In manufacturing layouts
  - Productivity has been a major concern
  - Opportunities for safety concern under emergency evacuation
- Motivation 2: In safety standards
  - E.g. NFPA (National Fire Protection Authority) Life Safety Code Handbook
  - Static (regardless of details of layout) and used as minimum requirements
    - (General) Travel distance to an exit <= 400ft
    - (In high hazard occupancies) Travel distance <= 75ft
    - Width of passageway serving as an exit >= 44in

Research Approach

- Consider both productivity and evacuation safety via
  - (Traditional) Discrete event simulation: productivity analysis
  - (Novel) Synthetic human decision behavior model + agent based simulation: evaluate evacuation safety
    - Varying layout configurations
    - Number of exits
    - Exit capacities
    - Arrangements of exits
    - Width of corridors

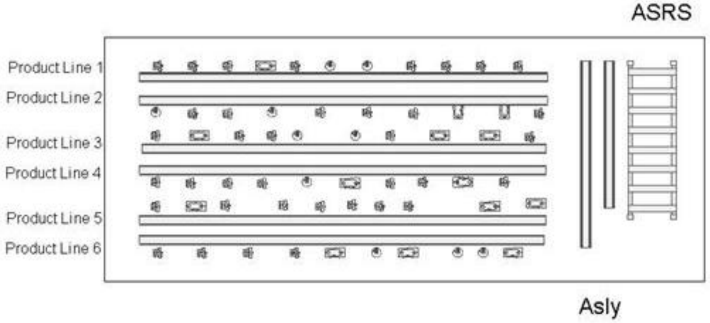
Case: Auto. Drive Train (Engine + Transmission)

- 265 feet * 625 feet (=165,625 ft^2)
- 70 ~ 220 people



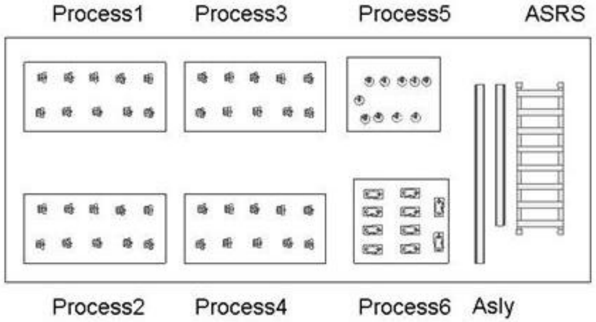
Considered Layout Configurations for **Fabrication Area**

Product Layout

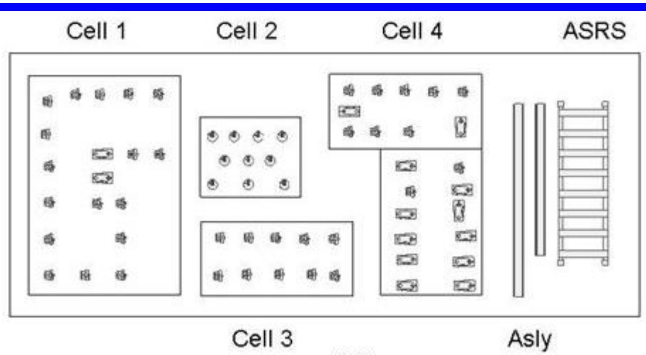


(a)

Process Layout

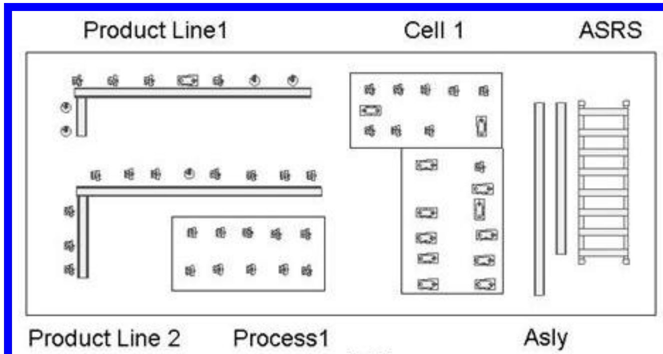


(b)



(c)

Group Technology Layout



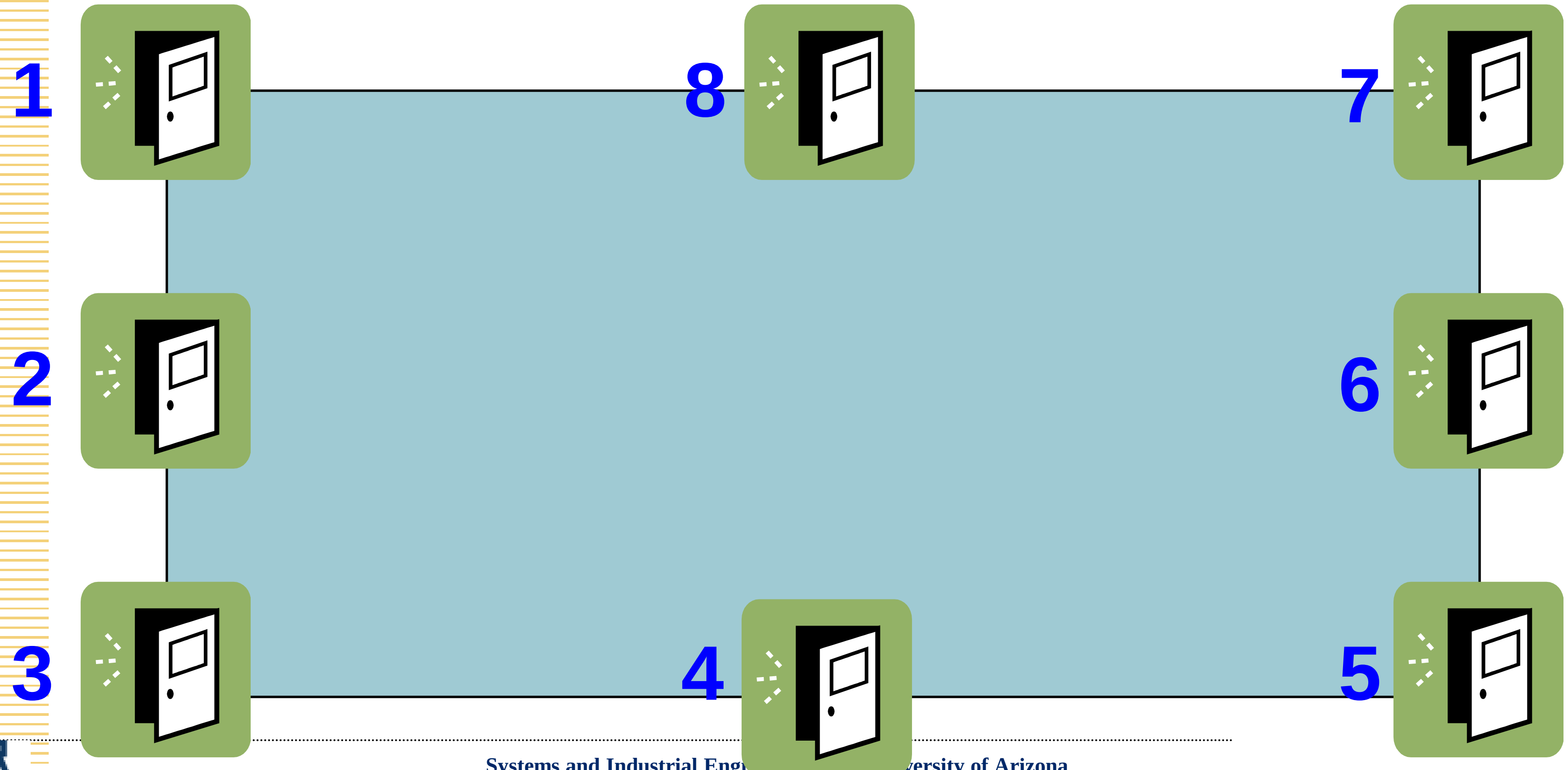
(d)

Hybrid Layout

Considered 70 Exit Configurations

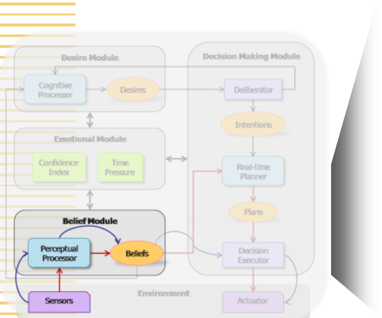
- Each configuration has 4 exits (8 possible locations)
- Total of 70 configurations considered

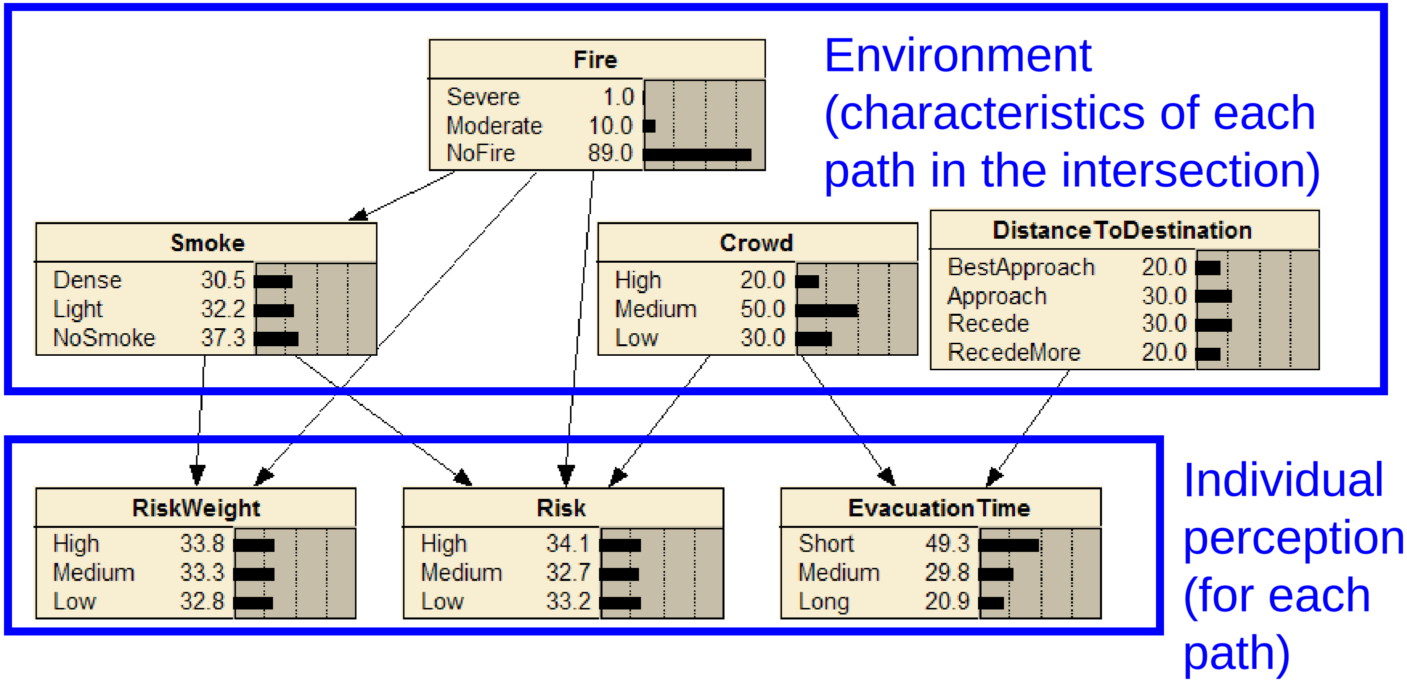
$$_{8}\pounds_{4} = 70$$



Belief Module (Perceptual Processor)

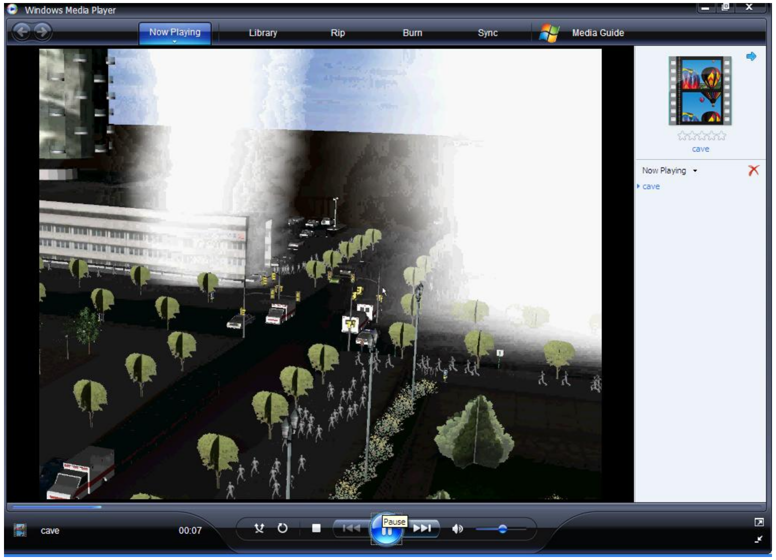
- Bayesian belief network
  - Mimic subjective evaluation of an environment
  - Training stage: HIL experiment (varying environment)
  - Operation stage: inferencing individual perception

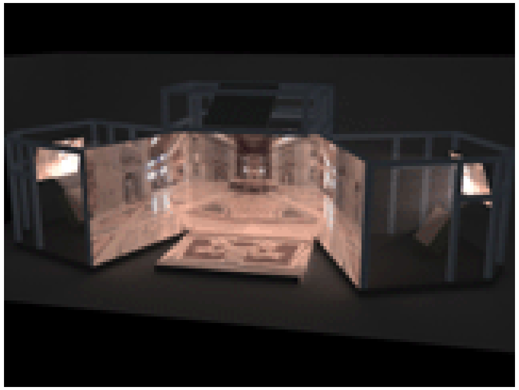




Human-in-the-loop Experiment in CAVE

- CAVE (VR) at UA
- Construction of 3D environment
  - Google SketchUp (OpenGL API)
  - AutoMod Simulator (3D Inventor
- Audio effects
  - Virtual Sound Server system
- VR wand
  - input to system
- Goggle



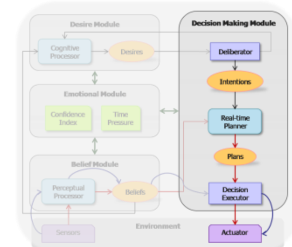


Validation of EDFT Decisions

Decisions made by each subject and EDFT model; 15/18 => 83%

Intersection	Actual Decision			Simulation		
	Path1	Path2	Path3	Path1	Path2	Path3
1	0.15	0.75	0.1	0	0.97	0.03
2	0.4	0.2	0.4	0.75	0	0.25
3	0.3	0	0.7	0	0	1
4	0.05	0.55	0.4	0	0	1
5	0.35	0	0.65	0.41	0	0.59
6	0.35	0.1	0.55	0	0	1
7	0.15	0.3	0.55	0	0.14	0.86
8	0.6	0	0.4	0.21	0	0.79
9	0.78	0.17	0.05	1	0	0
10	0.333	0.333	0.333	0.18	0	0.82
11	0.5	0.11	0.39	0.1	0	0.9
12	0.61	0	0.39	1	0	0
13	0.11	0.83	0.06	0	1	0
14	0	0.89	0.11	0	1	0
15	0.11	0.89	0	0	1	0
16	0.11	0.89	0	0	1	0
17	0.83	0.06	0.11	0.51	0	0.49
18	0.22	0.72	0.06	0.07	0.93	0

Real-time Planning Module (1) -- DFT



- Decision-Field-Theory
  - Busemeyer and Townsend (1993)
  - Evolution of preference of alternative options
    - Proven to explain several psychological phenomena
  - Extended DFT for dynamic environment (multi-stage decision-making)
    - Lee, Son, and Jin (2007) – *Information Sciences*
    - Abad, Jin, and Son (2008) – *IEEE SMC*

J. Busemeyer, J. Townsend, 1993, Decision Field Theory: A Dynamic-Cognitive Approach to Decision Making in an Uncertain Environment, *Psychological Review*, 100, 432-459.

S. Lee, Y. Son, and J. Jin, 2008, Decision Field Theory Extensions for Behavior Modeling in Dynamic Environment using Bayesian Belief Network, *Information Sciences*, 178(10), 2297-2314.

A. Abad, J. Jin, and Y. Son, Nov. 2007, Dynamic Modeling of Human Decision Behavior Using Decision Field Theory, *IEEE Transactions on Systems, Man, and Cybernetics A* (submitted).

Real-time Planning Module (2) -- DFT

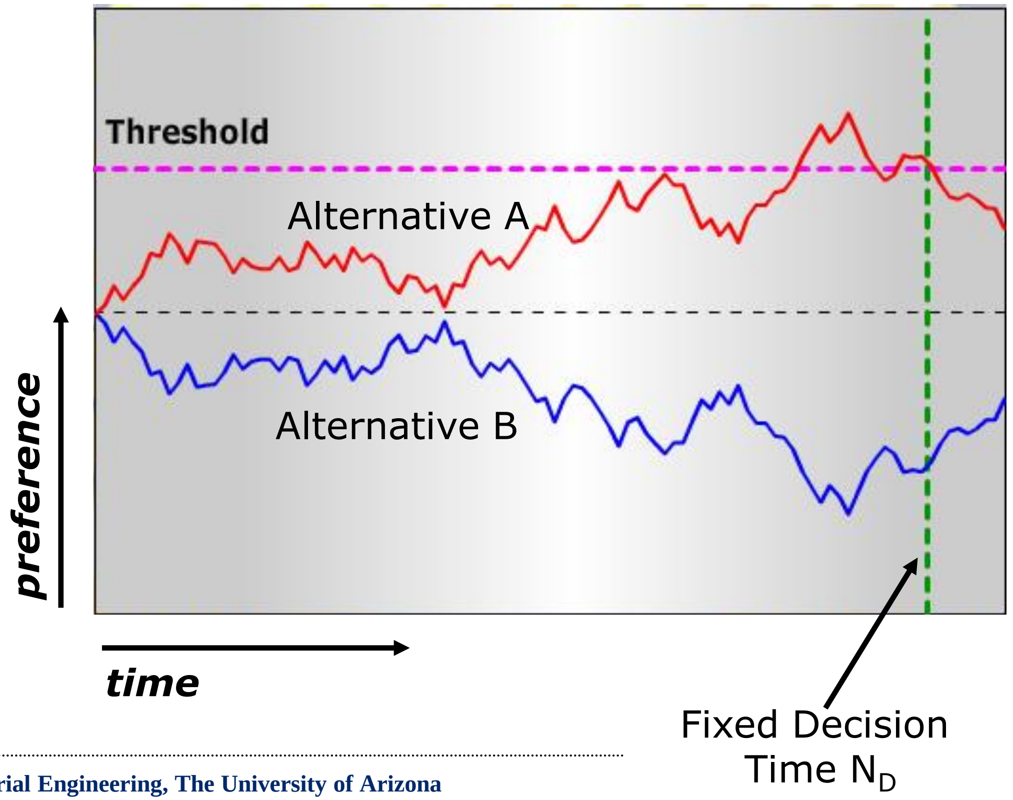
$$P(t+h) = SP(t) + CMW(t+h)$$

n×1 (n×n)×(n×1) (n×n)×(n×m)×(m×1)

n options
m attributes

- *P(t)*: *Preference state* vector at time *t*
- *S*: *Feedback* matrix
- *C*: *Comparison process* matrix that contrast the weighted evaluations
- *M*: *Personal evaluation* matrix of each option on each attribute
- *W(t)*: *Attention weight* vector allocated to each attribute at time *t*

$$\begin{pmatrix} p_1(t+1) \\ p_2(t+1) \end{pmatrix} = \begin{pmatrix} 0.9 & -0.01 \\ -0.01 & 0.9 \end{pmatrix} \begin{pmatrix} p_1(t) \\ p_2(t) \end{pmatrix} + \begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} 3.5 & 1.3 \\ 1.3 & 3.5 \end{pmatrix} \begin{pmatrix} w_1(t+1) \\ w_2(t+1) \end{pmatrix}$$



DFT Assumptions (1)

- S: stability
- W changes over time according to a stationary stochastic process, which allows us to derive four important theories regarding the expected preference values
  - Minimum amount of time steps needed for the preference values to be stabilized

Theorem 1. *In the two options decision-making problem of the original DFT, the expected value of preference is*

$$E(P(nh)) = \frac{1 - D^n}{1 - D} E(v_1(h)) \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

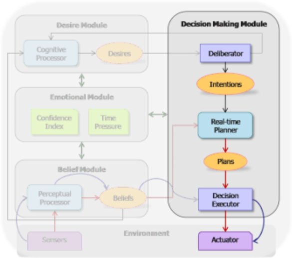
where $D = s_{11} - s_{12}$ *and* $E(v_1(h)) = E(w_1(h))(m_{11} - m_{21}) + E(w_2(h))(m_{12} - m_{22})$.

Furthermore

$$E(P(nh)) = \frac{1}{1 - D} E(v_1(h)) \begin{pmatrix} 1 \\ -1 \end{pmatrix} \quad as\ n \to \infty$$

Real-time Planning Module (3)

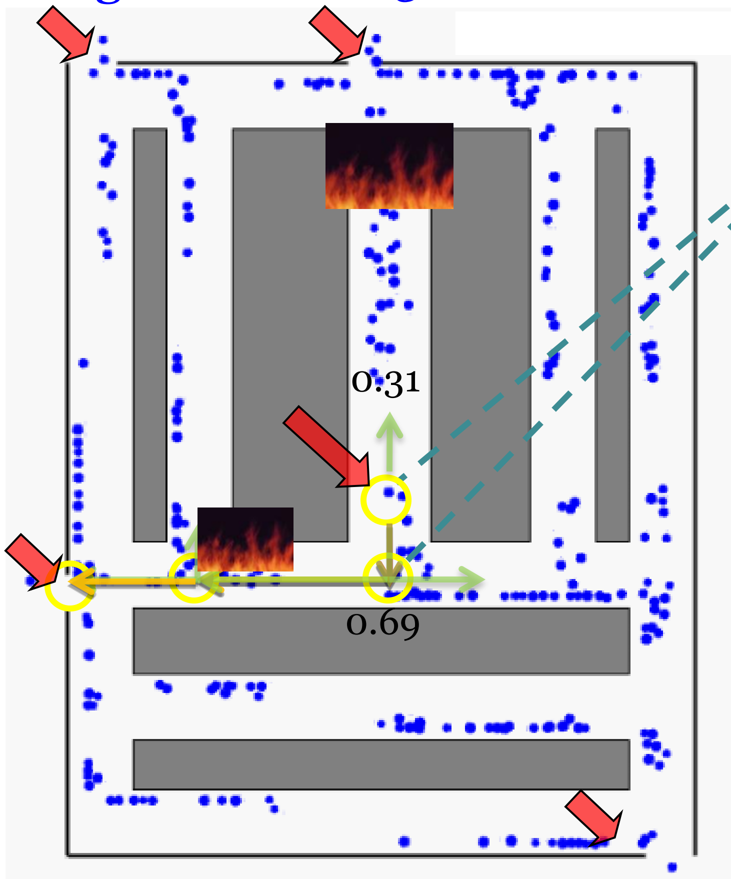
- Multi-horizon real-time planner involving
  - Extended DFT
  - Probabilistic depth first search technique
  - SOAR programming tool

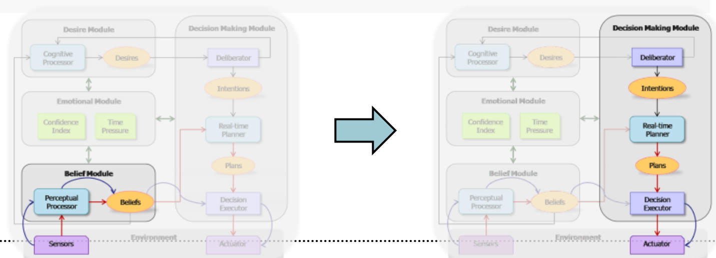


1: CALL EDFT to get the preferences of **PATH**s from the current position
2: IF Soar has the knowledge of local paths THEN
3:    REPEAT
4:       SELECT a **PATH** which is directly connected to the current position based on the probability distributed according to preference
5:       CALCULATE the preference for all **PATH**s that are connected t the current position based on the knowledge
6:       SET the preference of the selected **PATH** to *worst*
7:    UNTIL it reaches to End or has ***n*** intersections
8: ELSE
9:    SELECT a **PATH** which is directly connected to the current position based on the probability distributed according to preference
10: ENDIF
11: RETURN **PATH**

Illustration of Planning with Permanent Worker (1)

- Planning horizon $n=3$

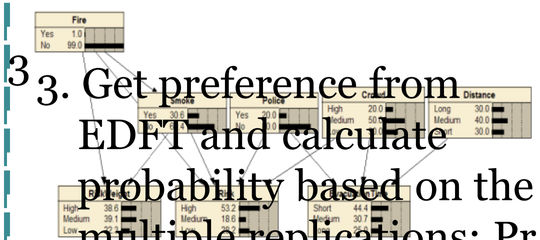




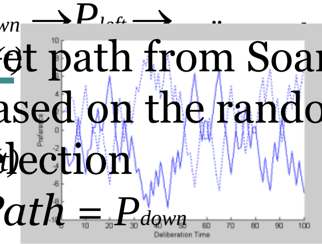
1. Get environmental information

   (Distance from knowledge)

2. Get M and W from BBN



3. Get preference from EDFT and calculate probability based on the multiple replications; Pr is fed into Soar



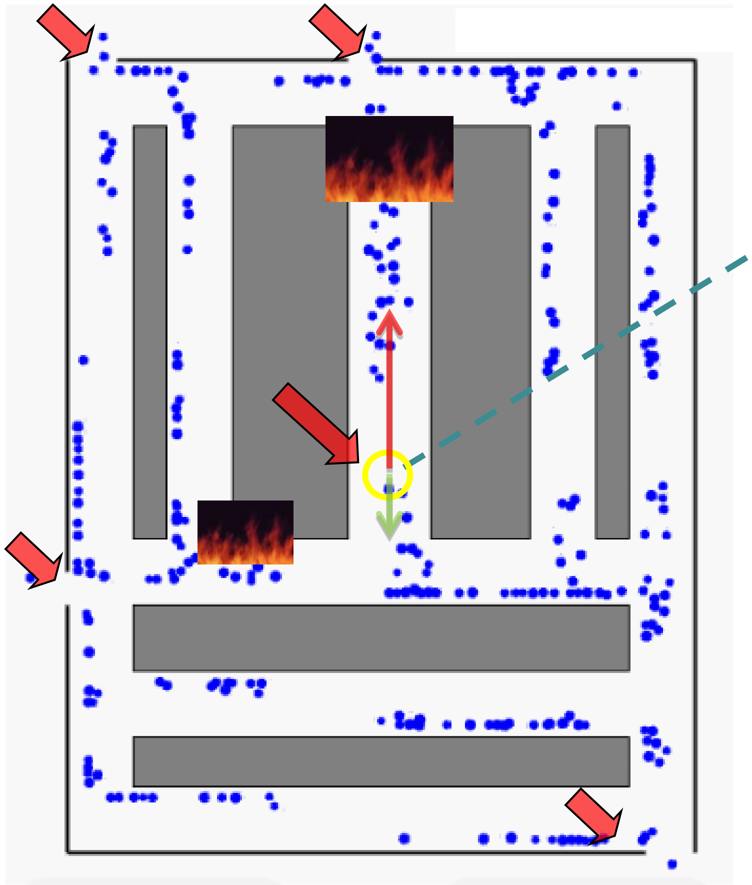
4. Get path from Soar based on the random selection

   $Path = P_{down}$

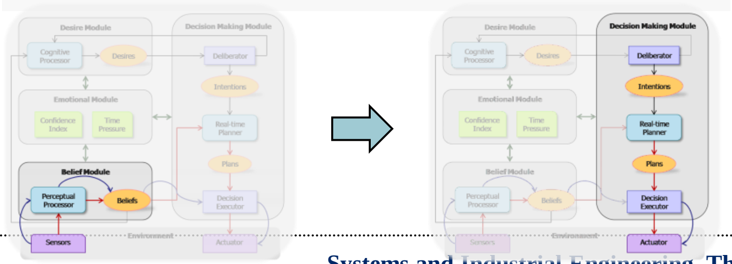
$$\Pr(t) = \begin{pmatrix} pr_1(t) \\ pr_2(t) \end{pmatrix} = \begin{pmatrix} 0.31 \\ 0.69 \end{pmatrix}$$

Planning in Visitors or Temporary Workers (2)

❖ Planning horizon $n=1$



1. Get environmental information (Fire, Smoke, Crowd, Distance)
2. Get M and W from BBN
3. Get preference from EDFT and calculate probability based on the multiple replications
4. Get path from Soar $P_{Straight}$



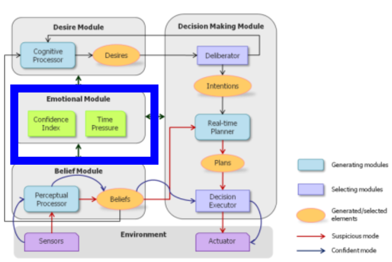
Emotion Module

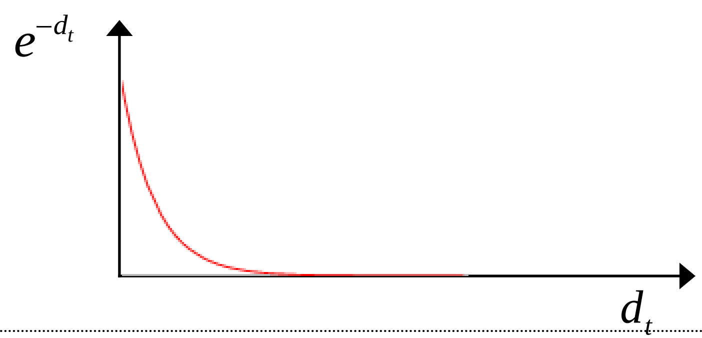
- Impact of Confidence Index (CI)
  - Commitment strategy (Suspicious / confident mode)
  - Planning horizon
  - Movement speed
  - Leader / follower behavior
  - CI improvement is used as immediate reward in the Q-Learning

$$CI_t = \alpha \cdot e^{-d_t} + (1-\alpha) CI_{t-1}$$

$$where\ d_t = \sum_{attribute} \left| m_{attribute}(t-1) - m_{attribute}(t) \right|,$$

$$0 \le \alpha \le 1,\ m_{attribute}(t) = \text{inferred value from BBN}$$





Force Model for Velocity Avoiding Collision

- Calculation of velocity for each agent given 1) desired destination and 2) force (Helbing et al., 2000)

$$\mathbf{f} = m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{v_i^0(t)\mathbf{e}_i^0(t) - \mathbf{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_W \mathbf{f}_{iW}$$

Desired vs. current | **Interaction with other agent** | **Force against wall**

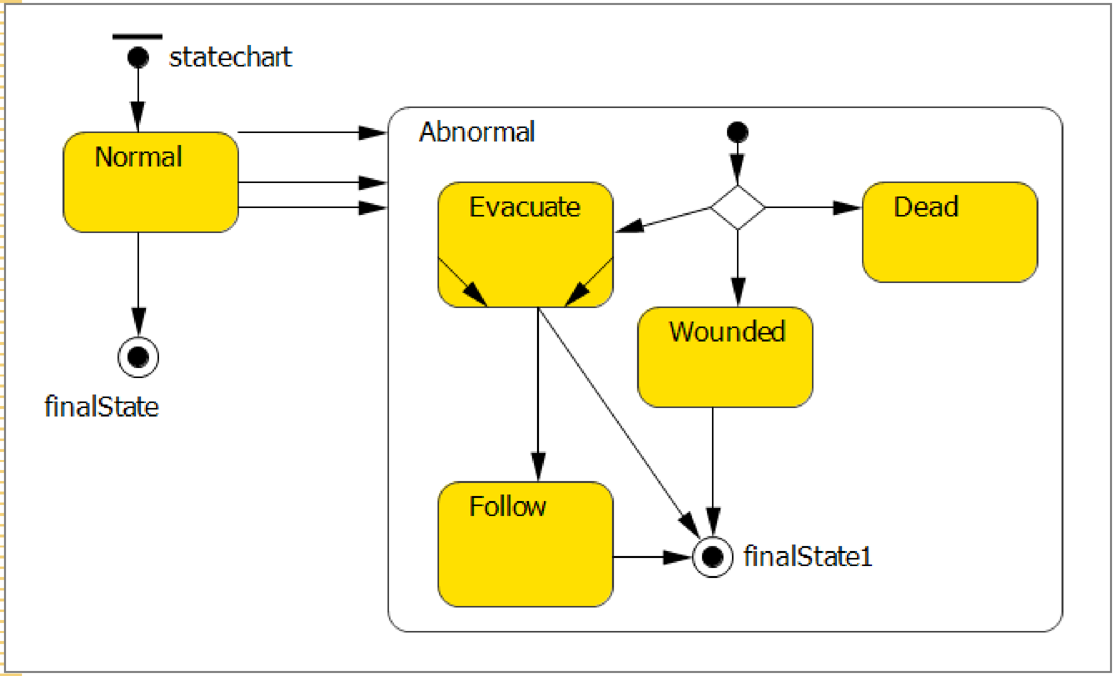
$$\mathbf{f}_{ij} = \left\{ A_i \exp\left[\left(r_{ij} - d_{ij} \right) / B_i \right] + kg\left(r_{ij} - d_{ij} \right) \right\} \mathbf{n}_{ij} + \kappa g\left(r_{ij} - d_{ij} \right) \Delta \mathbf{v}_{ji}^t \mathbf{t}_{ij}$$

Social force: psychological | **Body force: physical contact** | **Slide friction force: physical contact**

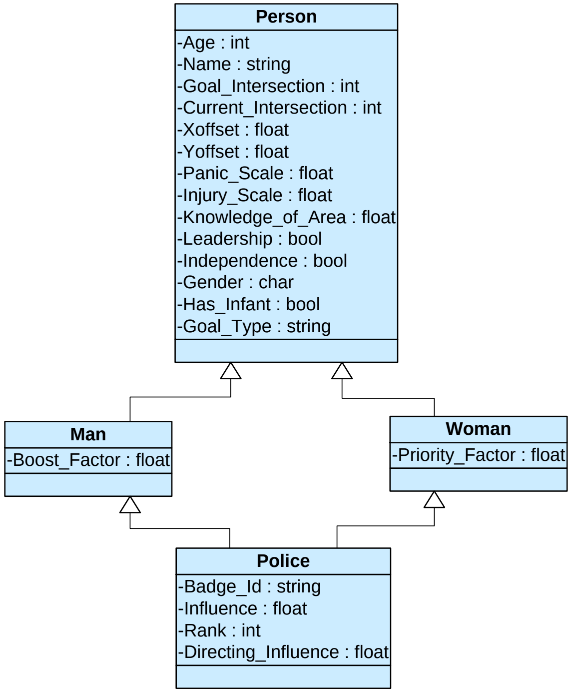
$$r_{ij} = (\mathbf{r}_i + \mathbf{r}_j) \qquad d_{ij} = \left\| \mathbf{r}_i - \mathbf{r}_j \right\| \qquad g(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise} \end{cases}$$

Modeling Constructs Agent-based Simulation

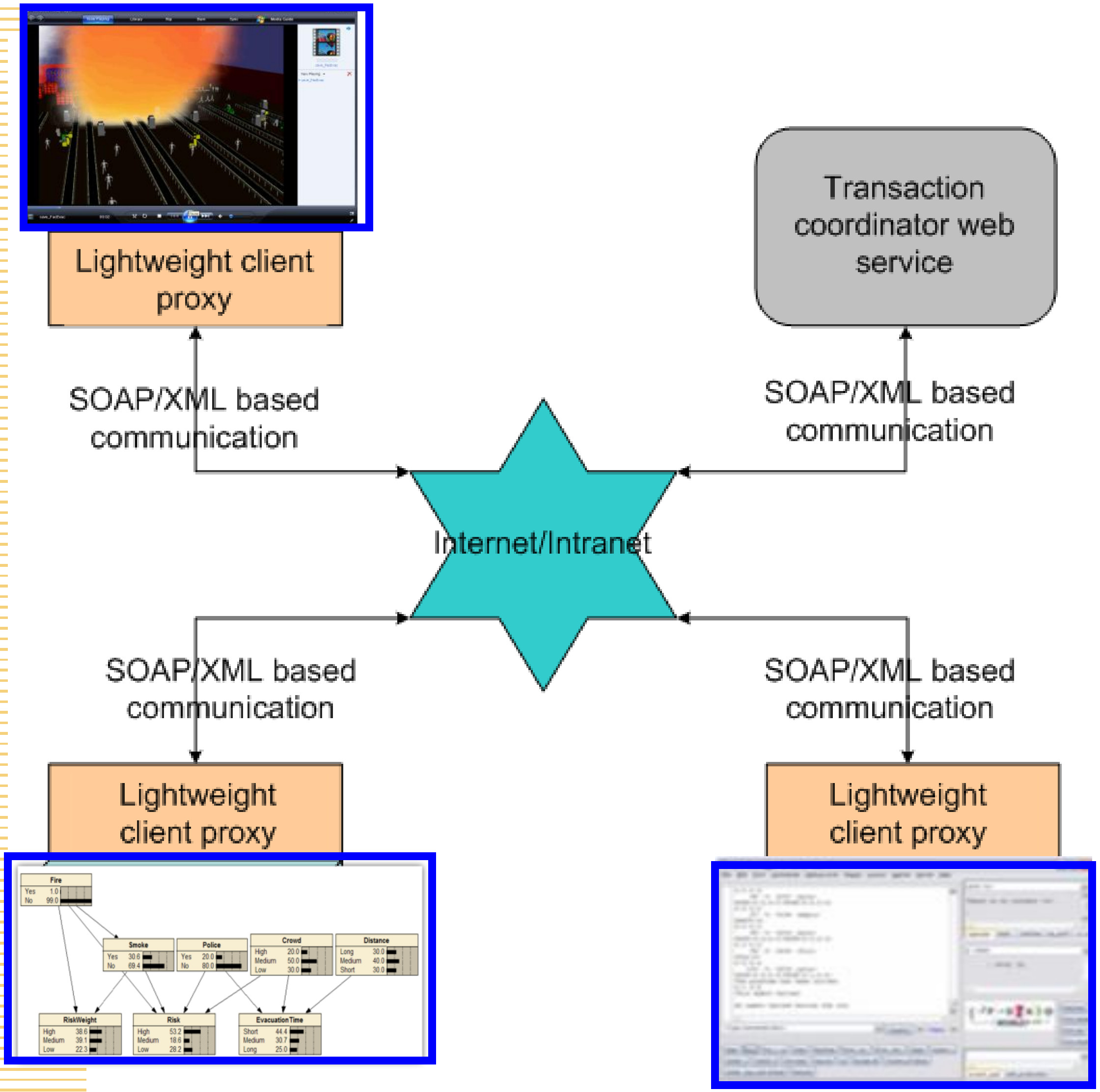
UML State-chart for dynamic behavior



UML Class diagram for Static information



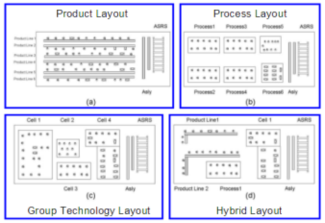
Implementation Infrastructure using WS

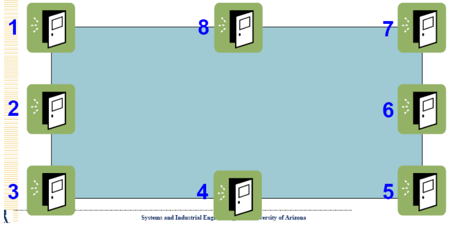


- Light-weight HLA/ RTI using Web Services technology
  - W3C standard protocols including XML, SOAP, WSDL
  - Platform independent
  - Less than 20 methods (*initialize*, *advanceTime*, *cons_advanceTime*, *sendMessage*, *getMessage*, *terminate*, and *cleanup*)
- Available in public
  - Used for integrating Anylogic, BBN (Netica BBN), Soar

Simulation Results (1) – Best Exit Configurations

Layout Type	Best Exit Configurations	Evacuation Times (s)	Average Evacuation Time (s)	Average Number of Decisions	Average Travel Distance (ft)
Process Layout	2-4-6-7	33.88	47.51	11.21	629.18
	1-2-6-7	35.09			
	2-5-7-8	35.78			
Product Layout	1-2-4-5	44.01	62.41	8.31	832.46
	2-3-6-7	46.12			
	1-2-3-5	46.75			
Group Tech Layout	2-4-6-7	35.27	53.20	8.95	698.25
	2-5-6-7	38.23			
	1-2-3-5	38.47			
Hybrid Layout	1-2-4-6	41.23	58.53	9.88	759.12
	2-3-6-7	43.55			
	1-3-6-7	43.89			

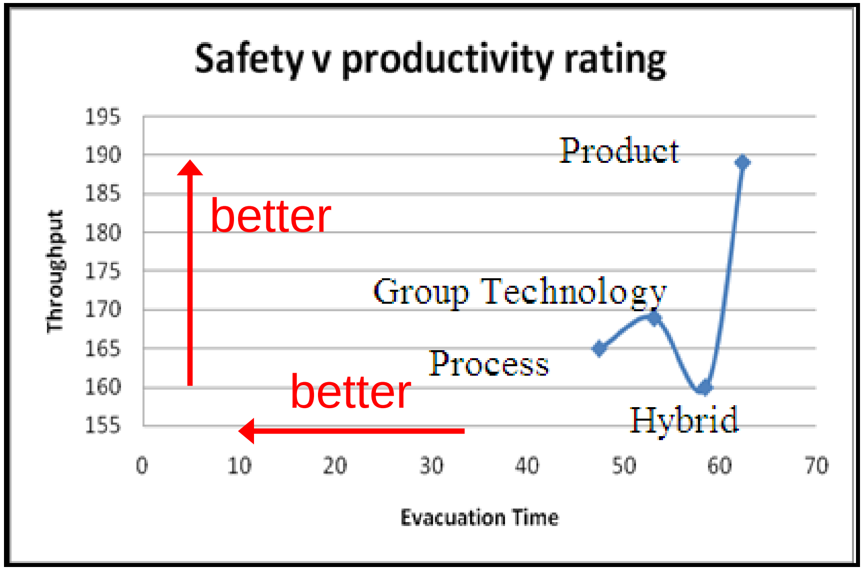




- A more spread out exit configuration pattern
- More decision points (passage alternatives), but faster evacuation

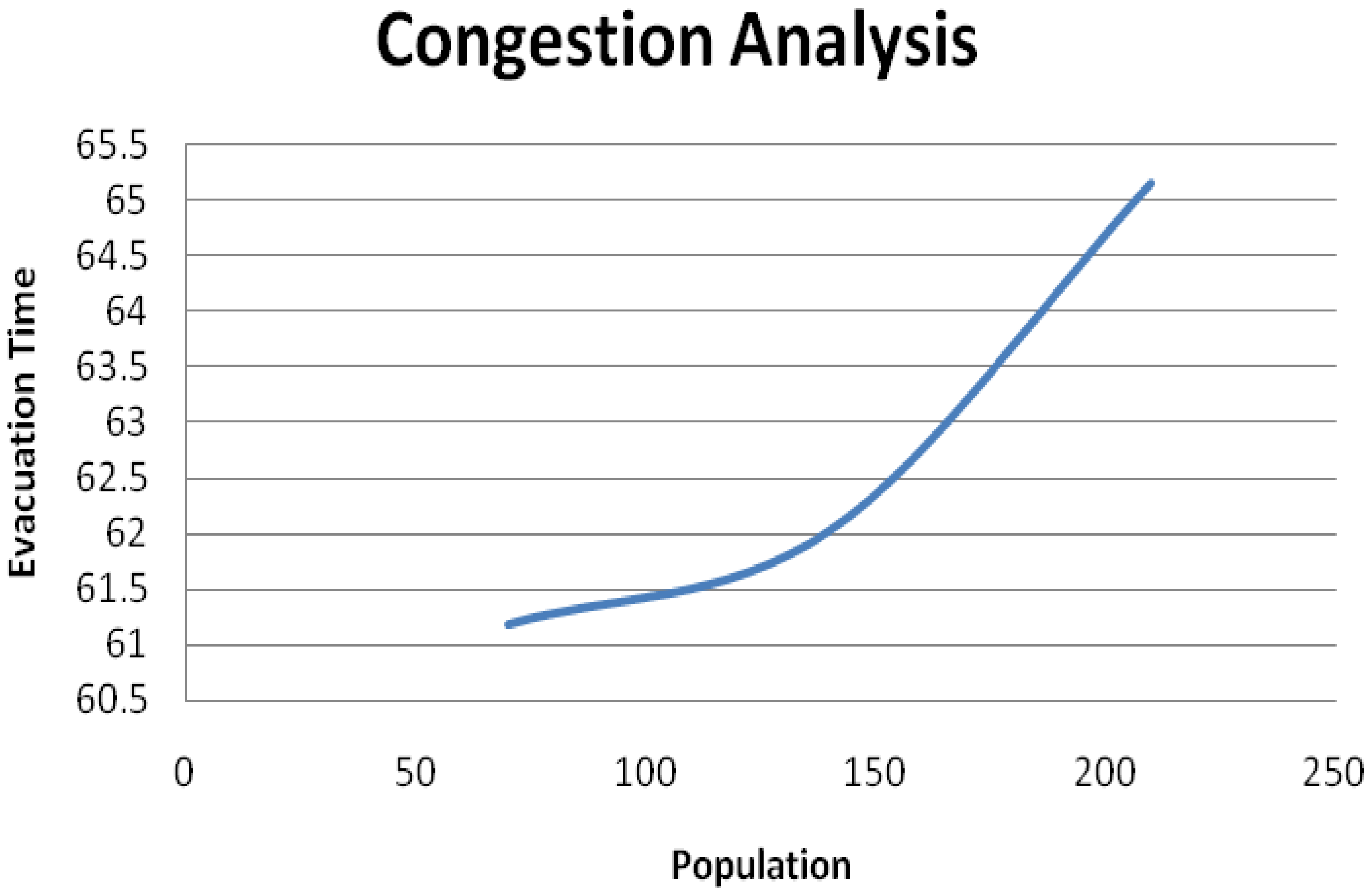
Simulation Results (2) -- Observations

- No inverse relationship between safety and productivity



Simulation Results (2) – Congestion

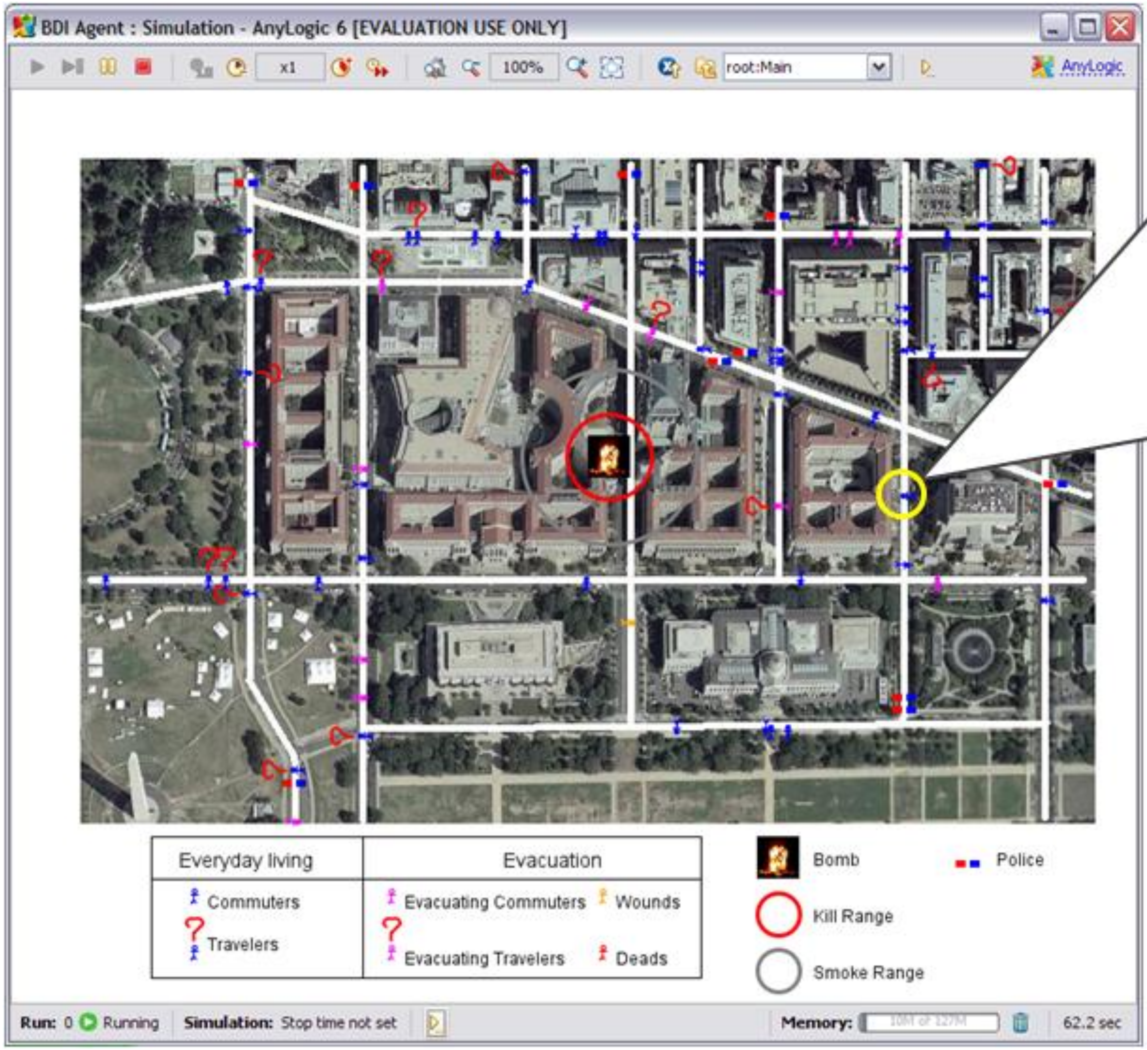
- For a given layout configuration, evacuation time vs. increasing number of people

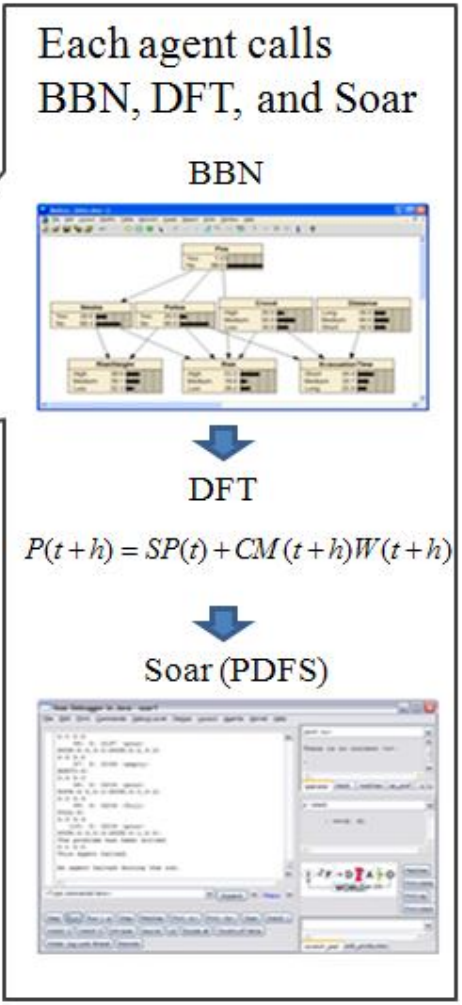


Summary

- In addition to productivity analysis in facility design
- Proposed to consider emergency (fire) evacuation safety via
  - Synthetic human decision behavior model
  - Agent based simulation
- Demonstrated the proposed approach for an automotive drive train facility
  - Differences of evacuation times for varying configurations with the same size
  - NFPA: Static minimum requirements

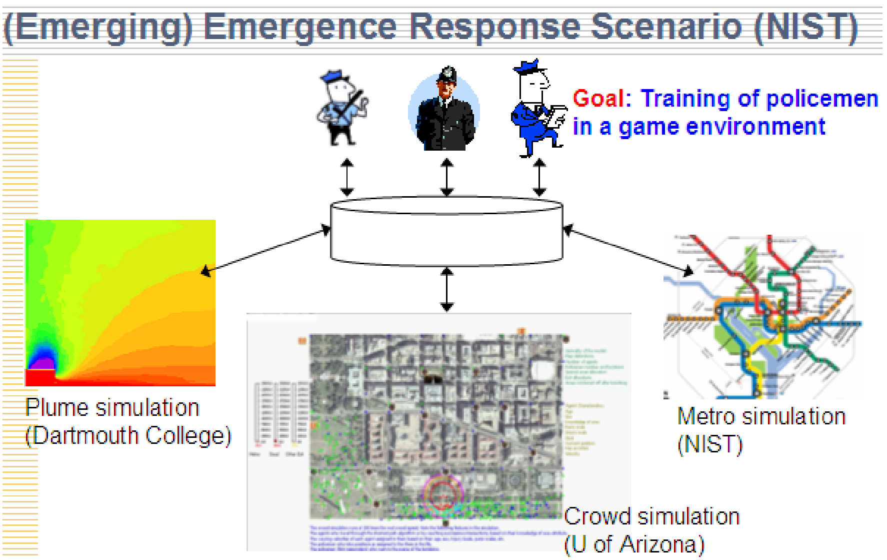
Demo: Evacuation from Bombing Attack



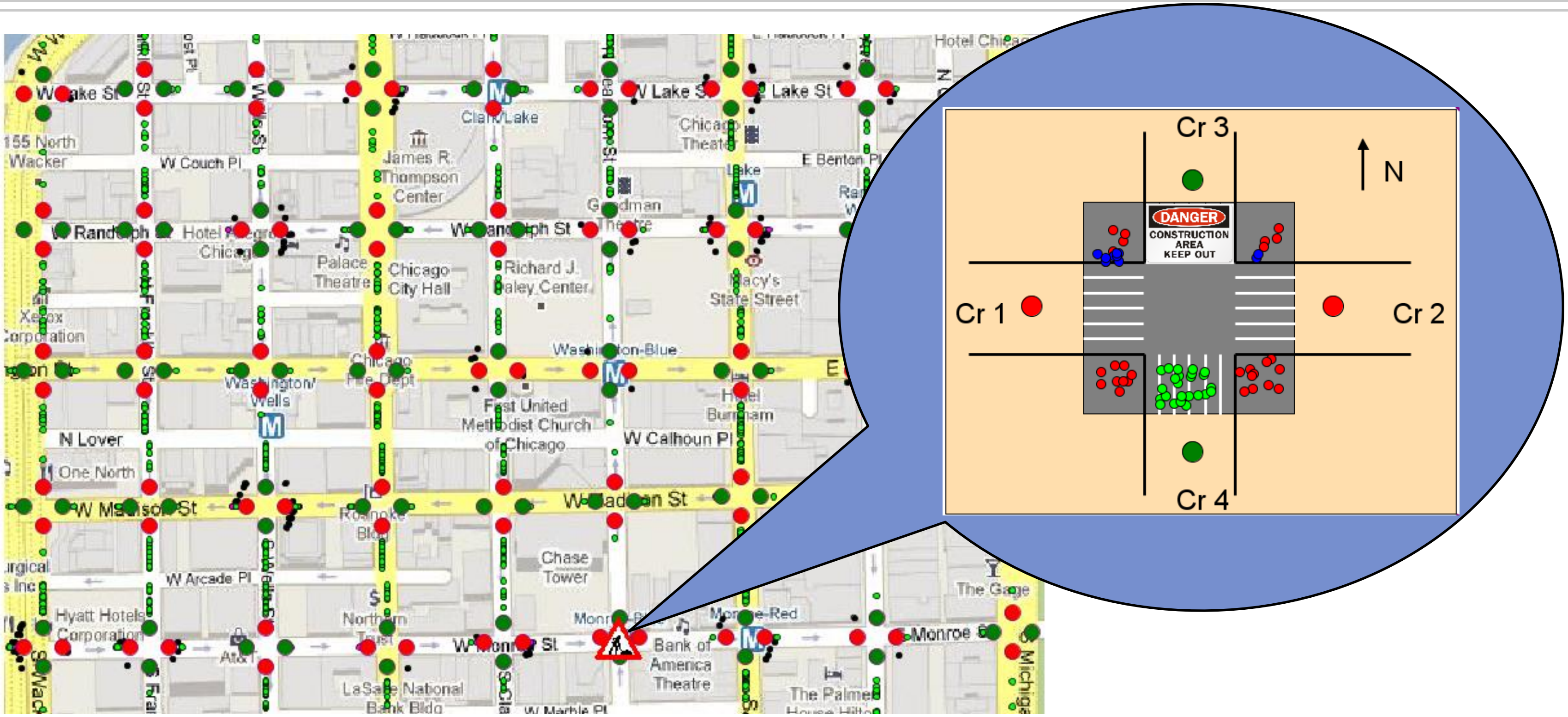


Other Modeling Concerns

- Behaviors of “followers” follow those of “leaders”
- Influence of speakers (state of other intersections)
  - Value of information (BBN)
- Influence of policemen (constraint; additional info.)
- Other modeling considerations
  - Geographic data (satellite image)
  - Demographic data
  - Constraints/interface to/from other simulations (plume, metro)



Vehicle/Pedestrian Interactions in Chicago



- FHWA projects (IIT; Argonne Lab)
- Chicago loop area (1.3 km^2; 87 intersections)
- Each intersection having 4 cross-walks
- Loosely coupled integration (transportation simulator; pedestrian)
- NSF-DDDAS; Need for a detailed model: construction; accident; vehicle/pedestrian interactions

Multi-Scale Model: Three Levels

Table 1: Three Levels in the Multi-scale Framework for Estimating Pedestrian Delay

	Agent Type	Agent Number	Scenario Scale	Time Step	Sidewalks
Aggregated Level	Crosswalk	87*4	Chicago Loop Area	30 seconds	One lane w/ both directions
Medium Level	Pedestrian	2000~4000	Chicago Loop Area	1 second	One lane w/ both directions
Detailed Level	Pedestrian	(30~50)*87	Chicago Loop Area (87 intersections)	1 second	Two lane w/ both directions

Table 2: Agent Characteristics and Delay Estimation Method at Each Level

	Agent Type	Pedestrian Movement	Congestion	Decision-making	Delay Estimation Method
Aggregated Level	Crosswalk	*N*	*N*	*N*	Extended Adams' model*
Medium Level	Pedestrian	*Y*	*N*	*N*	Extended Adams' model*
Detailed Level	Pedestrian	*Y*	*Y*	*Y*	Simulation

*Adams, 1936; Guo et al, 2004

Pedestrian Behavior

Simulating a person's behaviors under a normal situation at a shopping mall => allows shopping mall management to evaluate arrangement of stores

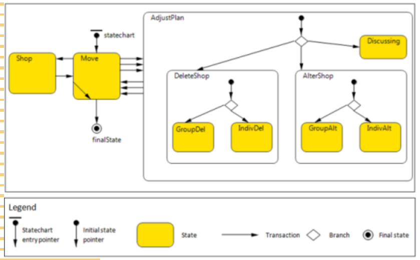
Agents are shoppers characterized by gender, age, preference, schedule, and grouping, and various environmental conditions are considered (e.g. different kind of shops, obstacles, promotions on the shops)

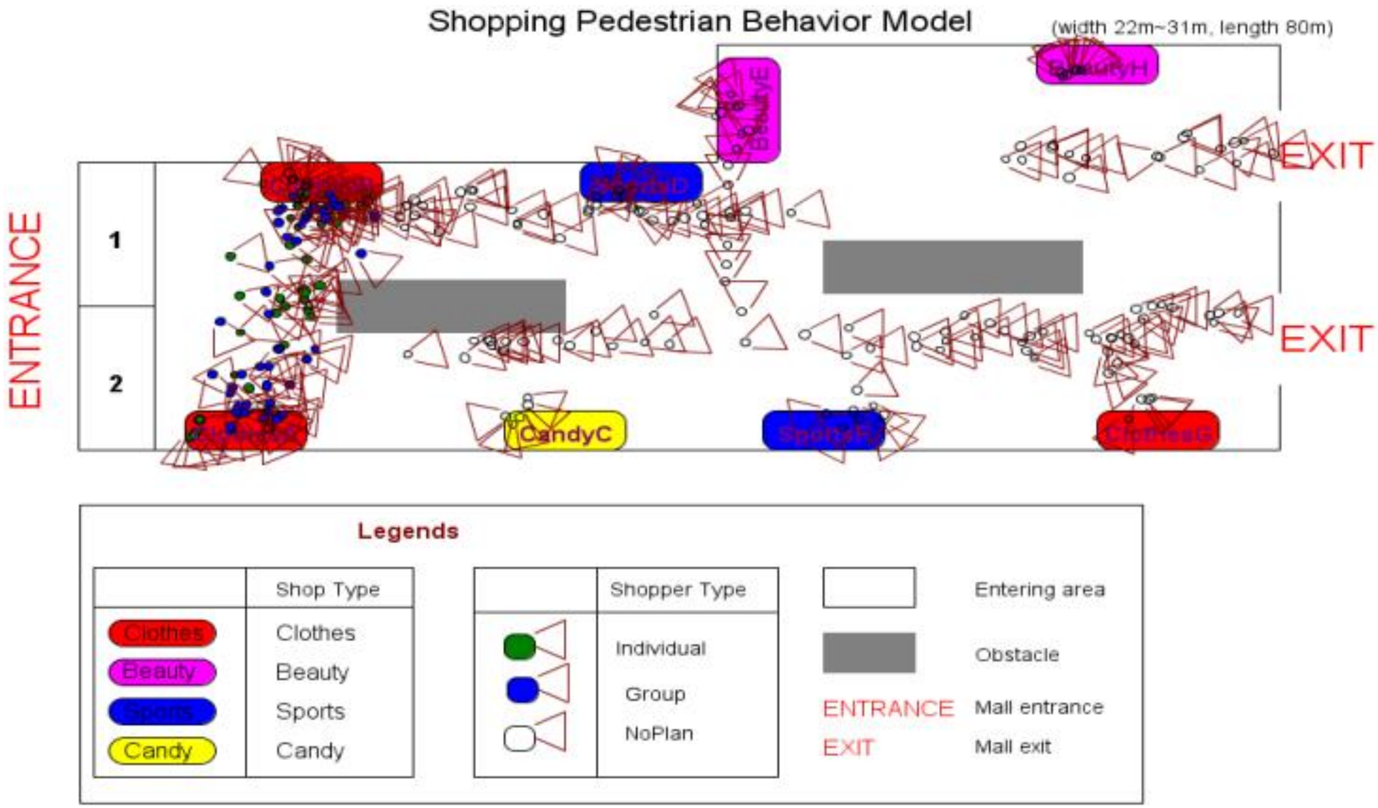
For each agent, tactical human decision-making (via the Extended Decision Field Theory (EFT)) and physical interactions and congestions (via the Social Force model) are considered in an integrated manner.

Models are continuous (social force model) for people movement

Shopping style		Agent type		
Unplanned		Female adult	Male adult	
Planned	Group	Female adult	Male adult	Child
Planned	Individual	Female adult	Male adult	

Pedestrian Behavior



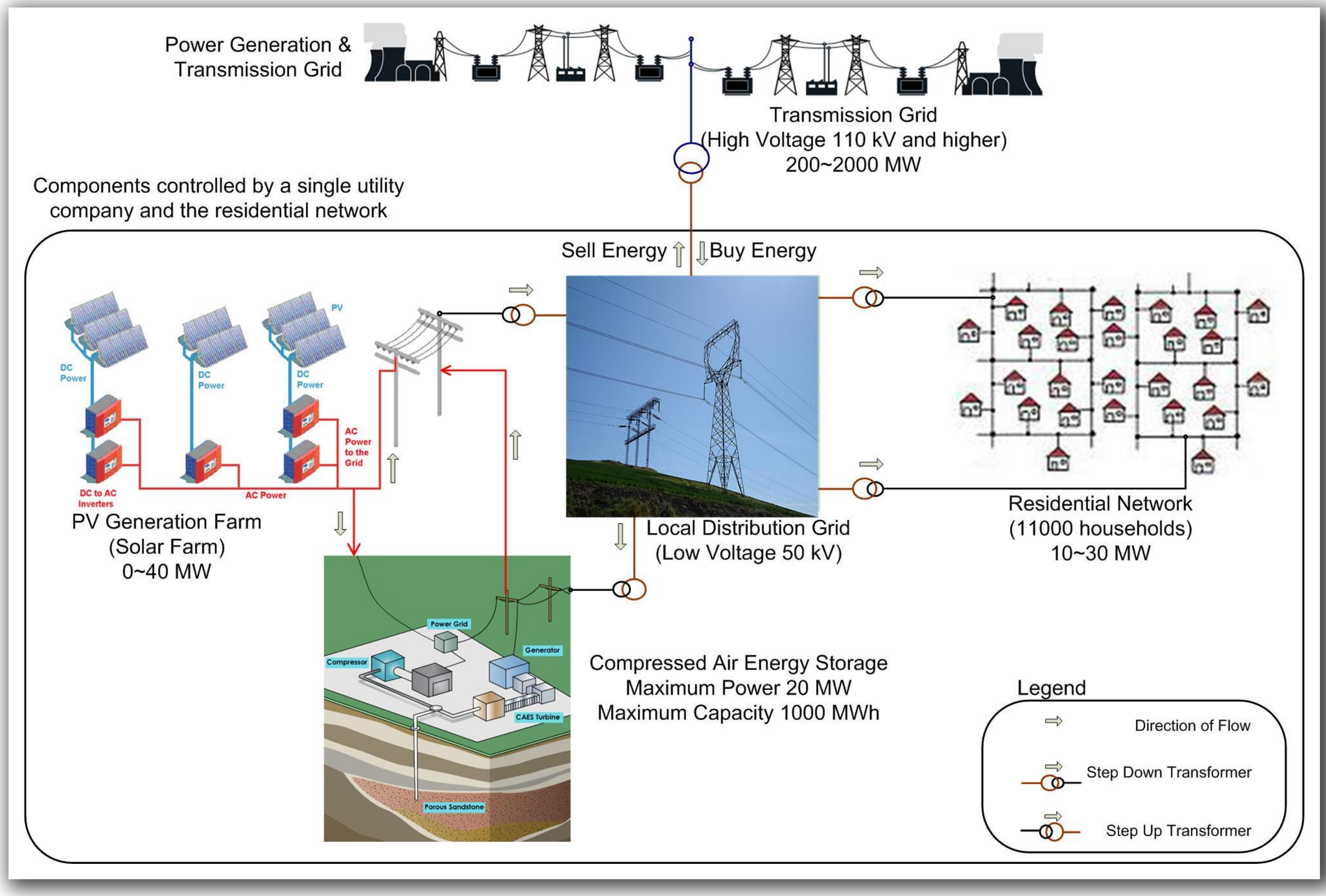


Experimental factors: 1) consideration of human's vision; 2) group shopping behavior; 3) arrangement of stores, 4) complexity of the model

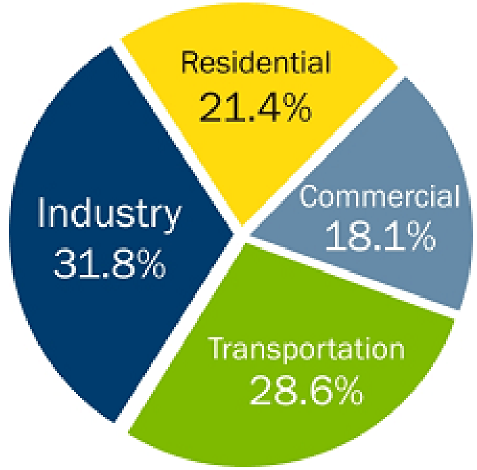
Metrics: 1) average distance among neighboring shoppers, 2) the movement speed of pedestrians, 3) the profit of the shopping mall, and 4) scalability

Xi, H., and Y. Son (2010), An integrated pedestrian behavior model based on extended decision field theory and social force model, In Human-in-the-loop simulation: Methods and practice. eds. L. Rothrock, and S. Narayanan. Springer (accepted)

Energy

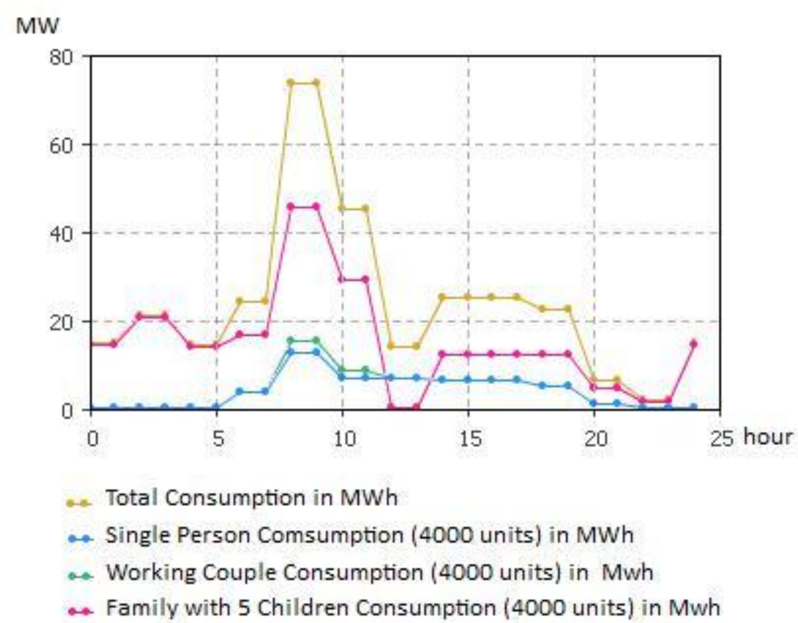

Power Generation &
Transmission Grid
Transmission Grid
(High Voltage 110 kV and higher)
200~2000 MW
Components controlled by a single utility
company and the residential network
Sell Energy
Buy Energy
PV
DC
Power
DC
Power
DC
Power
AC
Power
to the
Grid
DC to AC
Inverters
AC Power
PV Generation Farm
(Solar Farm)
0~40 MW
Local Distribution Grid
(Low Voltage 50 kV)
Residential Network
(11000 households)
10~30 MW
Power Grid
Compressor
Generator
CAES Turbine
Porous Sandstone
Compressed Air Energy Storage
Maximum Power 20 MW
Maximum Capacity 1000 MWh
Legend
Direction of Flow
Step Down Transformer
Step Up Transformer

Household Specific Demand Profile (Demographics)

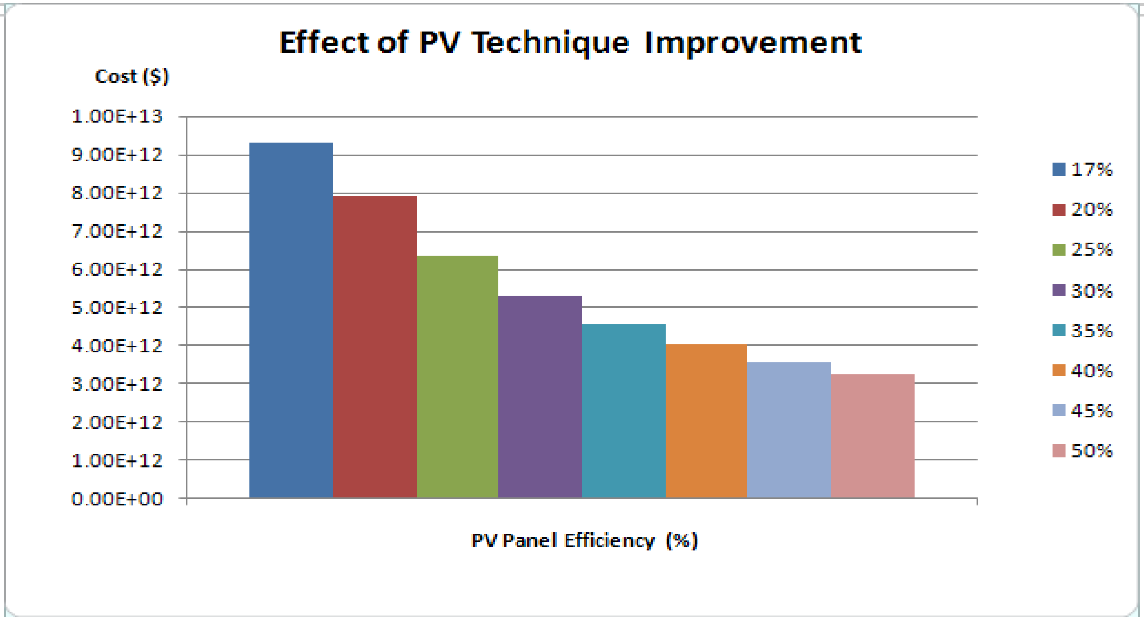


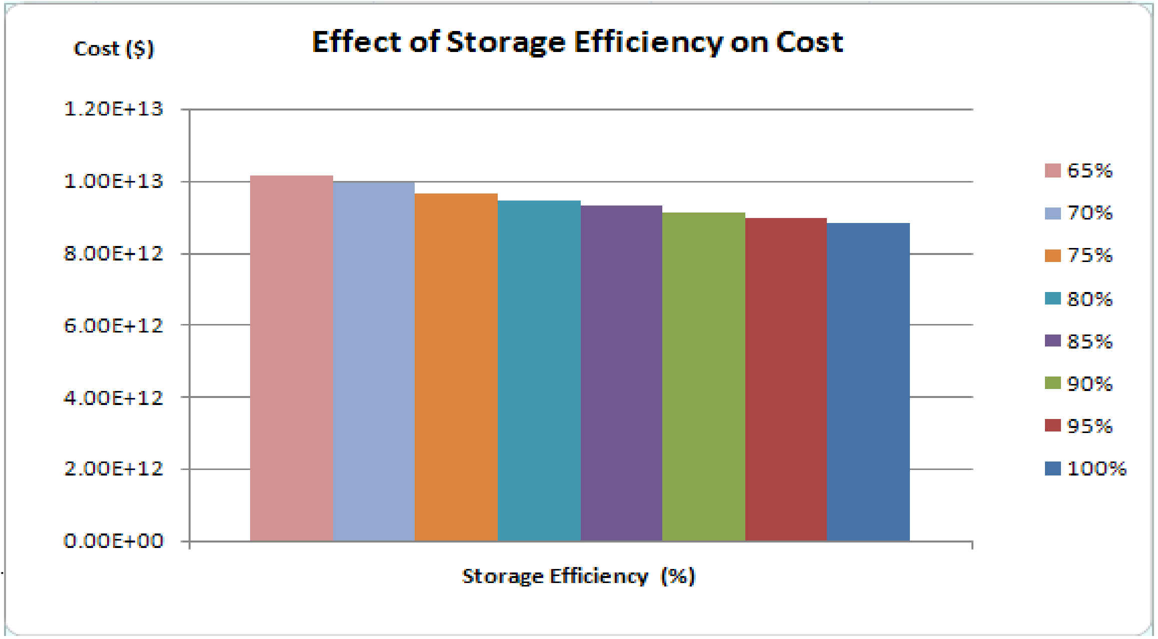
Energy Consumption Data for Family with 5 Children

Appliances	Quantity	Rated Power (Watt)	Time Period
AC	2	1500	12am - 6am, 10 am - 12am
Fan	5	70	8am-9am, 12pm-1pm, 5pm-9pm
Refrigerator	1	100	all day
TV	2	133	9am-11am, 2pm-4pm, 5 pm - 7pm, 9pm-11pm
lights	10	40	6pm - 12am
Microwave oven	1	1000	7am - 7:30am, 11:30am - 12:00 pm, 5:30 pm-6:30pm
Coffee maker	1	1000	7am - 7:15 am, 1:30pm - 1:45 pm
Dishwasher	1	1800	1pm - 2pm, 7pm-9pm
Personal computer	1	120	6pm - 11pm, 3pm-4pm
Monitor	1	150	6pm - 11pm, 3pm-4pm
Laptop	1	50	8pm - 11pm
VCR/DVD	1	20	2pm-4pm, 9pm-11pm
Toaster oven	1	1225	6pm-7pm
Toaster	1	1400	6am-6:20 am, 7am - 7:15am
Water heater	1	5500	7pm - 8pm



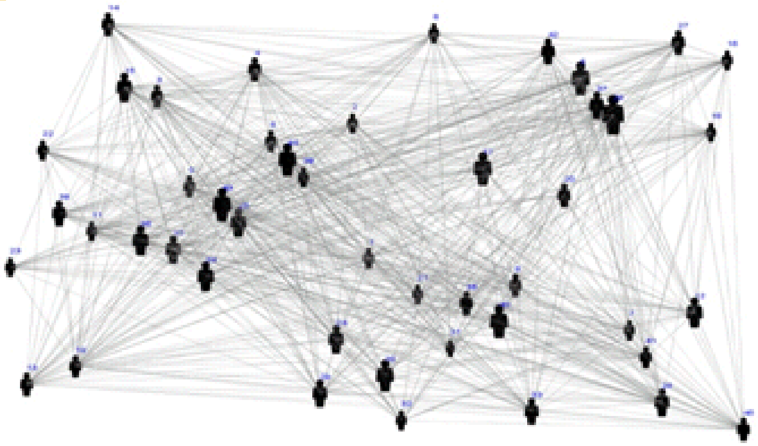
Effect of PV and Storage Efficiency on Costs

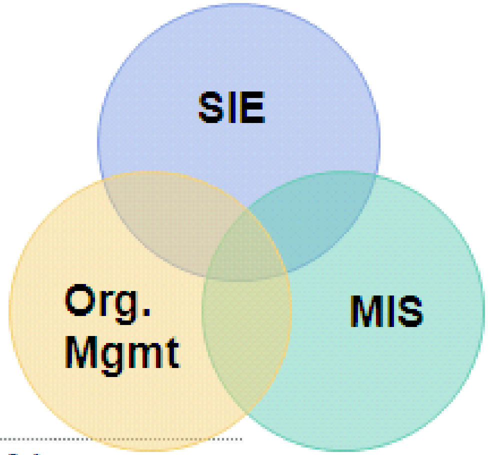




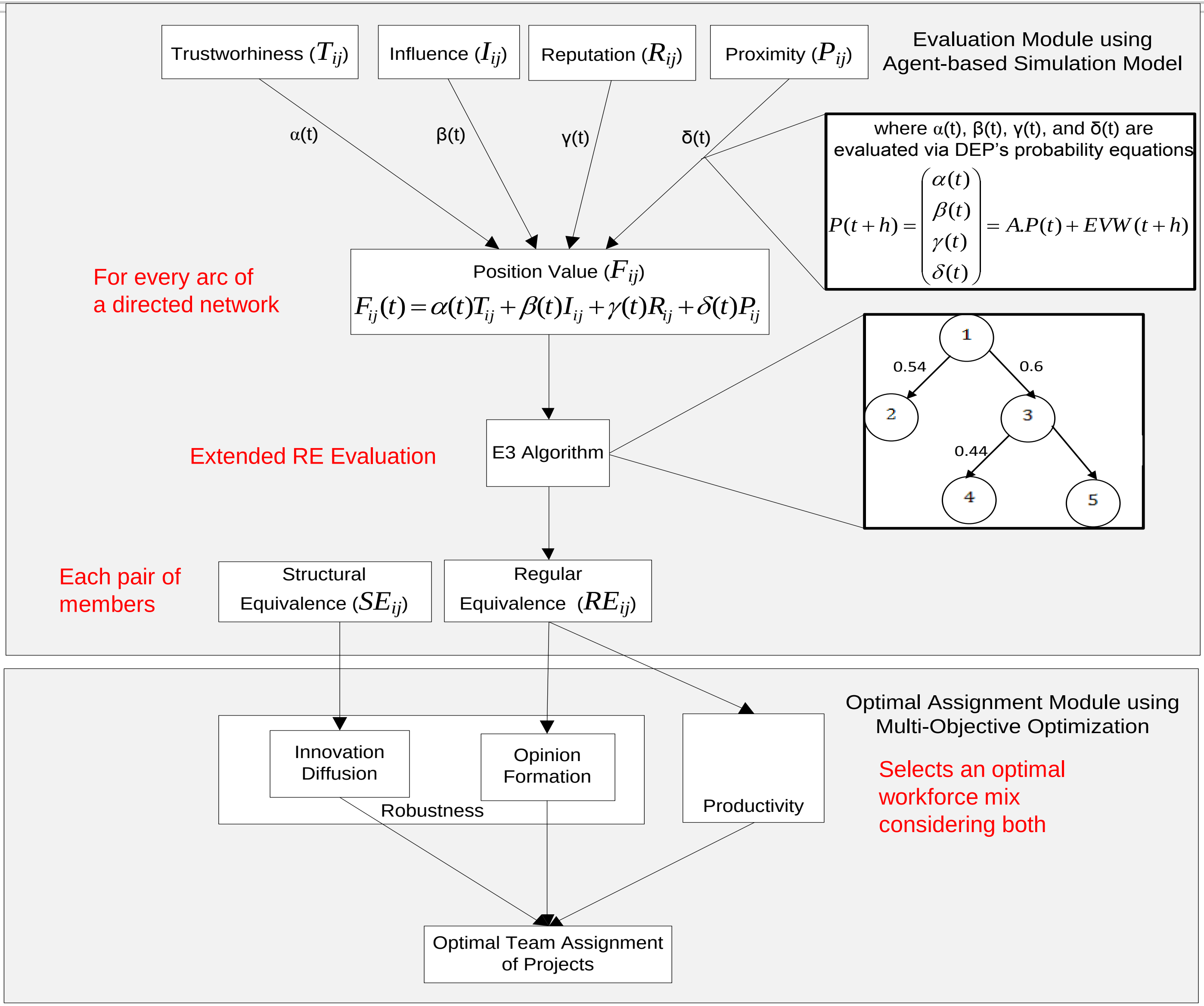
NSF-SOD: Simulation-based Workforce Assignment in a Social Network

- Goal: to develop an simulation framework to help managers devise optimal workforce assignment
  - short-term goal (productivity of projects)
  - long-term goal (robustness)
- under
  - Multi-organizational distributed software development environment (Kuali)
  - Considering the employees' position values in the social network





Workforce Assignment Framework Considering Position and Equivalence

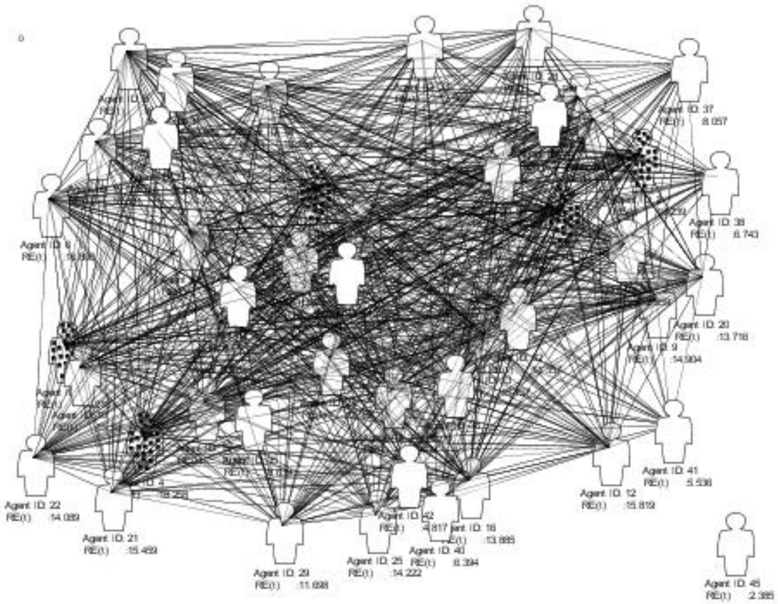


N. Celik, H. Xi, D. Xu, Y. Son, R. Lemaire, K. Provan, 2010, Simulation-based Workforce Assignment Considering Position in a Social Network, *Simulation*, in press.

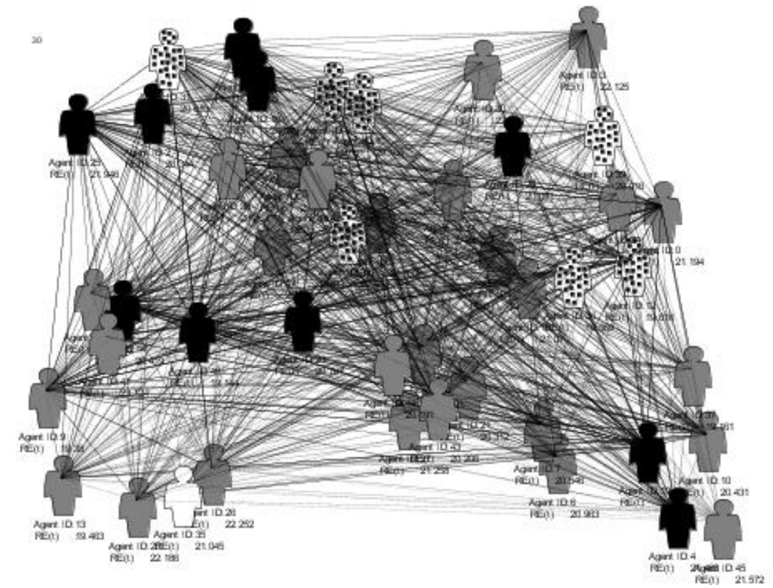
Simulation Results

- Dynamic change of regular equivalence levels in the agent based model
- Dynamic change of the preference state matrix $P(t)^T=[\alpha(t), \beta(t), \gamma(t), \delta(t)]$

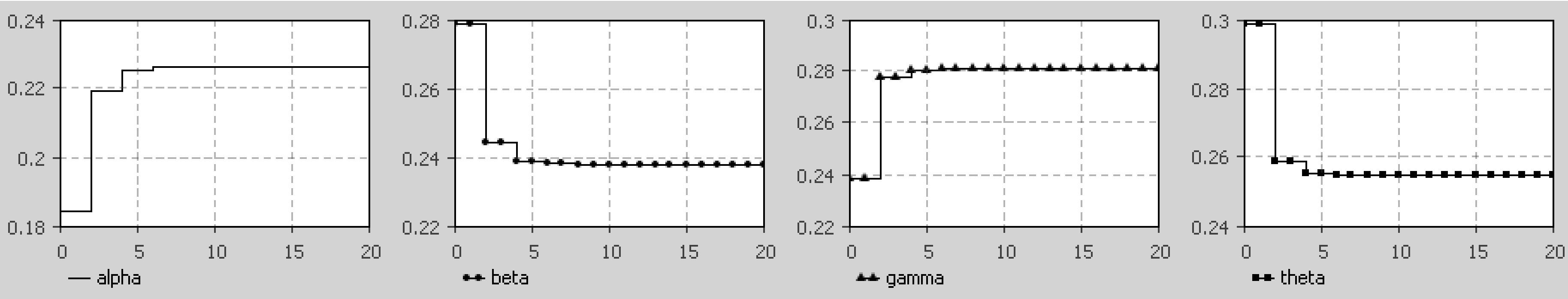
Instance: 3 projects assigned



Instance: 30 projects assigned



RE at Level 1 RE at Level 2 RE at Level 3 RE at Level 4



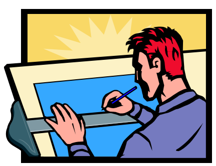
Son

EFRI-COPN: Optimal decision making: How do rats and humans solve the traveling salesman problem?

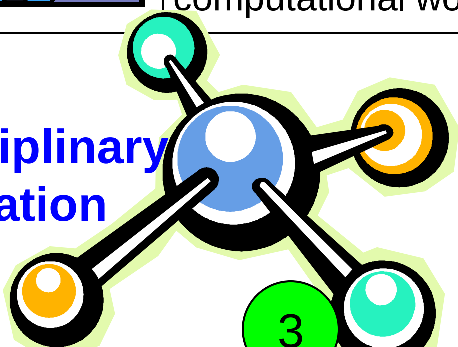
Overview: Project members (below) and their roles (right side)

1

System Engineers



Dr. Bahill
Dr. Son
(algorithmic and computational work)



Interdisciplinary Collaboration

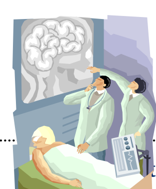
2

Neurophysiologists

Dr. Fellous
Dr. McNau-ghton
(animal work)

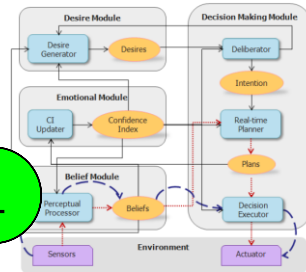
3

Psychologist



Dr. Frank
(neural model, human work)

Learning and decision-making algorithms in computational frameworks

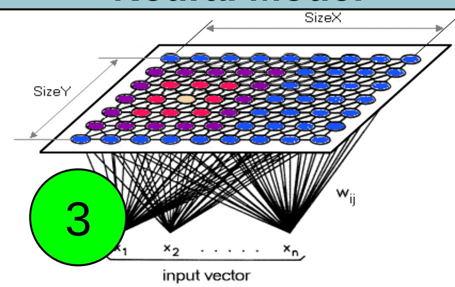


1

- Markov decision process
- Reinforcement learning
- BDI intelligent agent framework

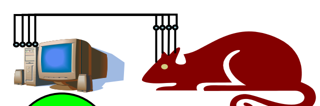
Neural Model

Bridge the gap via neural model



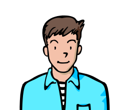
3

Rat and human experiments



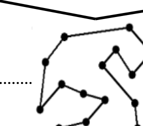
2

Hyperdrive technique



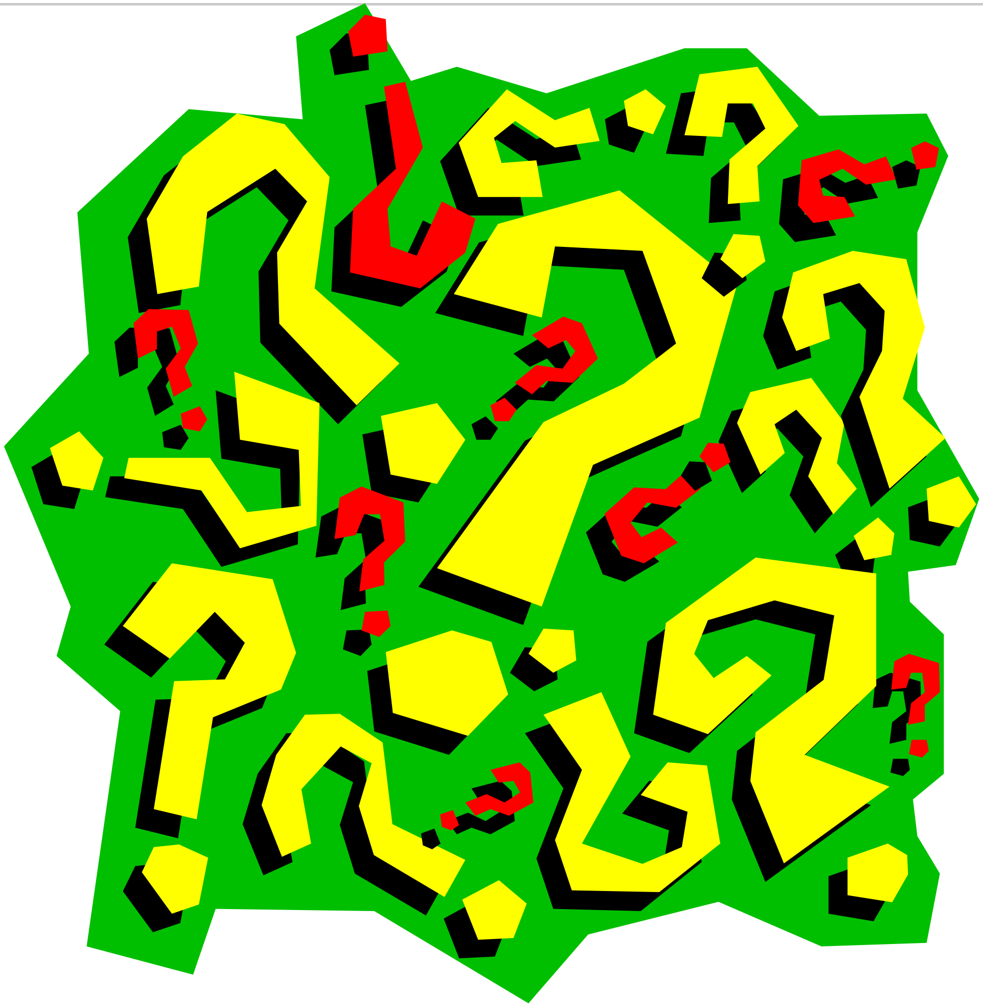
Human subjects

1,3



Traveling Salesman problem

QUESTIONS



Young-Jun Son

1-520-626-9530; son@sie.arizona.edu

http://www.sie.arizona.edu/faculty/son