Understanding Wind Turbine Interactions Using Spatiotemporal Pattern Network (STPN) Zhanhong Jiang and Soumik Sarkar **Department of Mechanical Engineering** Iowa State University, Ames, IA 50011

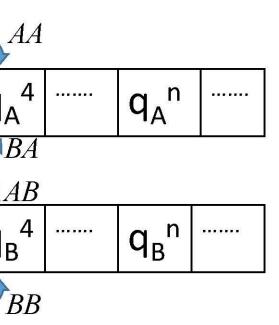
- source of energy.
- wind source.

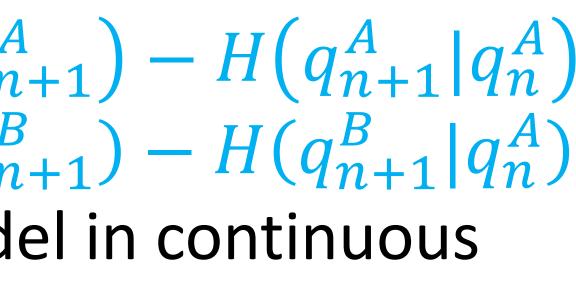
Spatiotemporal Pattern Network Introduction > Symbolic Dynamic Filtering (SDF): Wind power is a significant alternate Wind power prediction is difficult due to its stochastic nature and intermittence of The state-of-the-art techniques mostly Steps of generating a D-Markov machine : focus on predicting short-term farm-wide Data partition \rightarrow Symbolization \rightarrow PFSA energy production, not capturing various Extraction of atomic (D-Markov machine) complex spatiotemporal interactions of and **relational** (xD-Markov machine) turbine-turbine or turbine-wind pattern. patterns: Background Wind turbine A Probabilistic finite state automaton (PFSA): • A 4-tuple $K = (\Sigma, Q, \delta, \widetilde{\Pi})$ Wind turbine B where Σ is the symbol alphabet, Q is the set of Relational pattern representing A to B states, $\delta: \mathbb{Q} \times \Sigma \to Q$ is the state transition causal dependence (Π^{AB} : I^{AB}) Atomic pattern map, $\widetilde{\Pi}: Q \times \Sigma \rightarrow [0,1]$ is the symbol $(\Pi^{B}; I^{BB})$ $(\Pi^{A};I^{AA})$ Atomic pattern representing A > D-Markov machine: • Cross-state transition matrices Π^{AB} and Π^{BA} A PFSA in which each state is represented by are shown as follows: a finite history of D symbols. $\pi_{kl}^{AB} \triangleq P(q_{n+1}^B = l | q_n^A = k) \forall n$ • For a statistically stationary process S = $\pi_{ii}^{BA} \triangleq P(q_{n+1}^A = j | q_n^B = i) \forall n$ $\cdots s_{-1}s_0s_1\cdots, P[s_n|s_{n-1}\cdots s_{n-D}\cdots s_0] =$ Mutual information to quantify the $P[s_n|s_{n-1}\cdots s_{n-D}].$ information content in the atomic and > xD-Markov machine: relational patterns: $I^{AA} = I(q_{n+1}^A; q_n^A) = H(q_{n+1}^A) - H(q_{n+1}^A | q_n^A)$ A xD-Markov machine is defined as a 5-tuple $I^{AB} = I(q_{n+1}^B; q_n^A) = H(q_{n+1}^B) - H(q_{n+1}^B | q_n^A)$ that involves two symbol streams represented by $\{s_1\}$ and $\{s_2\}$: $\mathcal{M}_{1 \rightarrow 2} \triangleq$ Using learnt Markov model in continuous $(Q_1, \Sigma_1, \Sigma_2, \delta_1, \widetilde{\Pi}_{12}).$ domain to predict wind power: $E(Power_k) = \sum_{i=1}^{m} Pr_k(j)E(Power|j)$ where Q_1 is the state set of symbol sequence

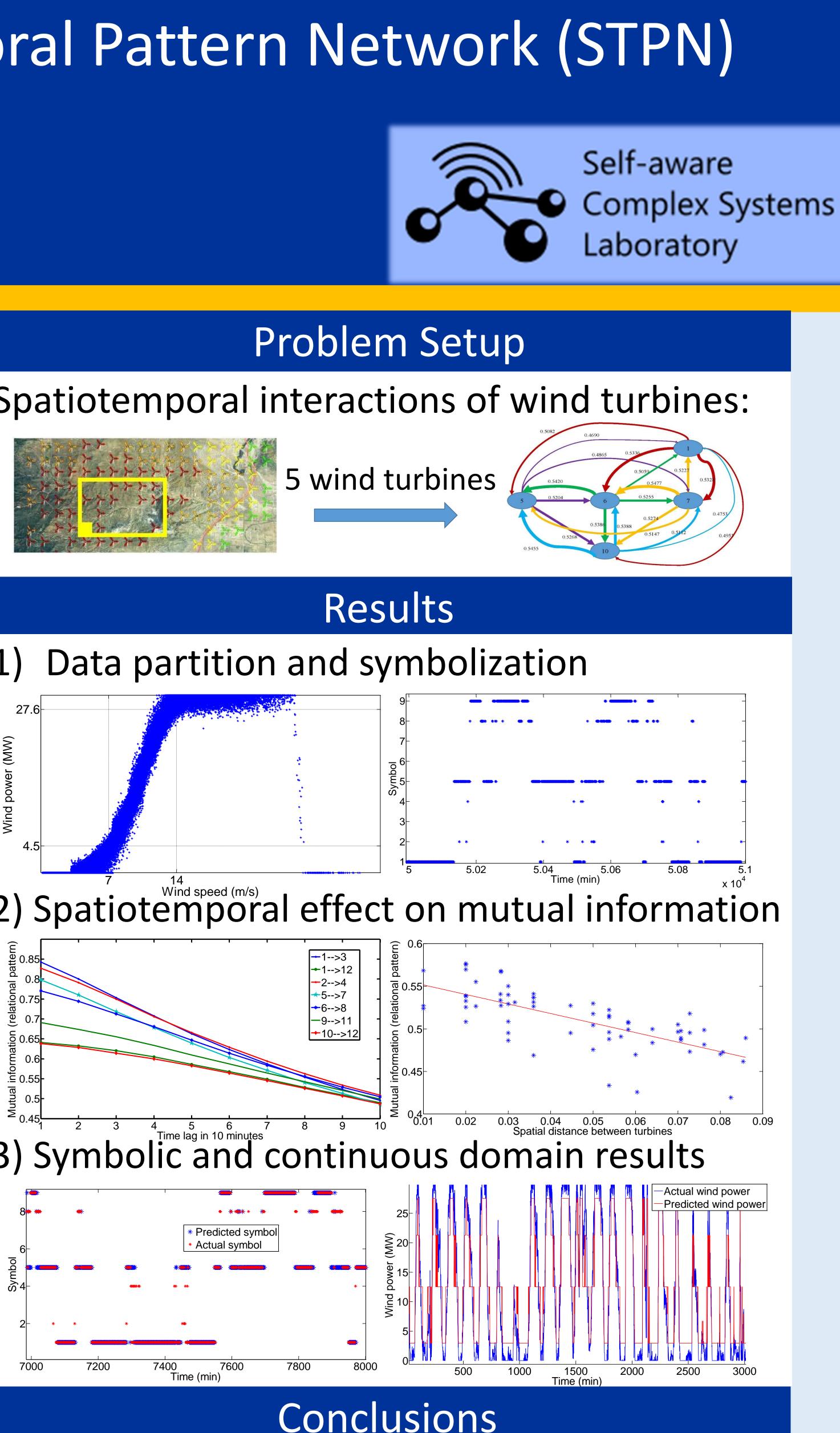
generation function.

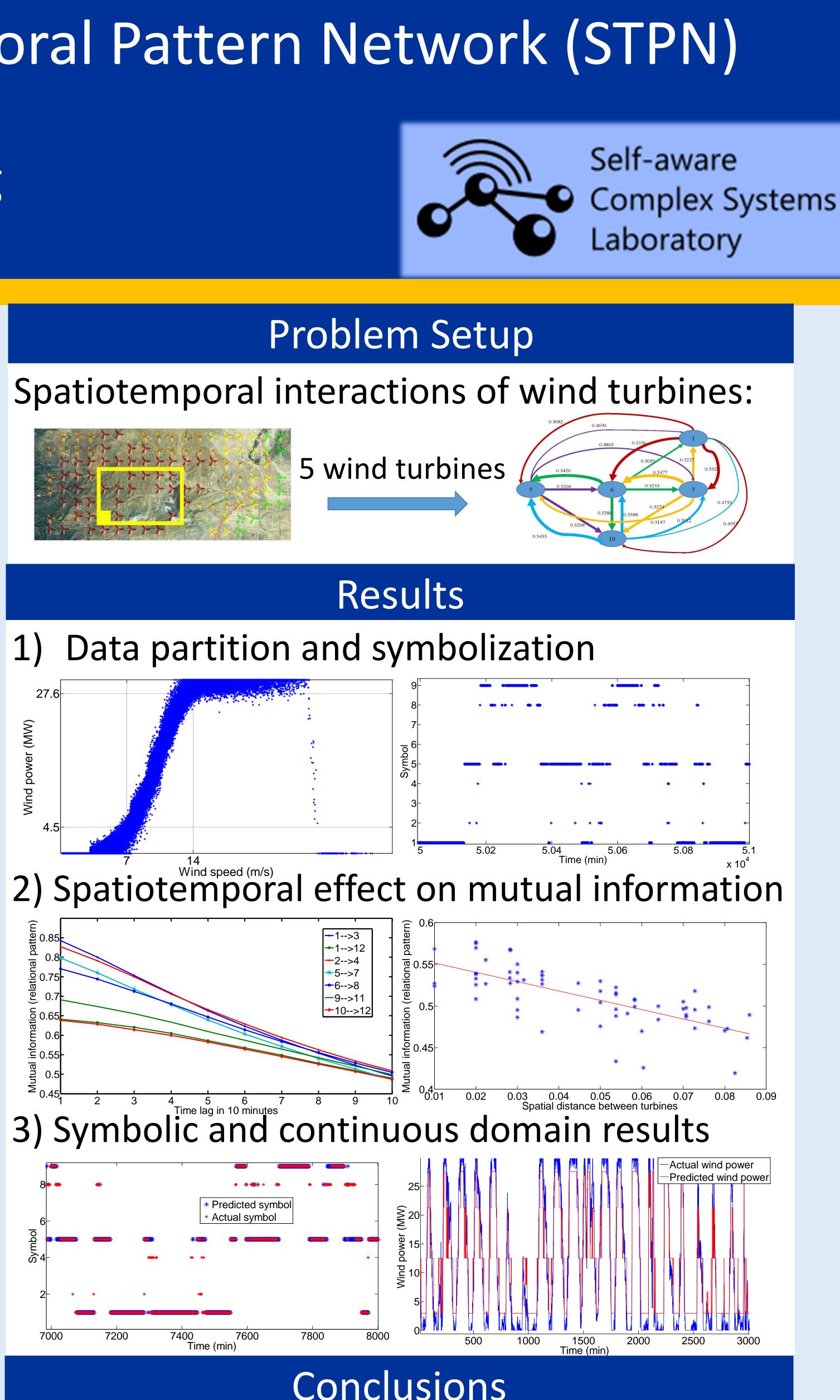
 $\{s_1\}, \widetilde{\Pi}_{12}$ is the symbol generation matrix.











Sarkar, S. et al, 2014 "Sensor fusion for fault detection & classification in distributed physical process". Frontiers in Robotics and AI-Sensor Fusion and Machine Perception.

A novel STPN framework is proposed to capture the interaction characteristics between multiple wind turbines; The proposed scheme shows a good predicting ability (validated with real data). References