Abstract: Analog computing and optimization paradigms exploit massive parallelism to search an exponentially large parameter space and employ computational primitives inherent in the physics of the underlying devices to achieve very high energy-efficiency. This makes them promising and practical candidates for solving difficult computational problems involving algebraic and differential equations that are considered almost intractable using their digital counterparts. My thesis proposes a dynamical systems approach that exploits naturally occurring analog conservation constraints to solve for a variety of optimization and learning tasks. To this end, I propose a continuous-time, real and complex domain analog computing framework based on a special class of multiplicative update algorithms called growth transforms. This computational model naturally satisfies conservation constraints for reaching the minimum energy state with respect to a system-level cost function and is generic enough to be applied to different computing paradigms. First, I will propose a continuous-time annealing algorithm for solving non-convex and discrete global optimization problems. The proposed method optimizes a target objective function by continuously evolving a driver functional over a conservation manifold. Preliminary results also demonstrate how a discrete variant of the model can be used for implementing decentralized optimization algorithms like winner-take-all and ranking. Future work involves investigating the connection between the global optimization framework and the asymptotic behavior of the tunneling current seen in Fowler-Nordheim quantum-tunneling. Next, I will propose an extension of the dynamical system model to the complex domain and show how the framework can be used for designing energy-efficient resonant machine learning models that conserve the network’s reactive energy while dissipating energy only during the process of learning and exploits the phenomenon of electrical resonance for storing the learned parameters. Going forward, I will extend the framework to complex deep neural networks and investigate if the complex domain operation leads to better convergence properties. I will also explore the use of the emergent oscillatory dynamics generated by a complex-growth transform network for data sonification to detect anomalies/novelties in high-dimensional data using human recognizable audio signatures.