

# Integrated Evolutionary Algorithms for Michaelis-Menten Model Parameter Identification

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## ABSTRACT

The proposed research centers on the development a parameter identification method for Michaelis-Menten (M-M) model in Biological System by Evolution Algorithms. The inference of M-M model without knowledge of system parameters is a complicated task due to its nonlinearity and derivation. In this research, a parameter estimation algorithm is proposed for inferring M-M model parameters. This algorithm combines two parameter estimation methods: Genetic algorithm (GA) and Particle Swarm Optimization (PSO) in the strategy of parallel hybridization. The decoupling method is applied to predefine the parameter values in order to improve the accuracy estimation. The performance of the proposed algorithm is evaluated on two aspects: the parameter estimation error and structure identification accuracy. The proposed algorithm is applied to three different M-M models with simulated data. The results show that the proposed algorithm has lower estimation error and higher identification accuracy than the existing method although it processed in a wider search space (from 0 to 5,000).

Keywords : Parameter Identification, System Estimation, Evolutionary Algorithms

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