

Optimizing Optimization

The Next Generation of Optimization Applications and Theory

Stephen Satchell



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