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لم ترد بالأصل

GAUSSIAN MIXTURE MODELING VERSUS AUTO ASSOCIATIVE NEURAL NETWORK FOR ANALOG CIRCUITS FAULT DIAGNOSIS

By

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B.Sc. in Electronics and Communications Engineering – Cairo University

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
Master of Science
in
Engineering Mathematics

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July 2006

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By

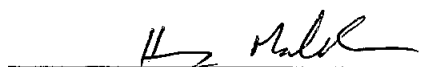
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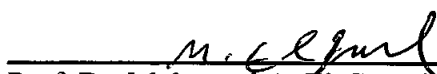
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