NEURO-FUZZY TECHNIQUE APPLICATION FOR IDENTIFYING FLOW REGIMES OF PARTICLES CONVEYING IN PNEUMATIC PIPELINE

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To my beloved mother and father

To my brothers and sisters

To the Islamic nation

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In The Name Of Allah, Most Gracious, Most Merciful

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ABSTRACT

The desire to satisfy demand of industrial sector by improving product quality and reducing environmental emission leads up to identify and monitor the behaving of the internal flows inside pipelines. The flow of solid particles through pipeline in vertical gravity flow rig system has been monitored by 16-electrodynamic sensors that measure the charge carried by solid particles. The identification model has been built and developed based on the training of the captured data at different flow patterns. The final identification model consists of four ANFIS based fuzzy C-means clustering where every ANFIS is able to identify the presence of the flow inside specific quarter in the cross section of the pipe. It is shown that the four ANFIS models are able to work simultaneously to provide the expected output after applying simple thresholding for the ANFIS' output. The identification model has been evaluated by ten different types of flow patterns. The accuracy of the identification model has improved at higher flow rate. As a result, the identified flow pattern has been used to acquire the concentration profile by using filtered back projection. The successful ANFIS model can be extended for horizontal pipeline to present the percentage of flow inside the pipe.

ABSTRAK

Keperluan untuk memenuhi permintaan sektor perindustrian dengan meningkatkan kualiti produk dan mengurangkan pelepasan gas beracun ke alam sekitar telah membawa kepada teknologi identifikasi dan pemantauan aliran di dalam saluran paip. Aliran zarah pepejal melalui saluran paip di dalam sistem pelantar minyak yang beraliran tegak telah dipantau melalaui 16 penderia elektronik yang mengukur cas yang dibawa oleh zarah pepejal tersebut. Model identifikasi telah dibangunkan dan dibina berdasarkan latihan data yang diperolehi daripada corak aliran yang berbeza. Model identifikasi ini terdiri daripada empat ANFIS yang berdasarkan konsep Fuzzy C-Means pengelompokan, di mana setiap ANFIS mampu mengenal pasti kehadiran aliran di dalam bahagian tertentu di dalam keratan rentas paip. Kesemua model ANFIS dinyatakan mampu beroperasi secara serentak dalam menghasilkan output terjangka selepas proses pengambangan untuk mendapatkan output ANFIS. Model identifikasi ini telah dinilai mengunakan 10 jenis corak aliran yang berlainan. Terdapat peningkatan di dalam ketepatan model identifikasi pada kadar aliran yang lebih tinggi. Model ANFIS ini boleh dilanjutkan untuk digunakan di saluran paip mendatar untuk menilai peratusan aliran di dalam paip.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

q	-	Electrical charge
r	-	Distance
ε_o	-	Permittivity of Free Space
E	-	Uniform Radial Field
w	-	Neural-Fuzzy Weight
μ	-	Neural-Fuzzy Membership
O	-	Neural-Fuzzy Node Output

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

Tomographic imaging systems are designed to analyze the structure and compositions of objects by examining them with waves, radiation or other electrical techniques and by calculating virtual cross section through them (Grangeat, 2010). Tomography means that the process to obtain the cross sectional image of a body or a process. The development of tomographic instrumentation, started in the 1950s, has led to the widespread availability of body scanners, which are so much a part of modern medicine (Beck & Williams, 1996). The first whole-body computerized tomography (CT) was been introduced in 1975.

Since 1990s, industry has become under pressure to utilize resources more efficiently and to satisfy demand and legislation for product quality and reduced environmental emissions. Hence there is an increasing need to know more about the exact way the internal flows in process equipment are behaving. Often this must be done non-invasively by tomographic instrumentation because conventional measuring instruments may either be unsuitable for exposure to the harsh internal conditions of the process, or by their presence upset the operation of the process. There is now a widespread appreciation of the need for the direct analysis of the internal characteristics of process equipment; the measuring instruments for such applications must use robust, non-invasive sensors which can operate in the proximity of aggressive and fast-moving fluids and multiphase mixtures.

Tomographic imaging systems also involve using tomographic imaging methods to manipulate the data from remote sensors in order to obtain precise quantitative information from inaccessible locations (Beck & Williams, 1996).

The process tomography is basically consist of set of sensors mounted around the cross section of the pipeline to sense some characteristics of the flow particles that will be used to reconstruct an image for the cross section of the pipe by using some reconstruction algorithms. There are a lot of reconstruction algorithm that are been used to obtain tomogram of the flow like back projection, iterative reconstruction and there are some analytical reconstruction approaches. But some reconstruction algorithms need to identify the type of flow for the conveying particles to better obtain the final tomogram of the flow.

Industrial processes use various methods for tomographic imaging and the selection between these techniques is affected by:

1. The nature of components contained in the pipeline, vessel, reactor or material being examined.
2. The information sought from the process and its intended purpose.
3. The size of the process equipment and the length scale of the phenomena being investigated.
4. The process environment (Williams & Beck, 1995).

1.2 Problem Statement

Electrodynamic sensors have been used to obtain the tomogram of the conveyed solid particles in the pneumatic pipeline. The collected data has been used to reconstruct the image of the flow in the cross section of the pipe by using filtered back-projection algorithm. Filtered back projection algorithm needs to know the type of the flow regime conveying inside the pipeline before it be able to calculate the filter mask which has been used to obtain the tomogram of the flow. Neuro-fuzzy system has been trained to classify the type of flow into quarter, half, three quarter, inverse quarter, inverse half, inverse three quarter, center, full flow in order to improve the previous researcher results using neural network and fuzzy logic.

1.3 Project objectives

The specific objectives of this project are:

- To use the outputs of the electrodynamic sensors, which are mounted around the cross section of the pipeline to obtain the tomography of the flow.
- To identify flow regime of particles inside the pipe of vertical gravity flow rig system by using neuro-fuzzy technique.
- To use feuro-fuzzy identification model and electrodynamic sensors' outputs to obtain the tomogram of the flow.

1.4 Scope of project

The scope of this project begins with collecting the output of the 16-electrodynamic sensors around the circumstance of the pipe at different flow regimes of particles in vertical flow rig system. The Neuro-Fuzzy model will be trained by using set of the output of the electrodynamic sensors as inputs for the model at different flow regimes, which is determined by using baffles of different shapes, and then the Neuro-Fuzzy model will be able to predict the type of flow inside the pipeline for other sets of inputs.

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