Study Spray Draying Modeling by Artifitual Neural Network

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***Abstract*—considering the large Caspian Sea water source have caused to propose a plan for the salt production from salt water by spray dryer. 300 ml salt water with %8 concentrate has been used during 56 experiments. The experiments have done with %35 efficiency for water product and %75 of that for the humid salt. Also, the data have been used for Artifitual Nerual Network (ANN) modeling and has been found in well agreement between the experiments result and predicted one by ANN.**

***Keywords*— spray dryer; moisture; salt water; Artifitual Nerual Network**

I. Introduction

Drying is the oldest method of preserving food [1]. The main purpose of drying is to allow longer periods of storage, minimize packaging requirements and reduce shipping weights [2]. Open-air sun drying has been used since ancient times to dry grain, vegetables, fruits and other agricultural products. However, this method of drying is not always suited to large-scale production. There are some problems, the most important ones are: lack of ability to control the drying operation properly, the length of the drying time, weather uncertainties, high labor costs, large area requirement, insect infestation, mixing with dust and other foreign materials and so on [3].The industrial drying processes have been established to overcome these problems [4]. Drying is defined as a process of moisture removal due to simultaneous heat and mass transfer [5]. This complicated process depends on different factors such as air temperature and velocity, relative humidity of air, air flow rate, physical nature and initial moisture content of the drying material, exposed area and pressure [6]. Knowledge of drying behavior is important in the design, simulation and optimization of drying process [7]. Drying behavior of different natural materials has been studied by several investigators [5,8]. Spray dryers are used to obtain a dry powder from a liquid feed. Although the process equipment is very bulky and operation is expensive, it is an ideal process for drying heat sensitive materials. Spray dryers have been used for nearly a century now, but it is still very difficult to model the performance of this type of process equipment, especially with respect to the quality of the dried product [9]. Some years ago, Bahu (1992) made the question of whether enough modeling of spray dryers had actually been done or not [10]. The rapid expansion of interest in spray drying research appears to indicate that there is still much to do [11]. At first sight, it might appear that the spray drying process is a simple one, with a liquid solution or slurry being fed through an atomizing device into a hot gas stream, with dried particles then being separated from the gas. However, the complexity of the process is that it includes many aspects of fluid mechanics, heat and mass-transfer, particle technology, reaction engineering, and materials science, in other words a large part of chemical, mechanical and process engineering [12]. The analysis of the process may also include many aspects of numerical analysis and mathematical modeling [13]. Spray drying consists of atomizing a solution into liquid drops in a hot air flow to get dry solid particles after solvent evaporation. The convective drying at the drop surface leads to a very fast evolution of temperature and water content due to initial high differences of temperature and water vapor pressure between the drop surface and the drying air [14]. One of the problems often encountered in the operation of spray dryers is wall deposition, which potentially causes fire hazards, reduced product quality and lower production efficiency. The characteristics of airflow significantly affect the drying process of atomized droplets, where recirculation of the droplets affects their drying times and histories. Understanding the features of the airflow inside a spray dryer is essential for the investigation of the resulting complicated droplet trajectories [15]. Several researchers have also developed simulation models for drying processes [16-18]. Artificial neural networks (ANN) models have been successfully used in the prediction of problems in bio-processing and chemical engineering [19]. Artificial neural network (ANN) is a general non-linear model based on a simplified model of human brain function and this technique is particularly useful when a phenomenological model of a process is not available or would be too far complex. Several studies have been reported ANN on modeling of drying [20-24]. ANN technique has also been applied for modeling of water sorption isotherms of black tea [25] and corn starch [26] and the ANN models were found to be better than other mathematical models [27].

II. MATERIAL AND METHODS

A. *Experiments with Spray drying*

We used an experimental spray dryer for the separation. In the dryer, the feed flow through pumped to the reduced (low) atomizer and then a chamber dryer is driven. A magnetic stirrer and a magnet for feed to remain consistent and not precipitated salt in a measuring cylinder is used during testing. With the help of air compressor inlet air flow ranging Debye 1.3 to 4 m^3/min, which is directed into the dryer chamber. Dryer in a room with a temperature of about 25 ° C was constant environmental conditions. In this study, the salt water (use the unrefined salt) at a concentration of 8% and no additives are used.56 tests in three Debye different feed flow and different temperature of inlet air flow is done, that the table (1) is given. During experiments, a magnetic stirrer is used to maintain uniform concentration of the feed brine. In each experiment, 300 ml of brine was used, it can be stated that an average of about 25% feed in each test, of liquid products were collected. Also, an average of 75% of salt in the input feed was seen as a solid product. Part of the water contained in the feed as moisture with salt output out of the system and much of it was evacuated with exhaust air from the dryer, with the placing a cooling metal plate on the front of the vapor output, we were able to collect some of the water vapor condenses and in each experiment, approximately 35% of the feed liquid product was collected.

In some experiments, the salt stick to the walls of the dryer due to high temperature or high Debye air flow, no salt product but the amount of liquid water output increased. Parts of the ultrafine particles of salt with exhaust air were removed from the tank. In each test sample of salt with polymeric tubes insulator heat and moisture collected and hygrometry were tested in the laboratory.

The amount of salt water just to gather information for the simulation of neural network was measured. The results are visible in Table (2).

TABLE (1): Details the conditions tested

Number of tests	**Temperature (°C)**	**feed Debye (m3/min)**	**air Debye (m3/min)**	**Number of tests**	**Temperature (°C)**	**feed Debye (m3/min)**	**air Debye (m3/min)**
1	150	8.64	1.4	29	180	13.95	3
2	150	8.64	1.8	30	210	13.95	1.4
3	150	8.64	2.2	31	210	13.95	1.8
4	150	8.64	2.6	32	210	13.95	2.2
5	150	8.64	3	33	210	13.95	2.6
6	150	8.64	3.4	34	210	13.95	3
7	180	8.64	1.4	35	240	13.95	1.4
8	180	8.64	1.8	36	240	13.95	1.8
9	180	8.64	2.2	37	240	13.95	2.2
10	180	8.64	2.6	38	240	13.95	2.6
11	180	8.64	3	39	240	13.95	3
12	210	8.64	1.4	40	150	13.95	1.4
13	210	8.64	1.8	41	150	22.1	3
14	210	8.64	2.2	42	180	22.1	1.4
15	210	8.64	2.6	43	180	22.1	1.8
16	210	8.64	3	44	180	22.1	2.2
17	240	8.64	1.4	45	180	22.1	2.6
18	240	8.64	1.8	46	180	22.1	3
19	240	8.64	2.2	47	210	22.1	1.4
20	240	8.64	2.6	48	210	22.1	1.8
21	240	8.64	3	49	210	22.1	2.2
22	150	13.95	1.4	50	210	22.1	2.6
23	150	13.95	2.6	51	210	22.1	3
24	150	13.95	3	52	240	22.1	1.4
25	180	13.95	1.4	53	240	22.1	1.8
26	180	13.95	1.8	54	240	22.1	2.2
27	180	13.95	2.2	55	240	22.1	2.6
28	180	13.95	2.6	56	240	22.1	3

TABLE (2): Results of measuring moisture content of salt in each test

Number of tests	Percent of Moisture	Number of tests	Percent of Moisture	Number of tests	Percent of Moisture	Number of tests	Percent of Moisture
1	2.15	15	1.14	29	2.07	43	3.01
2	2.31	16	1.05	30	3	44	3.46
3	1.34	17	1.43	31	2.56	45	6.54
4	1.27	18	2.19	32	2.24	46	12.06
5	1.93	19	1.26	33	1.9	47	10.22
6	1.11	20	1.49	34	2.39	48	5.26
7	1.36	21	1.34	35	1.39	49	2.35
8	3.12	22	4.79	36	1.49	50	1.60
9	1.85	23	9.29	37	1.51	51	1.35
10	2.11	24	6.2	38	3.27	52	2.64
11	1.96	25	2.82	39	5.61	53	4.05
12	0.99	26	3.26	40	4.18	54	2.83
13	2.9	27	4.53	41	7.03	55	2.13
14	1.41	28	3.13	42	1.93	56	1.90

B. The characteristics of neural network and input data.

56 tests were performed and in total 224 data for four sets were collected. Initially, all data that including parameters: air temperature, air Debye, feed Debye and the moisture in the form of dimensionless numbers were changed. Sample of dimensionless at the temperature of 210 ° C is expressed in the following calculations. Thus, all parameters were in the range of zero to one. This has increased the speed of network convergence.

Maximum temperature interval is 90 ° C.
Minimum temperature is 150 ° C.
Dimensionless temperature at 210 ° C.
(210-150)/90= 0.666

Experimental data were divided randomly into two groups. one group for training and another group for testing. Overall, 70% of data were used for training. In fact, the number of neurons depends on the number of independent variables in the input, and dependent variables in the output. In these experiments, the dependent variable (the amount of salt water output) and three independent variables (air temperature, air Debye and brine inlet Debye) and the one- and three neurons were assigned to the input and output layers. The number of hidden layers and their neurons are dependent on the complexity of the problem. Leading (Ahead) network and its input data is described in the following tables.

TABLE (3) Input data and dimensionless of them

Number of Tests	Temperature (°C)	Dimensionless temperature	feed Debye (m3/min)	Dimensionless feed Debye	air Debye (m3/min)	Dimensionless air Debye	Percent Of Moisture	Dimensionless Moisture
1	150	0	8.64	0	1.4	0	2.15	0.104
2	150	0	8.64	0	1.8	0.2	2.31	0.119
3	150	0	8.64	0	2.2	0.4	1.34	0.031
4	150	0	8.64	0	2.6	0.6	1.27	0.025
5	150	0	8.64	0	3	0.8	1.93	0.084
6	150	0	8.64	0	3.4	1	1.11	0.010
7	180	0.333	8.64	0	1.4	0	1.36	0.033
8	180	0.333	8.64	0	1.8	0.2	3.12	0.192
9	180	0.333	8.64	0	2.2	0.4	1.85	0.077
10	180	0.333	8.64	0	2.6	0.6	2.11	0.010
11	180	0.333	8.64	0	3	0.8	1.96	0.087
12	210	0.666	8.64	0	1.4	0	0.99	0
13	210	0.666	8.64	0	1.8	0.2	2.9	0.172
14	210	0.666	8.64	0	2.2	0.4	1.41	0.037
15	210	0.666	8.64	0	2.6	0.6	1.14	0.013
16	210	0.666	8.64	0	3	0.8	1.05	0.005
17	240	1	8.64	0	1.4	0	1.43	0.039
18	240	1	8.64	0	1.8	0.2	2.19	0.108
19	240	1	8.64	0	2.2	0.4	1.26	0.024
20	240	1	8.64	0	2.6	0.6	1.49	0.045

21	240	1	8.64	0	3	0.8	1.34	0.031
22	150	0	13.95	0.394	1.4	0	4.79	0.343
23	150	0	13.95	0.394	2.6	0.6	9.29	0.749
24	150	0	13.95	0.394	3	0.8	6.2	0.470
25	180	0.333	13.95	0.394	1.4	0	2.82	0.165
26	180	0.333	13.95	0.394	1.8	0.2	3.26	0.205
27	180	0.333	13.95	0.394	2.2	0.4	4.53	0.319
28	180	0.333	13.95	0.394	2.6	0.6	3.13	0.193
29	180	0.333	13.95	0.394	3	0.8	2.07	0.097
30	210	0.666	13.95	0.394	1.4	0	3	0.181
31	210	0.666	13.95	0.394	1.8	0.2	2.56	0.141
32	210	0.666	13.95	0.394	2.2	0.4	2.24	0.112
33	210	0.666	13.95	0.394	2.6	0.6	1.9	0.082
34	210	0.666	13.95	0.394	3	0.8	2.39	0.126
35	240	1	13.95	0.394	1.4	0	1.39	0.036
36	240	1	13.95	0.394	1.8	0.2	1.49	0.045
37	240	1	13.95	0.394	2.2	0.4	1.51	0.046
38	240	1	13.95	0.394	2.6	0.6	3.27	0.205
39	240	1	13.95	0.394	3	0.8	5.61	0.417
40	150	0	13.95	0.394	1.4	0	4.18	0.288
41	150	0	22.1	1	3	0.8	7.03	0.545
42	180	0.333	22.1	1	1.4	0	1.93	0.084
43	180	0.333	22.1	1	1.8	0.2	3.01	0.182
44	180	0.333	22.1	1	2.2	0.4	3.46	0.223
45	180	0.333	22.1	1	2.6	0.6	6.54	0.501
46	180	0.333	22.1	1	3	0.8	12.06	1
47	210	0.666	22.1	1	1.4	00	10.22	0.8330
48	210	0.666	22.1	1	1.8	0.2	5.26	0.385
49	210	0.666	22.1	1	2.2	0.4	2.35	0.122
50	210	0.666	22.1	1	2.6	0.6	1.6	0.055
51	210	0.666	22.1	1	3	0.8	1.35	0.032
52	240	1	22.1	1	1.4	0	2.64	0.149
53	240	1	22.1	1	1.8	0.2	4.05	0.276
54	240	1	22.1	1	2.2	0.4	2.83	0.166
55	240	1	22.1	1	2.6	0.6	2.13	0.102
56	240	1	22.1	1	3	0.8	1.9	0.082

TABLE (4): Percent of training data

Train	70%
Valid	15%
Test	15%

C. Simulation output data.

In this study, many hidden layers were examined, and finally, a hidden layer of 18 neurons was suggested as the best mode. To find the best state, at each step of the regression and least square error was evaluated. The case that the higher regression and least-square error is less, Conditions is desirable.

TABLE (5): least squared error and the final regression

MSE	0.00482
Regression	0.94451

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TABLE (6): humidity was calculated by the software

Num	ANN result for humidity	Num	ANN result for humidity	Num	ANN result for humidity	Num	ANN result for humidity
1	0.053	15	0.031	29	0.186	43	0.229
2	0.030	16	0.005	30	0.099	44	0.279
3	0.061	17	0.015	31	0.128	45	0.414
4	0.071	18	0.023	32	0.104	46	0.625
5	0.059	19	0.024	33	0.102	47	0.559
6	0.059	20	0.023	34	0.112	48	0.336
7	0.003	21	0.032	35	0.079	49	0.175
8	0.105	22	0.294	36	0.069	50	0.112
9	0.095	23	0.565	37	0.098	51	0.167
10	0.047	24	0.6	38	0.186	52	0.205
11	0.037	25	0.172	39	0.294	53	0.201
12	0.052	26	0.219	40	0.294	54	0.159
13	0.084	27	0.229	41	0.570	55	0.112
14	0.061	28	0.195	42	0.167	56	0.150

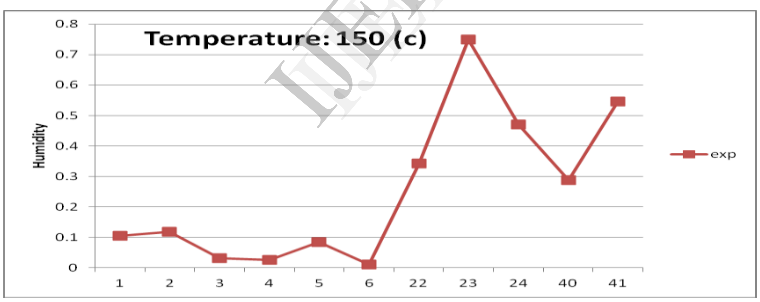
III. *Discussion and Conclusion*

During the experiments, in areas where moisture was lower, more salt and more liquid product was collected. Namely, at higher Debye due to the shorter contact time feed with hot air, less salt and more humid were obtained. According to tests done in four temperature ranges, to compare the efficiency of the dryer, considering the low moisture in the solid salt product is more desirable, moisture curves are plotted (graphs (1) to (4)).

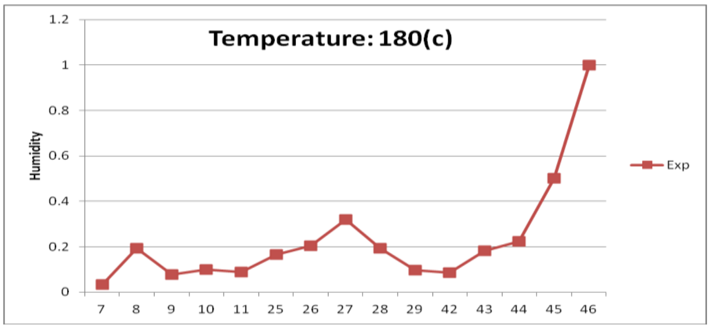
The average moisture content of the product, graphs (3) and (4) are very similar and in both graphs, about 87% experiments show moisture below 20%.

Sudden maximum points in each of the graphs are due to an increase in both the feed Debye and hot air Debye, or are only due to an increase in feed Debye.

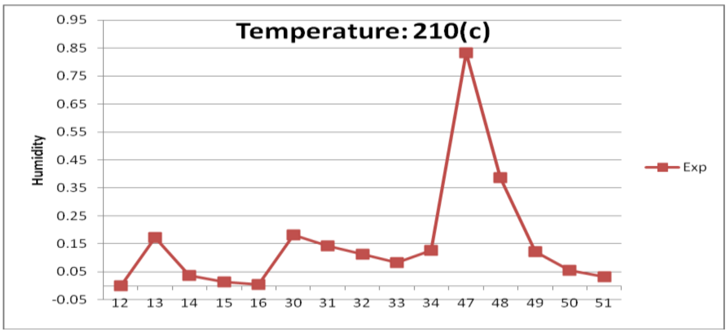
It can be stated that the increase in feed Debye is due to liquid surface contact time with the hot air and thus reduces mass transfer and heat and increases the moisture content.



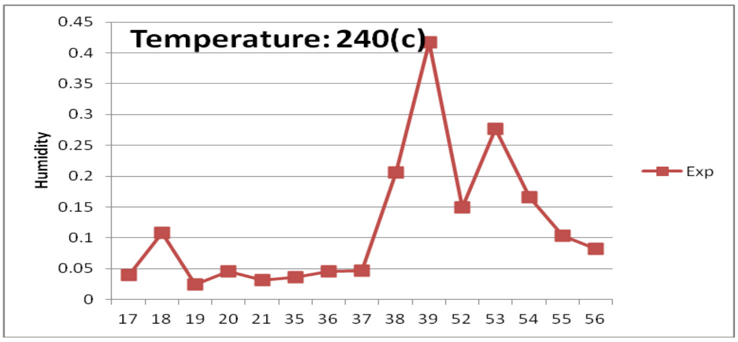
Graph (1): Moisture content at 150 ° C.



Graph (2): Moisture content at 180 ° C.

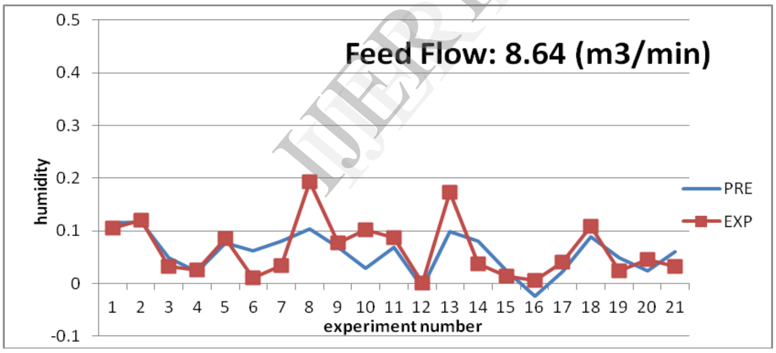


Graph (3): Moisture content at 210 ° C.

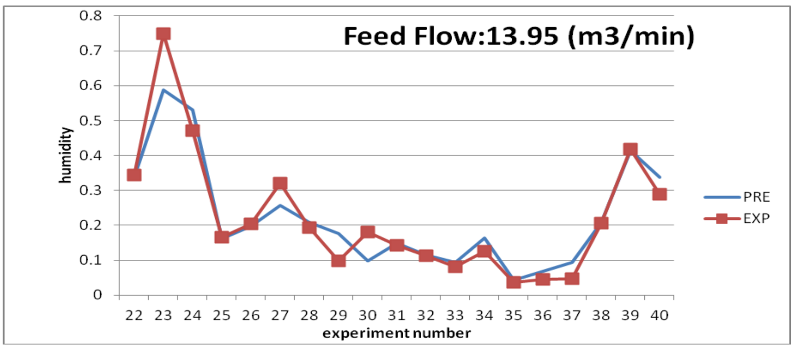


Graph (4): Moisture content at 240 ° C.

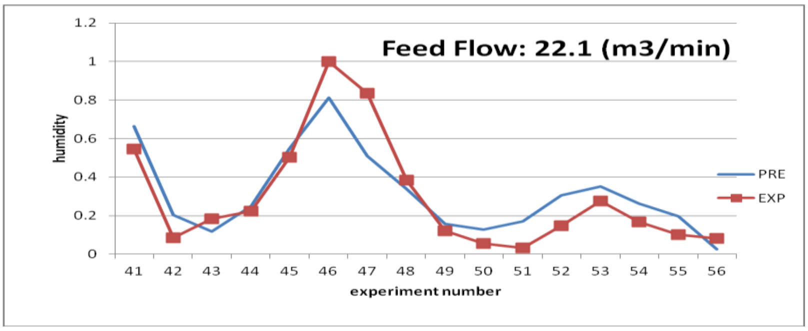
The results for each of the three areas identified for feed Debye are shown as diagrams (5) to (7).



Graph: (5) Moisture in Debye 64/8 (m3/min).

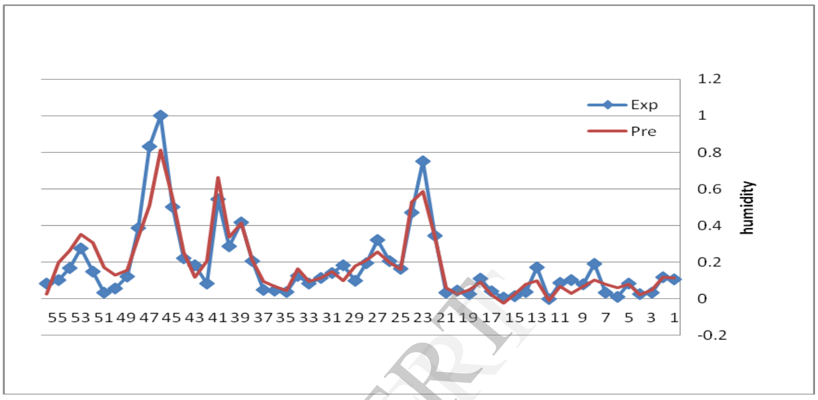


Graph: (6) Moisture in Debye 13.95 (m3/min).



Graph (7): Moisture in Debye 22.1 (m3/min).

In the diagram (8) measurement of moisture content during 56 tests were compared with the values predicted by the software, as it was shown, there is a good agreement.



Graph (8): Measuring Moisture in the 56 experiments.

Experiments 46, 23 and 41 respectively show the greatest amount of salt moisture, and are related to conditions that there are almost simultaneously the high feed Debye and the air Debye.

The best state is diagram (5), that there are humidity under 20% to almost 100% of the samples, and test 12 with low feed Debye and air Debye in 210 ° C temperature, has the best conditions during testing. In this case, there is sufficient time for heat and mass transfer.

The lower simulation lines than experimental lines in graph (5) is partly due to the openness of the system, low feed Debye and also measurement errors.

This networks solve problems that simulation is difficult through logical, analytical techniques and advanced systems.

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