Prediction of Water Production Rate Using Fuzzy Logic Approach

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*Abstract—***this paper describes a fuzzy expert system approach for prediction of water production rate in a desalination plant. The goal of the study is to predict water production rate based on several inlet variables determined by steam flow, steam pressure, seawater temperature, and seawater flow. The data used were collected from plant history records of the operation department log sheets. These data were analyzed and a model was constructed using fuzzy expert system. In the proposed model, both input and output variables are parameterized and classified into several fuzzy sets. A set of fuzzy rules are constructed based on the knowledge extracted from the data collected. Once the rules are evaluated, the variables are defuzzified and converted into corresponding output variable (water production rate). The results showed that inlet variables of the plant could predict water production rate with 95% prediction accuracy.**

Index Terms: fuzzy logic, desalination plant, prediction, water production rate.

I. INTRODUCTION

A. Background

The desalination industries are considered to have a major role in developing human life. Recently, this technology became widely distributed, and its construction along the coastal area has been widely reported. Many countries are adopting these technologies for securing the fresh water supply for consumer consumption allover the world.

General Desalination Company of Libya (GDCOL), consists of eight plants, which are distributed on the Libyan coast. Tobruk desalination plant is one of these plants which is located in the eastern area. Tobruk desalination plant consists of three identical units, with a total capacity 40000 m^3 of fresh water per day, which means 13334 m^3/day for each. The process to calculate the production in each unit is by fixing flow transmitter in production line for each unit, all resulted readings which comes through transmitters will feed the unit automatic control system.

All incoming signals (readings) for production rate enter the automatic control system which converted finally to one signal to indicate the actual product value. This reading is obtained once every 24 hrs.

Estimation of distilled water quantity of flow rate is very important for the management, it gives a clear idea about the plant performance, it gives also an actual indication for production efficiency compared to the standards. Finally these calculations drive decision makers whether to continue the operation, start a maintenance job or completely shut down the unit

Accurate calculations for water production is very important economically, because this product is depends on inlet vital parameters variables such as fuel consumption, power consumption and all these variables are costly. The chances for failures in flow process can occur due to electrical or mechanical faults, or due to error in devices, these failures and faults lead us to think about artificial intelligence (AI) methods. Artificial intelligence (AI) methods, including neural networks, fuzzy logic and genetic algorithms, which are the major applications in engineering fields since the past decade. The main objective of this research is to build a model that can be used to predict the water production rate of Tobruk Desalination Plant, based on fuzzy logic theory.

B. Introduction to Fuzzy Logic

The concept of the fuzzy set was first introduced by Zadeh5 in 1965. In Boolean logic, an element either has full membership in a set or is not a member of the set at all. That is, it either has a degree of membership of 1 or 0. Fuzzy logic allows an element to have a degree of membership in a set which can take on any value between 0 and 1. If-then rule bases can then be developed that reason with these fuzzy sets [1, 2].

The advantages of using fuzzy logic for process modeling include the ability to work with imprecise and noisy data, the ability to incorporate operator expertise directly into the modeling process, and the ability to easily work with qualitative data. In many situations, fuzzy logic systems have been successful in modeling systems where more traditional techniques have failed.

Anbuky [3] presented a fuzzy model that can be used efficiently to predict an area's power demand. Marseguerra [4] presented a fuzzy approach for building a predictive model of an evolving signal. Biyiko [5]

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predicted temperature distributions in the combustion chamber of a coal fired boiler with a fixed bed using fuzzy logic based on data obtained from numerical solution methods for various coal and air feeding rates. Altab [6] presented a fuzzy logic model for prediction of power generation of small scale vertical axis wind turbine. In this research work a fuzzy expert system approach will be developed for prediction of water production rate in a desalination plant.

II. DEVELOPMENT OF THE PREDICTION MODEL

A fuzzy expert system model was developed for prediction of water production rate in a desalination plant. Figure 1 shows the overall structure of the proposed model. Four variables are presented as crisp continuous inputs into the proposed model; steam flow (SF), steam pressure (SP), seawater temperature (SWT), and seawater flow (SWF). Given these input values, which were obtained from the desalination process, the proposed model predicted distillate flow (DF) by implementing an inference scheme based on a fuzzy expert controller. The rule-base used in the proposed model is developed through expert-experience by analyzing data collected from plant history records of the desalination processes.

The development process of the proposed model consists of four main steps. The following subsections will explain detailed steps on how these components of the proposed model are implemented.

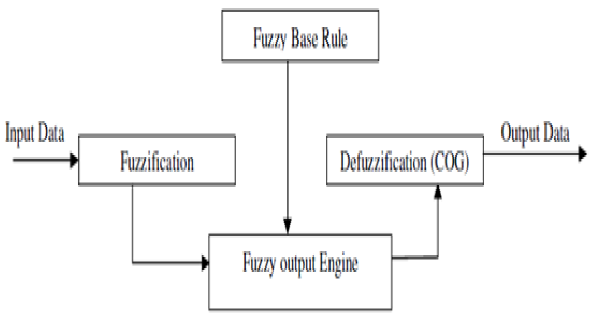

Figure 1. Structure of the Proposed Fuzzy Model

A. Development of the membership functions

A membership function for a variable shows the degree of membership in each of the variable's fuzzy sets for each value in the range of interest. The membership functions for input and output variables were developed through a fuzzification process. A Fuzzification is a mathematical procedure for converting an element in the universe of discourse into the membership value of a fuzzy set. Fuzzification dividing the input and output variables into fuzzy regions (sets). The first step of fuzzification process is to define the fuzzy sets in the input and output variables. The possible domain interval of both the inputs and outputs are divided into a number of regions in such a way that they overlap each other. The length of region may differ for each variable and one membership function is assigned to each region [7, 8].

The input variables in this research work are steam flow (SF), steam pressure (SP), seawater temperature (SWT), and seawater flow (SWF). The output variable is distillate flow (DF). Table 1 presents the inputs, outputs, and the domain intervals of the variables used in the developed fuzzy models as well as the range of each variable. The universe of input and output variables have been partitioned according to their minimum and maximum values allowed controlling the models. Table 2 shows the fuzzy sets of the variables and their associated values and labels. The number of fuzzy sets for each input and output variable is five sets. Each fuzzy set has a defined linguistic term and specified range which can be modified to control the fuzzy model.

Different types of membership functions can be applied such as triangular, trapezoidal, ball shaped, Gaussian, etc. for fuzzification process . Triangular or trapezoidal waveforms could be applied for the systems which have large variation of data [9]. In this research work, a triangular membership function is used for all input and output variables. It is defined by the following equation:

$$Triangle(x,a,b,c) = \begin{cases} 0 & (x \le a) \\ \dfrac{x-a}{b-a} & (a \le x \le b) \\ \dfrac{c-x}{c-b} & (b \le x \le c) \\ 0 & (c \le x) \end{cases} \quad (1)$$

It has three parameters 'a' (minimum), 'b' (middle), and 'c' (maximum) that determine the shape of the triangle. Figure 2 shows a triangular membership function of a fuzzy set. Figures 3 and 4 show the membership functions for the input and output variables of the developed fuzzy model.

Table 1. Domain Intervals of Input and Output Variabies

Variable	Range	Notation	Symbole	Units
Input variables				
Steam flow	0 → 55	SF	X1	Ton/h
Steam pressure	0 → 28	SP	X2	Bar
Seawater temperature	0 → 28	SWT	X3	C
Seawater flow	0 → 1872	SWF	X4	Ton/h
Output variables				
Distillate flow	0 → 570	DF	Y1	Ton/h

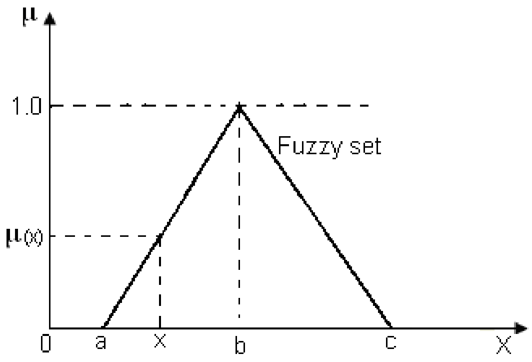

Figure 2. A Triangular Membership Function

Table2. Fuzzy Sets of Input and Output Variables

Fuzzy set	Range A	Range B	Range C	Symbol
Steam flow				
Very slow	0	0	150	VS
Slow	0	150	250	S
Medium	150	250	350	M
Fast	250	350	450	F
Very Fast	350	450	550	VF
Steam pressure				
Very low	0	0	6	VL
Low	0	6	13	L
Medium	6	13	26.5	M
High	13	26.5	55	H
Very High	26.5	55	80	VH
Seawater temperature				
Very cold	0	0	1	VC
Cold	0	1	2.5	C
Medium	1	2.5	4	M
Hot	2.5	4	6	H
Very hot	4	6	10	VH
Seawater flow				
Very slow	0	0	0.5	VS
Slow	0	0.5	1.5	S
Medium	0.5	1.5	2.5	M
Fast	1.5	2.5	3.5	F
Very Fast	2.5	3.5	4.5	VF
Distillate flow				
Very slow	0	0	0.5	VS
Slow	0	0.5	1.5	S
Medium	0.5	1.5	2.5	M
Fast	1.5	2.5	3.5	F
Very Fast	2.5	3.5	4.5	VF

B. Development of the Rules Knowledge Base

Fuzzy rules play a key role in representing expert modeling knowledge and experience and in linking the input variables of fuzzy models to output variables. A fuzzy model uses fuzzy rules, which are linguistic IF-THEN statements involving fuzzy sets and fuzzy inference. A set of fuzzy rules have been constructed for the proposed fuzzy model. These rules are based on the knowledge extracted from data collected from plant history records of the desalination processes. The proposed model can utilize four input variables, one output variable, and five fuzzy sets. With these numbers of parameters, the fuzzy logic model needs a maximum number of rules about 571 rules.

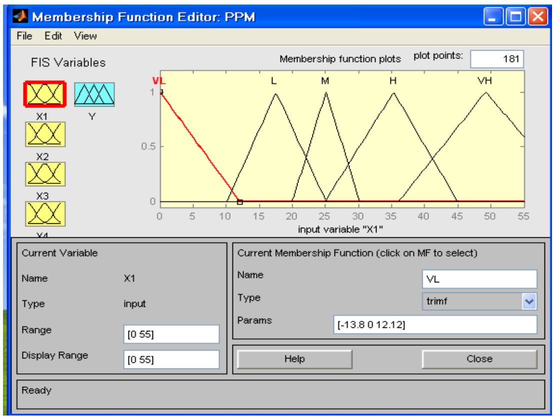

Figure 3a. Steam Flow Membership Function

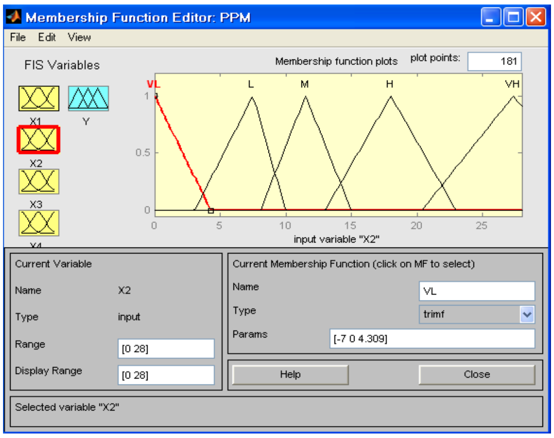

Figure 3b. Steam Pressure Membership Function

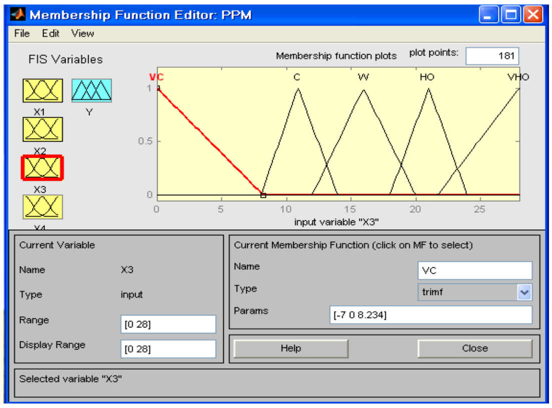

Figure 3c. Seawater Temperature Membership Function

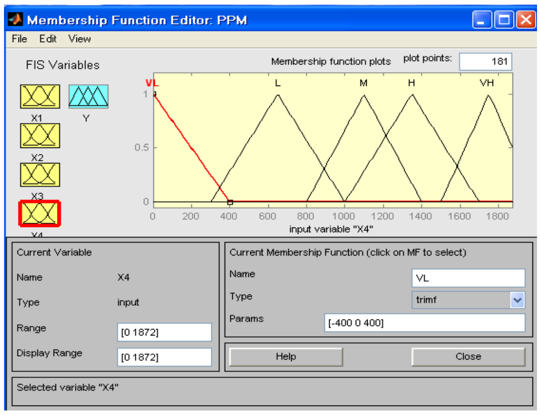

Figure 3d. Seawater Flow Membership Function

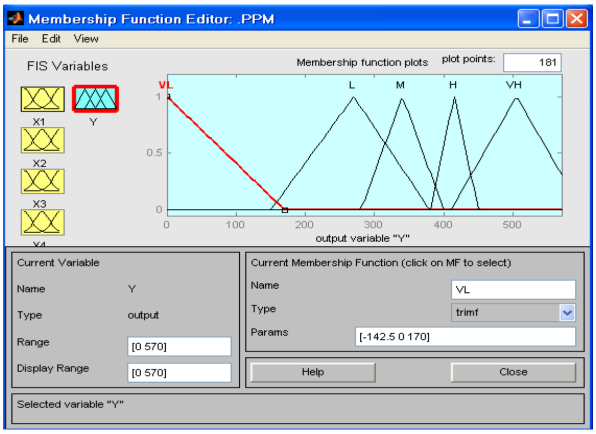

Figure 4. Membership Function for Output Variable (Distillate Flow)

For the purpose of explanation on how these rules are utilized, figure 5 shows the fuzzy rules as given in the rule-base editor. The most used type of fuzzy rules is known as Mamdani fuzzy rules [7, 9]. A simple but representative Mamdani fuzzy rule describing the prediction of distillate flow is given as:

R323: If X_1 is M AND X_2 is H AND X_3 is C AND X_4 is H then Y is M.

where X1, X2, X3, and X4 are input variables, Y is an output variable (a name for a data value to be predicted), M is a medium fuzzy set defined on X1, H is a high fuzzy set defined on X2, C is a cold fuzzy set defined on X3, H is a high fuzzy set defined on X4, and M is a medium fuzzy set defined on Y. The antecedent (the rule's premise) describes to what degree the rule applies, while the conclusion (the rule's consequent) assigns a membership function to each of one or more output variables. Most tools for working with fuzzy expert systems allow more than one conclusion per rule. The set of rules in a fuzzy expert system is known as the rule base or knowledge base.

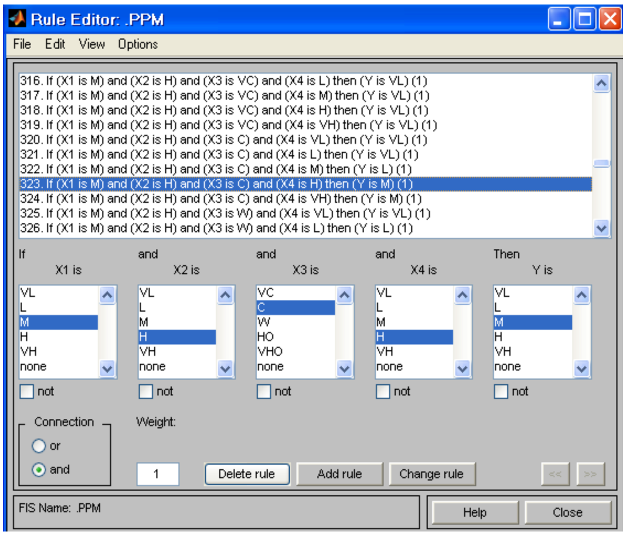

Figure 5. Rule-knowledge Base of the Fuzzy Model

C. *Fuzzy Inference and Defuzzification*

Fuzzy inference is sometimes called fuzzy reasoning. It is used in a fuzzy rule to determine the rule outcome from the given rule input information. Fuzzy rules represent modeling knowledge or experience. When specific information is assigned to input variables in the rule premise, fuzzy inference is needed to calculate the outcome for output variables in the rule conclusion. In other words, for the general Mamdani fuzzy rule, the question is how to compute "Then-part" in the rule. Calculating "THEN" is called *fuzzy inference*.

A number of fuzzy inference methods can be used to accomplish this task. In this research work, the Max-Min inference method is used. In this method, all the fuzzy AND operations are applied into all the input's value of the corresponding fuzzy sets. Applying a fuzzy AND operation will yield a result that is the minimum of the fuzzy value of the number of input variables. The aggregation of the rule will be the truncation of the output fuzzy set. This method is applied to all rules to obtain the final result which gives the final shape of the output fuzzy membership function after aggregation of all the rules, respectively. Then the union operation is applied to all the output fuzzy sets to yield the final fuzzy set [8].

Defuzzification is a mathematical process used to convert a fuzzy set or fuzzy sets to a real number. It is necessary step because fuzzy sets generated by fuzzy inference in fuzzy rules must be somehow mathematically combined to come up with one single number as the output of a fuzzy model [8]. In this research work, the centroide or center of area (COA) is used as a defuzzifier for all output variables of the developed models. In COA defuzzification the crisp value y* is taken to be the geometrical center of the output fuzzy value $\mu_{out}(y)$, where $\mu_{out}(y)$ is formed by taking the union of all fuzzy rule contributions. The defuzzified output is defined as:

$$y^* = \frac{\sum_{i=1}^{N} y_i \mu_{out}(y_i)}{\sum_{i=1}^{N} \mu_{out}(y_i)} \qquad (2)$$

Figure 6 shows a sample set of defuzzified distillate flow from validation data set. The model applies a defuzzification process for each data point one by one. The crisp output values obtained by including each input dataset in the validation data set are given in Table 3.

III. RESULTS AND DISCUSSIONS

In this section, the results obtained after applying the proposed model to inlet variables of the plant are presented in Table 3. Each data set consists of four input variables and their corresponding measured production rate. Input variables are presented to the proposed fuzzy model and the predicted water production rate is obtained and compared with the measured value. The percentage average absolute error (PAAE) is calculated for each data set using the following equation:

$$PAAE = \frac{Measured\ output - Predicted\ output}{Measured\ output} x100 \quad (3)$$

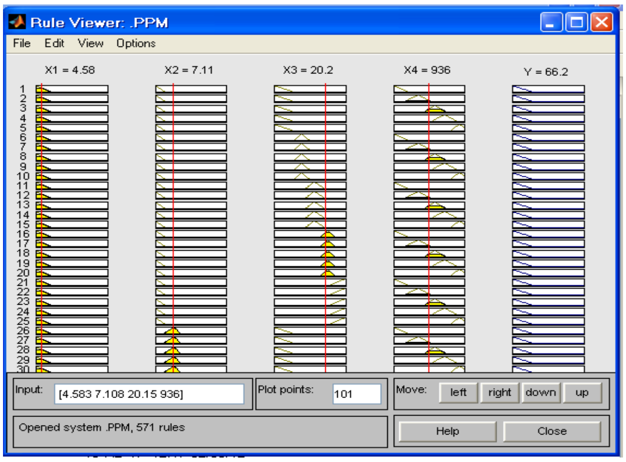

Figure 6. Fuzzy Inference and Defuzzification Process.

As given in table 3, the results obtained present a 3.37% an average absolute error which is an acceptable value, as the predicted water production rate is based on historical record values. This gain shows that the possibility of using a fuzzy model is feasible for prediction of water production rate in a desalination plants.

In addition, a statistical support for the proposed fuzzy model performance is obtained from the coefficient of determination R^2=0.712 and the correlation factor R=0.844, which indicating high fitting between the measure and predicted values.

Figure 7 shows a graphical comparison between the measured and predicted values of water production rate.

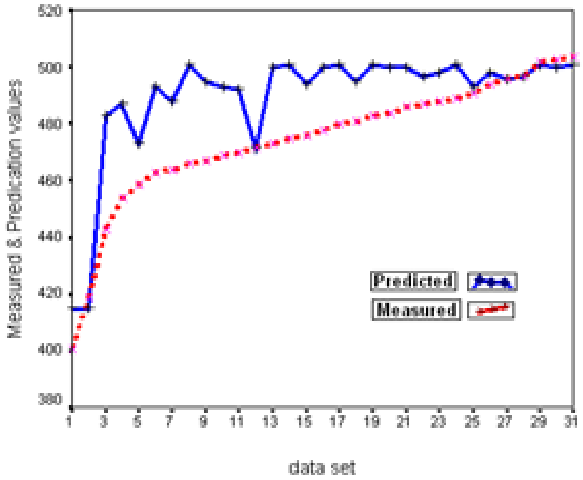

Figure 7. Comparison between Measured and Predicted Water Production Rate

IV. CONCLUSIONS

The present research work studied the feasibility of using fuzzy logic technique to solve the problem of water distilled prediction for desalination plant. The proposed fuzzy model can utilize for input variables and one output variable, and five fuzzy sets. It uses a knowledge base extracted from data collected from plant history records of the desalination processes.

It was observed that the proposed fuzzy model presented a prediction error of 3.37% as an average absolute error which is an acceptable value. In addition, the model performance is measured by the coefficient of determination $R^2=0.712$ and the correlation factor $R=0.844$, which indicated high statistical correlation.

It is concluded that the application of fuzzy logic technique in predicting water production rate is feasible, and the prediction performance of the proposed model is good and acceptable. Therefore, the proposed model can be used with other factors such as historical data, knowledge, experience, etc. to assist and enable the decision makers to make the correct decision about monitoring and controlling the production of distilled water in desalination plants.

Table 3. Data Sets and Results

No.	Input data				Production Rate		Av. Err
	SF	SP	SWT	SWF	M.	P.	%
1	39.3	20	22.5	1872	401	415	3.49
2	39.5	20.2	24.7	1584	419	415	0.95
3	43.2	22.1	22.3	1872	443	483	9
4	43.6	22.3	22.6	1872	454	487	7.26
5	43	22	23.5	1872	459	473	3.05
6	44.6	22.9	23.3	1802	463	493	6.47
7	44	22.5	23.3	1872	464	488	5.17
8	47.4	24.3	22.5	1872	466	501	7.5
9	44.6	22.9	23.1	1833	467	495	5.99
10	44.1	22.6	23	1810	469	493	5.11
11	44	22.6	23	1834	470	492	4.68
12	44.3	22.7	23.8	1872	472	472	0
13	45	23.1	22.6	1872	473	500	5.7
14	47.9	24.6	21	1872	475	501	5.74
15	45.7	23.4	23.6	1773	476	494	3.78
16	45.9	23.5	22	1872	478	500	4.6
17	46.5	23.9	22.2	1862	480	501	4.37
18	44.4	22.8	23	1842	481	495	2.9
19	47.8	24.4	22.3	1872	483	501	3.7
20	45.9	23.5	22.6	1872	484	500	3.3
21	46.8	24	22.7	1872	486	500	2.8
22	45.7	23.4	23.3	1814	487	497	2
23	50	25.7	19.8	1855	488	498	2
24	50.4	25.9	20.6	1872	489	501	2.45
25	51	26.3	19.4	1872	491	493	0.4
26	46	23.6	23.1	1872	494	498	0.8
27	51.5	26.5	19.6	1872	496	496	0
28	51.5	26.5	19.7	1872	497	497	0
29	53.3	27.5	22	1872	502	501	0.19
30	51.2	26.4	22.8	1872	503	500	0.59
31	51.9	26.7	20.9	1872	504	501	0.59

For more illustrations of the results obtained a scatter plot of measured versus predicted values for the proposed fuzzy model is presented in figure 8.

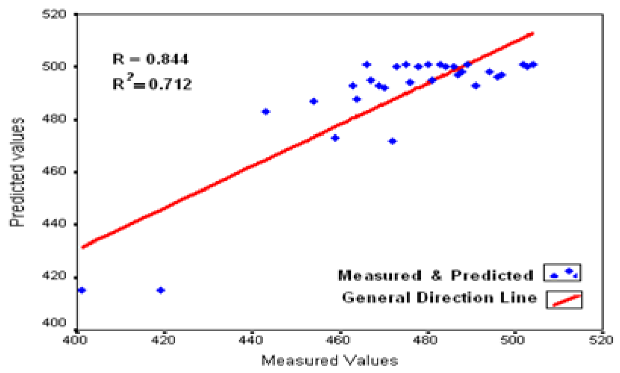

Figure 8. Comparison between Measured and Pedicted Water Production Rate

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