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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Detection of Vortex Cavitation With The Method Adaptive Neural Fuzzy Networks in the Deep Well Pumps

Derin Kuyu Pompalarında Uyarlanabilir Sinir Bulanık Ağları ile Girdap Kavitasyonunun Saptanması

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Abstract

Nowadays submersible deep well pumps are the most used irrigation systems in agriculture field. Efficient operation and economical life of pumps is an important issue. One of the most important parameters affecting pump efficiency and life is cavitation The cavitation is one of the problems frequently faced in the pump systems that widely used in the agriculture field. The cavitation could cause more undesired effects such as loss of hydraulic performance, erosion, vibration and noise. This paper presents a novel model for the detection of vortex cavitation in the deep well pump used in the agriculture system using adaptive neural fuzzy networks. The data submergence, flow rate, power consumption, pressure values, and noise values used for training the ANFIS (Adaptive-Network Based Fuzzy Inference Systems) network are acquired from an experimental pump. In this study, we use to the sixty-seven data for training process, while the fifteen data have used for testing of our model. The average percentage error (APE) has obtained as 0.08 % and as 0.34 % respectively for 67 training data and for 15 test data. The performance of the implemented model shows the advantages of ANFIS. The result of this study shows that ANFIS can be successfully used to detect vortex cavitation. This paper has two novel contributions which are the usage of noise value on cavitation detection and find out cavitation by using adaptive neural fuzzy networks. During the cavitation, the pump parameters must change by controller for prevent unwanted pump errors. The strategy proposed could be preliminary study of automatic pump control. Also proposed novel control strategy can be used for cavitation control in agriculture irrigation pumps, because of easy set up and no need extra cost. The ANFIS based model has real-time applicable thanks to rapid and easy control. It is possible to set safe boundaries in submergence in this model. Thus, users by adjusting controllable parameters can prevent cavitation and increase pump efficiency.

Keywords: Adaptive fuzzy neural networks, Cavitation, Submergence, Vortex cavitation, Deep well pumps.

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Öz

Günümüzde tarım alanlarının sulanma işlemlerinde en çok dalgıç derin kuyu pompaları kullanılmaktadır. Pompaların verimli çalışması ve ekonomik ömrü önemli bir konudur. Pompa verimlerini ve ömrünü etkileyen en önemli parametrelerden biri kavitasyondur. Kavitaasyon tarım alanında yaygın olarak kullanılan pompa sistemlerinde sıklıkla karşılaşılan sorunlardan biridir. Kavitasyon, hidrolik performans kaybı, erozyon, titreşim ve gürültü gibi daha fazla istenmeyen etkilere neden olabilir. Bu makale, uyarlanabilir sinirsel bulanık ağları kullanarak tarım sisteminde kullanılan derin kuyu pompasında girdap kavitasyonunun tespiti için yeni bir model sunmaktadır. ANFIS (Uyarlanabilir Ağ Tabanlı Bulanık Çıkarım Sistemleri) ağını eğitmek için kullanılan dalma derinliği, debi, güç tüketimi, basınç değerleri ve gürültü değerleri deneysel bir pompadan elde edilmiştir. Bu çalışmada, eğitim süreci için altmış yedi veriyi kullanırken, on beş veri modelimizi test etmek için kullanılmıştır. Ortalama yüzde hata (APE) 67 eğitim verisi ve 15 test verisi için sırasıyla%0.08 ve% 0.34 olarak elde edilmiştir. Uygulanan modelin performansı ANFIS'in avantajlarını göstermektedir. Bu çalışmanın sonucu, ANFIS'in girdap kavitasyonunu tespit etmek için başarıyla kullanılabileceğini göstermektedir. Bu çalışmanın iki yeni katkısı kavitasyon tespitinde gürültü seviye değişiminin kullanımı ve uyarlanabilir sinirsel bulanık ağları kullanarak kavitasyonun belirlenmesi olmuştur. Kavitasyon sırasında, istenmeyen pompa hatalarını önlemek için pompa parametreleri kontrolör tarafından değiştirilmelidir. Önerilen strateji, otomatik pompa kontrolünün ön çalışması olabilir. Ayrıca önerilen yeni kontrol stratejisi, kurulumunun kolay olması ve ekstra maliyet gerektirmemesi nedeniyle tarımsal sulama pompalarında kavitasyon kontrolü için kullanılabilir. ANFIS tabanlı model, hızlı ve kolay kontrol sayesinde gerçek zamanlı uygulanabilirliğe sahiptir. Bu modelde dalma derinliğinin güvenli sınırları ortaya koymak mümkündür. Böylece kullanıcılar kontrol edilebilir parametreleri ayarlayarak kavitasyonu önleyebilir ve pompa verimini artırabilir.

Anahtar kelimeler: Uyarlanabilir bulanık sinir ağları, Kavitasyon, Dalma derinliği, Vorteks kavitasyonu, Derin kuyu pompaları

1. Introduction

Nowadays submersible deep well pumps are the most used irrigation systems in agriculture field. Efficient operation and economical life of pumps is an important issue. The vortex which one of the factors that adversely affect the efficiency of the pump can occur due to pumps are placed at low submergence. Due to the vortex, when the air inlet interferes with the pump wing, it affects negatively the efficiency and economical life of the pump (Nagahara et al. 2001). Therefore, in order to prevent vortex formation in deep well pumps, the submergence of the pump must be operated within the safe limit (Albayrak et al. 2013). The vortex formed by the effect of the diameter and height of the water inlet pipe in the pumps causes the pressure of the pump to decrease and to work more loudly (Gurbuzdal, 2009; Hanson, 2000). If the pump absorbs air because of the vortex, cavitation may ocur (Nurşen, 2011).

The cavitation is a physical effect that adversely affects performance in pump applications, causes abrasions (Yüksel and Eker, 2009a) in pump elements and causes severe reductions in pump life. Advanced wear causes efficiency losses in pumps (Yüksel and Eker, 2009b).

In the case of vortex cavitation due to submergence, it is important to observe various types of vortex and determine the beginning of cavitation in the vortex area. Cavitation causes the pump to operate loudly and vibration (Nasiri et al. 2011). The noise and vibration caused by the pressure changes cause the pump to move away from the optimum efficiency point (Karadoğan and Ürün, 1996)

In the case of cavitation of pumps the noise levels that occur are different values according to the cavitation-free state. The noise frequency and levels in the case of cavitation are specified as 147 Hz to 70-80 dBA. It is also indicated that noise level is differentiated in the case of cavitation-free operation and cavitation estimation can be done from noise level measurements (Čdina, 2003).

In this study, an artificial intelligence based approach to determine cavitation problem in deepwater pumps is proposed. In many engineering applications, artificial intelligence based methods are being developed as alternative methods for problem detection. An example of this is to analyze the signal obtained from the vibration by means of fuzzy logic (Sakthivel et al. 2010; Wang and Hu, 2006). It is proposed a model for the breakdown detection of water pump system using binary adaptive resonance network and feed forward network with back propagation algorithm (Rajakarunakaran et al. 2008). The Support Vector Machines (SVMs) based model for detecting and classifying pump faults is presented (Sakthivel et al. 2010a). The hybrid approach that consists of the decision tree and fuzzy classifier is proposed for creating rules from statistical parameters derived from vibration signals under both conditions (good and faulty) (Sakthivel et al. 2010b). It has been used artificial immune recognition system for the fault classification of centrifugal pump(Sakthivel et al. 2011). The fuzzy neural network has used for classification to determine errors and differentiate between error type (Wang and Chen, 2007). The other study demonstrated an artificial neural network (ANN)-based approach for fault detection and identification in gearboxes (Rafiee et al. 2007). It is discussed a ANFIS based error diagnosis model for induction motor (Yang and Tan, 2009).

In this study, an approach to detect vortex cavitation in submersible pumps using adaptive neural fuzzy networks is presented. As seen *Figure 1*, an experimental setup was developed to study the behavior of water in deep wells during pumping in deep wells. In the different submergence depths, the speed of the water at different points of the well and the pump, the output pressure of the pump, the level of fall in the well, the power the pump draws from the network, and the noise level generated are instantaneously measured. In addition, water movements detected by video cameras (K1-K2) located at two different points of the well were recorded. Pump submergence (S), flow rate (Q), power consumption (N), pressure values (Pb) and noise (G) values obtained from the experimental environment were used in network training. Using an adaptive neural fuzzy network, the accuracy of cavitation detection was obtained as nearly 99 %.

The presented study is outlined as follows Section 2 describes the data collection system that enables the acquisition of the experimental environment and the data used in this study. In section 3, adaptive neural fuzzy networks are defined and their layers are given in detail. The networks, network structures and parameters used to determine cavitation in the pumps are described in Section 4. concludes the manuscript.

2. Materials and Methods

2.1. Model of Experimental Pump

This study was carried out in the Department of Agricultural Machinery and Technology Engineering of the Faculty of Agriculture of Selcuk University in the Deep Well Pump Test Tower *(Figure 1)*, which was established under the project number TUBITAK 213O140.

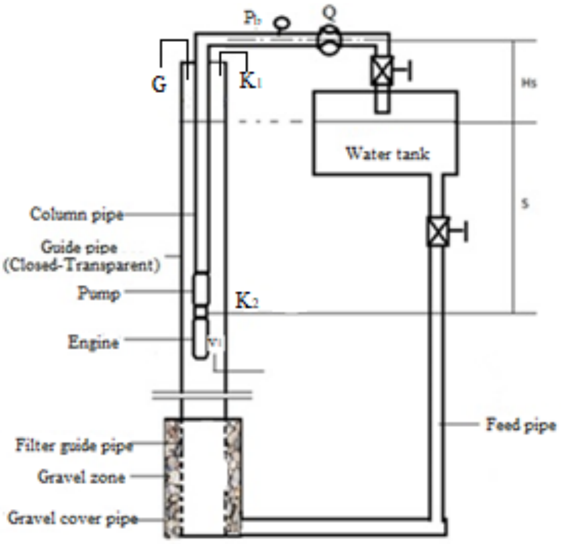

Figure 1. Deep Well Pump Test Tower and Installations

A typical submersible deep well pump placed in the well are given in *Figure 2* as the basic elevation terms appropriate to the terminology.

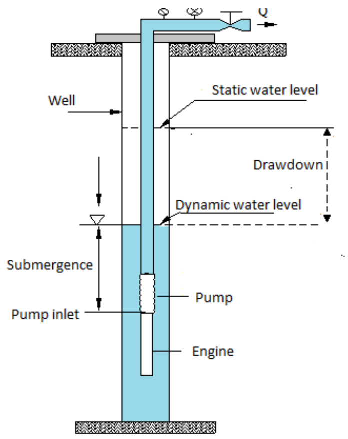

Figure 2. Deep well characteristic curve and basic height terms

Submersible deep well pump was used in the experiments. For pump actuation, 4 kW motor was used for pump. Technical specifications for measurement devices used in present experiments were provided in *Table 1*.

Test assembly with deep wells equipment is high 10 m. Test assembly is kept constant during trials 4 m plexiglass pipe and 2 m well screen pipe from the bottom, 4 m steel casing pipe. Besides around the well screen pipe of 10 cm in width has filled with gravel which bulk density 1.54 kg m^{-3} geometrical diameter between 7-15 mm. Thus it has formed environmental working of deep well. Submersible pump has mounted form may seem at plexiglass pipe 2 m column pipe by connecting *(Figure 3)*.

Table 1. Technical specifications for measurement devices

Device	Technical specifications
Flow meter	S MAG 100 TİP, DN 80 flange connection electromagnetic flow meter, 220 V supplied digital indicator, instant flow, percent flow, total flow indicators. Adjustable 4-20 m/A plus and frequency output. Measurement error: 0.5%.
Manometer	WİKA, 0-10 bar, Bottom installed, 4-20 m/A output.
Water level meter	Hydrotechnik brand, 010 type/1.5 V, 150 m scaled cable, voice and light indicator type.
Velocimeter	FLS brand, F3.00 winged-type, measurement range 0.1-8 m s^{-1}, accuracy ± %0.75, output type: pulse.
Noise Sensor	CT-2012 model, input 4 mA, DC 24V power supply output indicator. Sound level Transmitter model: TR-SLT1A4, Measurement range:30-80 dB, 50-100 dB, 80-130 dB, output 4-20 mA, 90-260 ACV 50Hz/60Hz, Operation temperature 0-50 ^{0}C.
Temperature sensors	Turck brand, 10-24 VDC, -50...100 0C, 4-20mA output.
Computer	Asus intel core i7

Figure 3. Submersible pump and connection of the camera

The standard of EN ISO 9906 is used for measurements and calculations of the pump operating characteristics and the standard of EN ISO 3740 is measurement of the noise level. Noise meter which is next to the drain header has remained stationary throughout the whole measurement. Two cameras for side-view and top-view are used to view the of vortex cavitation. The place of the camera for top-view is changed according to the water level and the camera angle. Side camera is connected to outside of the transparent pipe in order to track the pump-inlet and the of vortex cavitation *(Figure 3)*.

Experiments were conducted at 1880 mm pump submergence (constant hydraulic head). Depression was measured with a water level meter and submergence depth was calculated with the aid of Eq. 1;

$$S = 1880 - \Delta \qquad \text{(Eq.1)}$$

Where; S= Submergence (mm) and Δ = Drawdown (mm).

Figure 4 and *Figure 5* show images of vortex cavitation occurring at low submergence

Figure 4. The images of vortex cavitation ($Q = 60\ m^3h^{-1}$; $S = 30\ mm$)

Figure 5. The images of vortex cavitation ($Q = 60\ m^3h^{-1}$; $S = 20\ mm$)

2.2. Record Process

A software and automation system has been implemented to record the measured quantities in the study. The block diagram of this system was given in *Figure 6*. As you can see from the block diagram, the information received from the sensors in the system is transferred to the computer wirelessly (Bluetooth) via a central data collection card *(Figure 7)*.

The information stored in the central processor is registered with the appropriate names at the intervals requested by the operator via the software interface prepared on the computer. The recording system was designed for can receive one data at a each second. After the pump has entered the regime, the recording process has started and 50 data have been received from a sensor. The average of these data is given in tables *(Table 2)*.

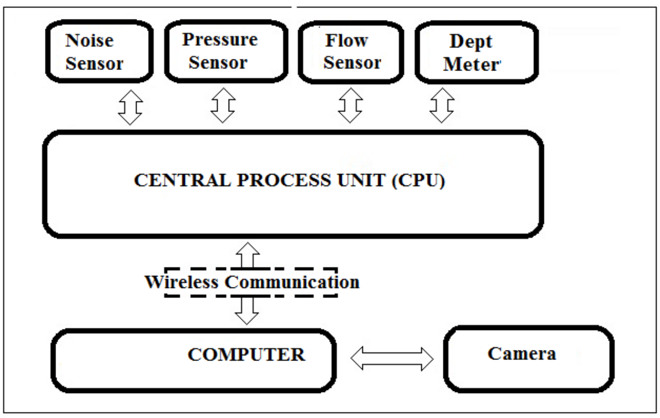

Figure 6. Block Diagram of the Automation System

The submersible pump has taken measurements at 5-7 different dynamic levels for each of the 4 different flow ranges (40-50-55-60 $m^3 h^{-1}$) at the optimum operating speed. The pump is operated at any specified flow rate and the submergence is reduced after the initial values are recorded. With the drop of the water level, the changing flow rate is readjusted by the valve in the measuring pipe. In this way, five different levels of submergence measurements at one flow rate are recorded and displayed.

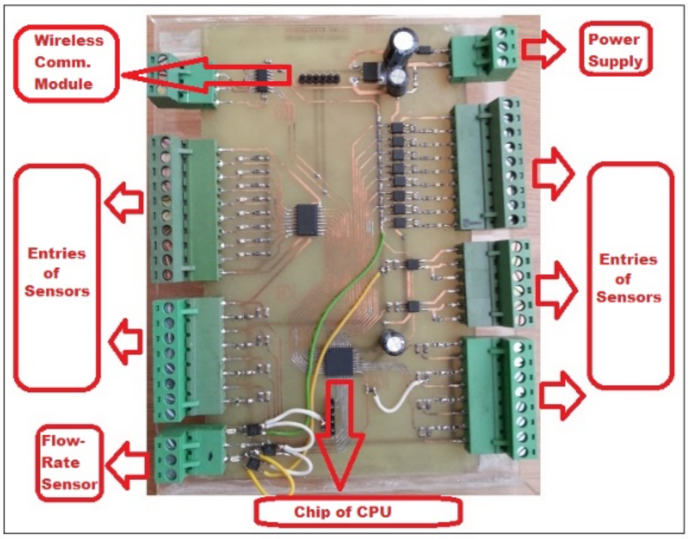

Figure 7. Data collection card used in the automation system

Table 2. A part of the data in different flow belonging to a pump

Q ($m^3 h^{-1}$)	S (mm)	Δ (mm)	G (dBA)	N (kW)	V_1 (ms^{-1})	Pb (kPa)
40.02	159	290	75.84	4.37	0.21	152.19
40.10	1305	570	74.97	4.37	0.21	149.48
40.07	870	1010	73.48	4.37	0.21	143.71
40.14	250	1630	72.73	4.36	0.21	138.74
40.06	100	1780	70.73	4.38	0.21	136.95
37.75	20	1860	82.29	4.19	0.20	126.85
50.12	1430	450	71.42	4.50	0.27	122.83
50.06	1195	685	72.17	4.50	0.27	120.27
50.13	810	1070	72.70	4.51	0.27	116.92
50.15	240	1640	73.04	4.51	0.27	110.37
49.99	40	1840	72.16	4.50	0.27	109.16
38.64	20	1860	82.59	3.49	0.21	60.28
60.11	1250	630	73.10	4.51	0.32	87.30
60.09	1160	720	73.07	4.51	0.32	86.61
60.20	905	975	74.98	4.51	0.32	83.61
60.12	600	1280	71.61	4.52	0.32	80.61
60.08	180	1700	74.63	4.50	0.32	76.85
60.12	70	1810	72.10	4.53	0.32	75.75
53.63	20	1860	83.91	4.15	0.29	63.46

2.3. Adaptive Neural Fuzzy Networks

In the section 3, it is presented the basic theory of ANFIS model. A detailed coverage of ANFIS can be found in (Jang, 1993; Jang, 1996). An adaptive neuro-fuzzy inference system (ANFIS) developed by Jang is a hybrid artificial intelligence method that uses parallel computing and learning ability of artificial neural networks and fuzzy logic extraction (Atmaca et al. 2001; Jang, 1996). ANFIS consists of if–then rules and couples of input–

output which as a part of fuzzy logic. The learning algorithms of neural network are used for training process in ANFIS model (Atmaca et al. 2001; Avci and Akpolat, 2006; Avci et al. 2005; Boyacioglu and Avci, 2010; Jang, 1993).

The ANFIS networks consist of directly connected nodes that exemplify a processing unit (Demirel et al. 2010). The links between the nodes indicate a weight value. The weight value has an important role in adaptation. It determines the output of nodes for suitable adaption. The other significant part of the ANFIS is the learning rules. These rules minimize the error value which is the difference between the output of the whole network and the target value.

ANFIS is one of the very powerful approach to establishing a complex, nonlinear relationship between a set of input and output data sets (Guney and Sarikaya, 2007). ANFIS consists of a set of rules and input / output information pairs in the fuzzy inference system (Kumaş, 2014). ANFIS can make rules for the problem or make use of expert opinions to create rules possible.

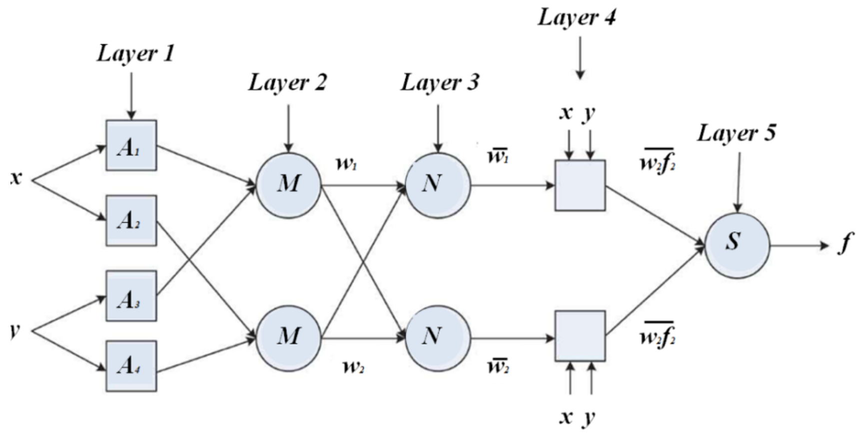

Figure 8. ANFIS Architecture

The ANFIS' architecture with two inputs and one output is as shown in *Figure 8*. ANFIS architecture consists of 5 different layers (Avci and Akpolat, 2006; Caner and Akarslan, 2009; Jang, 1993). These layers are as follows;

***Layer (i)*: It is also called fuzzification layer. The fuzzification layer fuzzyfies the input signals. The output of each node consists of membership values that depend on the input values and the membership function used. The node output is the result of a predetermined membership function.

Layer (ii): Rule layer. Each node in this layer represents the rules and number of rules generated by the fuzzy logic inference system.

Layer (iii): Normalization layer. Each node in this layer accepts all nodes coming from the rule layer as input values and calculates the normalized value of each rule.

Layer (iiii): Defuzzification layer. The weighted result values of a given rule are calculated at each node in the defuzzification layer. The parameters in this layer are called result parameters.

Layer (iiiii): This layer has only one node and is labeled with Σ. Here, the output value of each node in the fourth layer is summed up, resulting in the real value of the ANFIS system.

The most important parameters of an ANFIS structure are the initial and result parameters. The data to be used in education are introduced to the artificial neural network and the input-output functional relation of the training data is best learned with a random training algorithm. This is an optimization process. It is aimed to determine the minimum conditions (difference function) between the model output and the output of the training data, that is, to determine the appropriate values of the parameters (Caner and Akarslan, 2009).

3. Results and Discussion

3.1. The Training of ANFIS and Training Results

The research data used in this study derived from the experimental pump (submergence, flow rate, diameter of pipe, power consumption, pressure and noise values) were used for train the ANFIS. These parameters given as input of ANFIS while corresponding status of cavitation (1 or 0) was given as target, as indicated in *Figure 9*. In this figure, the parameters are taken from *Table 3.*

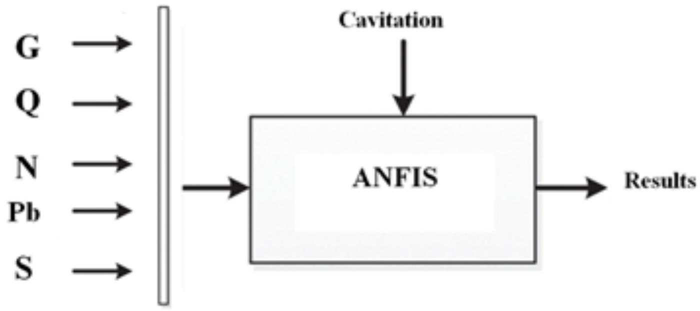

Figure 9. Training Schema of ANFIS

Totally, the eighty-two data were utilised for both process; the sixty-seven data for training and the fifteen data for testing.

Table 3. The ANFIS Training Parameters

Parameter	Value
The number of epochs	100
The accept ratio	0.5
The reject ratio	0.15
The squash factor	1.25
The range of influence	0.5
The number of MFs	12
The number of linear parameters	112
The number of nonlinear parameters	192
The nodes	233

The used ANFIS parameter values were shown *Table 4*. The triangular-shaped membership function (MF) was selected as an input member function, and the linear function was used for output.

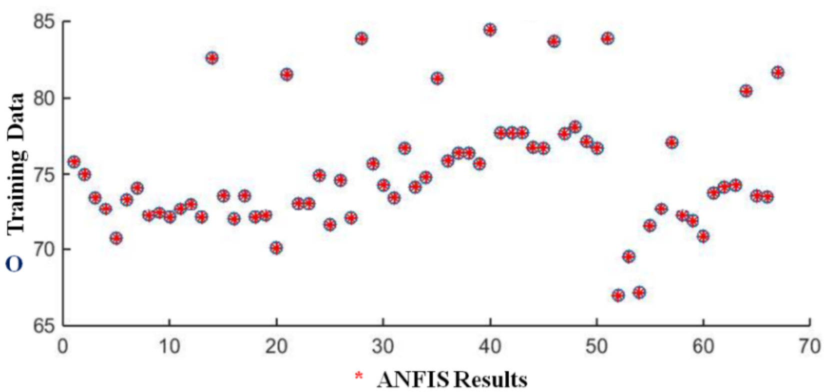

Figure 10. Comparative Results of Training ond ANFIS Training Outputs

Figure 10 shows that the experimental data and training findings are in really good agreement. The performance criteria (APE) has found to really good value that 0.08 for 67 training data.

3.1. The Test of ANFIS and Test Results

The fifteen data which were obtained from the experimental pump, were employed to test the model. The test of ANFIS is described in *Figure 11*.

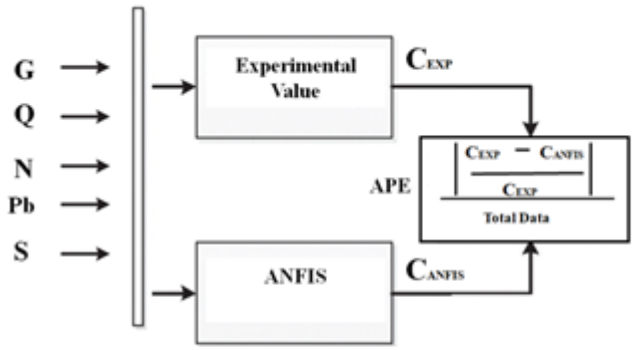

Figure 11. ANFIS Testing Process

As indicated in *Figure 12*, there is a good agreement between the experimental outputs and our model results. The result is that is the APE value 0.34 % fairly good for 15 inputs. The results show that the ANFIS based approach accurately detects the cavitation of the water pump. The experimental outputs and ANFIS model's results are very close to each other. So the success of this model supports the validity of the ANFIS model presented here. It is shown that automatic cavitation detection is possible with the ANFIS model proposed in this work.

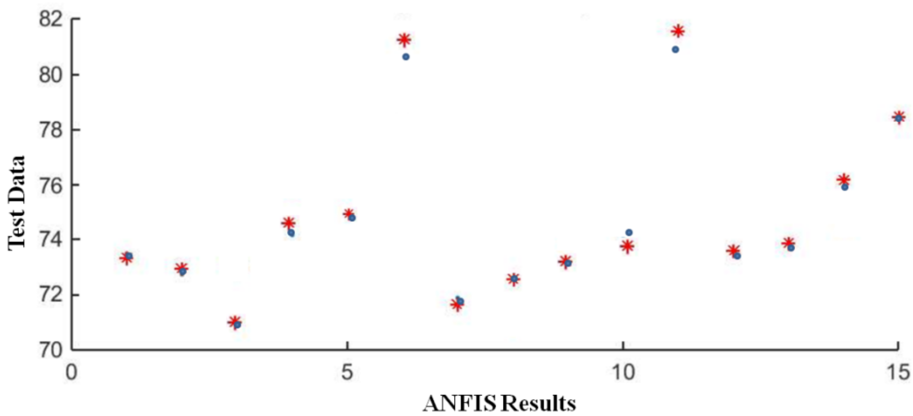

Figure 12. Comparative Results of Test Data and Anfis Outputs

4. Conclusions

Cavitation is formation of vapour bubbles within a liquid at low-pressure regions. It may make mechanical damage to the pump and may reduce the capacity of the pump over time. Therefore, cavitation shortens pump life and causes noisy operation. Detecting the cavitation is a significant task because the successful detection may increase pump efficiency and economic life. We recommend an ANFIS based approach (Sugeno-type FIS) for detection of cavitation phenomenon in deep well pump used in agriculture system. They used data from the experimental pump contains of input (submergence, flow rate, power consumption, noise value and pressure values) and target data (cavitation status). For the obtain experimental data, 82 different cases are investigated. To training process, the 67 data was used and remain 15 data was for the test of ANFIS. The study shows that the detection of cavitation in deep well pump can be significantly succeed by using ANFIS. The results of proposed model are very satisfying. The APE has obtained as 0.08 % and as 0.34 % respectively for 67 training data and for

15 test data. The performance of implemented model shows the advantages of ANFIS. These findings demonstrate that ANFIS can be a useful tool for detection of cavitation. During the cavitation, the pump parameters must change by controller for prevent unwanted pump errors. The strategy proposed could be preliminary study of automatic pump control. Also proposed novel control strategy can be used for cavitation control in agriculture, because of easy set up and no need extra cost.

Furthermore, the ANFIS based model has real-time applicable thanks to rapid and easy control. It is possible to set safe boundaries in submergence in this model. Thus, users by adjusting controllable parameters can prevent cavitation and increase pump efficiency.

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References

Albayrak, K., Konuralp, O., & Canbaz, Ö. (2013). Dünya Dışındaki Gökcisimleri İçin Santrifüj Pompa Seçimi ve Olasi Sorunlar. *8. Pompa ve Vana Kongresi*.2-4 May, P.82-87. İstanbul, Turkey.

Atmaca, H., Cetisli, B., & Yavuz, H. S. (2001). The comparison of fuzzy inference systems and neural network approaches with ANFIS method for fuel consumption data. *The Second International Conference on Electrical and Electronics Engineering Papers*. (ELECO). 7-11 November, P.4. Bursa, Turkey.

Avci, E., & Akpolat, Z. H. (2006). Speech recognition using a wavelet packet adaptive network based fuzzy inference system. *Expert Systems with Applications*, 31(3), 495-503.

Avci, E., Turkoglu, I., & Poyraz, M. (2005). Intelligent target recognition based on wavelet adaptive network based fuzzy inference system. *Iberian Conference on Pattern Recognition and Image Analysis*. 7-9 June, P.594-607. Estoril, Portugal

Boyacioglu, M. A., & Avci, D. (2010). An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. *Expert Systems with Applications*, 37(12), 7908-7912.

Caner, M., & Akarslan, E. (2009). Estimation of specific energy factor in marble cutting process using ANFIS and ANN. *Pamukkale University Journal of Engineering Sciences*, 15(2), 221-226.

Čdina, M. (2003). Detection of cavitation phenomenon in a centrifugal pump using audible sound. *Mechanical Systems and Signal Processing*, 17(6), 1335-1347.

Demirel, O., Kakilli, A., & Tektas, M. (2010). Electric energy load forecasting using ANFIS and ARMA methods.

Guney, K., & Sarikaya, N. (2007). Adaptive neuro-fuzzy inference system for computing the resonant frequency of electrically thin and thick rectangular microstrip antennas. I*nternational Journal of Electronics*, 94(9), 833-844.

Gurbuzdal, F. (2009). *Scale effects on the formation of vortices at intake structures*. (Master Thesis) The Graduate School of Natural and Applied Sciences of Middle East Technical University, Ankara, Turkey.

Hanson, B. (2000). Irrigation Pumping Plants Retrieved from UC Irrigation and Drainage Specialist:

Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. I*EEE transactions on systems, man, and cybernetics*, 23(3), 665-685.

Jang, J. (1996). Input selection for ANFIS learning, fuzzy systems. *Proceedings of IEEE 5th International Fuzzy Systems*. v2, 1493-1499.

Karadoğan, H., & Ürün, N. (1996). Pompa Çıkışında Basınç Dalgalanmaları. *2. Pompa Kongresi*. 3-5 Nisan, P.194-202. İstanbul, Turkey.

Kumaş, K. (2014). *Binalarda ısıtma yükü ihtiyacının belirlenmesi için yeni bir yaklaşım*. Süleyman Demirel Üniversitesi, Fen Bilimleri Enstitüsü, Isparta, Turkey.

Nagahara, T., Sato, T., & Okamura, T. (2001). Effect of the submerged vortex cavitation occurred in pump suction intake on hydraulic forces of mixed flow pump impeller. http://resolver. caltech. edu/cav2001: sessionB8. 006.

Nasiri, M., Mahjoob, M., & Vahid-Alizadeh, H. (2011). Vibration signature analysis for detecting cavitation in centrifugal pumps using neural networks. *Proceedings of the 2011 IEEE International Conference on Mechatronics*, April 13-15, P.632-635. Istanbul, Turkey.

Nurşen, E. C. (2011). Santrifüj Pompalarda Kavitasyon Problemi ve Maksimum Emme Yüksekliği (MEY) Hesabı. 7*. Pompa ve Vana Kongresi*. 28-30 Nisan, P.51-56. İstanbul, Turkey.

Rafiee, J., Arvani, F., Harifi, A., & Sadeghi, M. (2007). Intelligent condition monitoring of a gearbox using artificial neural network. *Mechanical Systems and Signal Processing*, 21(4), 1746-1754.

Rajakarunakaran, S., Venkumar, P., Devaraj, D., & Rao, K. S. P. (2008). Artificial neural network approach for fault detection in rotary system. *Applied Soft Computing*, 8(1), 740-748.

Sakthivel, N., Nair, B. B., Sugumaran, V., & Rai, R. S. (2011). Decision support system using artificial immune recognition system for fault classification of centrifugal pump. *International Journal of Data Analysis Techniques and Strategies*, 3(1), 66-84.

Sakthivel, N., Sugumaran, V., & Babudevasenapati, S. (2010). Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications*, 37(6), 4040-4049.

Sakthivel, N., Sugumaran, V., & Nair, B. B. (2010a). Application of support vector machine (SVM) and proximal support vector machine (PSVM) for fault classification of monoblock centrifugal pump. I*nternational Journal of Data Analysis Techniques and Strategies*, 2(1), 38-61.

Sakthivel, N., Sugumaran, V., & Nair, B. B. (2010b). Comparison of decision tree-fuzzy and rough set-fuzzy methods for fault categorization of mono-block centrifugal pump. *Mechanical systems and signal processing*, 24(6), 1887-1906.

Wang, H., & Chen, P. (2007). Fault diagnosis of centrifugal pump using symptom parameters in frequency domain. Agricultural Engineering International: the CIGR Ejournal. Manuscript IT 07 005. Vol. IX.

Wang, J., & Hu, H. (2006). Vibration-based fault diagnosis of pump using fuzzy technique. *Measurement*, 39(2), 176-185.

Yang, B.-S., Oh, M.-S., & Tan, A. C. C. (2009). Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, 36(2), 1840-1849.

Yüksel, E. and Eker, B., (2009a). Determination of Possible Wear on the Centrifugal Pump Wheel Used for Agricultural Irrigation Purposes. *Journal of Tekirdag Agricultural Faculty*, 6(2): 203-214.

Yüksel, E. and Eker, B., (2009b). Determination of Wear That Can be Formed at the Stainless-Steel Wheels of the Centrifuge Pumps Used at Agricultural Irrigation. *Journal of Tekirdag Agricultural Faculty*, 2009; 6(3): 303-314.