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Prediction of Maximum Oil-Film Pressure in Journal Bearing using Fuzzy Logic and Particle Swam Optimization approaches

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Abstract: Oil-film pressure response is one of the key parameters that describe the operating conditions in hydrodynamic lubrication regimes. In the present study, a fuzzy logic (FL) and particle swam optimization (PSO) approaches were employed to model and predict the maximum oil-film pressure in hydrodynamic plain journal bearing. In the development of predictive models, journal bearing parameters of rotational speed, bearing load and oil-feed pressure are considered as model independent variables. For this purpose, a number of experiments, based Box-Behnken experiment Design technique (BBD), are performed to observe the maximum oil-film pressure values to be used as input data. The results revealed that both models are able to predict the maximum oil-film pressure. However, PSO approach is more accurate than the FL.

Key words: Journal Bearing, Hydrodynamic Lubrication, Oil-Film Pressure, Fuzzy Logic, Particle Swam Optimization.

INTRODUCTION

Hydrodynamic journal bearings are typical critical power transmission components that carry high loads in different machines (Bouyer and Fillon, 2011). Therefore, it is essential to know the expected operating conditions of the bearings to gain high performance and avoid failure at the initial stage. The available predictive techniques for bearing analysis can be categorized into rigorous and rapid techniques (Campbell *et al*., 1968; Martin, 1983; Majumdar, 1994). The use of numerical methods involves very detailed analysis of bearing geometry but tend to be expensive in skill and time and lack of accuracy in the determination of the overall performance of sliding bearings (Mahieux, 2005; Podevin *et al*., 2005; Arghir *et al*., 2003; Sahlin *et al*., 2005; De Kraker *et al*., 2007; Rezaei *et al*., 2009). Traditionally, the classic one-factor-at-a-time experimental approach had been applied to evaluate journal bearing behaviour by changing one variable while the other factors are constant. This technique is laborious and time consuming and seldom guarantees the determination of optimal conditions (Survase *et al*., 2006; Deligant *et al*., 2011; Dimitrios *et al*., 2011).

The existing literature shows that most authors concerned with the study of the oil-film pressure response by using the one-factor-at-a-time technique. (Pawel Krasowski, 2011) has simulated the oil-film pressure distribution for laminar and steady oil flow in journal bearing. (Nuruzzaman *et al*., 2010) have calculated the pressure distribution and load capacity of journal bearing using finite element method. Their results were compared with analytical results. In another studies (Sharma and Pandey, 2009; Tsuneo Someya, 2003; Valkonen, 2010), experimental investigations were performed based on one-factor -at-a-time procedure to discuss the development of pressure profiles in the oil-film of slide journal bearing. These studies revealed that without considering the effects of other factors led to incorrect conclusions, due to the presence of interactions between the factors. In another work, (Stolarski, 2010), the inconsistency of the pressure profiles from experimental study with the theory results and has shown insufficient agreement. These limitations of one-factor-at-a-time technique can be defeated by using fuzzy logic (FL) and particle swam optimization (PSO) approaches. The simplicity associated with the use of those methods allow for the researcher to circumvent the need for rigorous mathematical modeling.

To the best knowledge of authors, no investigation is yet available in literature that addresses to the prediction of maximum oil-film pressure by artificial intelligence methods. Thus, the aim of the present work is therefore to apply FL and PSO approaches to predict the maximum oil-film pressure in hydrodynamic journal bearing. The key process parameters taken into consideration are: rotational speed (S), bearing load (L) and oil-feed pressure (O). The solutions predicted by the developed models are compared with the actual values.

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MATERIALS AND METHODS

Journal Bearing Test Rig:

In this study a sturdy versatile journal bearing test rig CM-9064 (Fig. 1) was used to conduct the experiments. This test rig is easy to operate with provision to measure bearing friction, pressure and temperature profiles at different angular position on the circumference of journal bearing. The journal is mounted horizontally on a self-aligned bearings, it is rotated by a servo-motor with timing belt 2:1 pulley ratio. A centrifugally casted flawless bearing freely slides over journal with 100 microns clearance and as it rotates hydrodynamic bearing is formed.

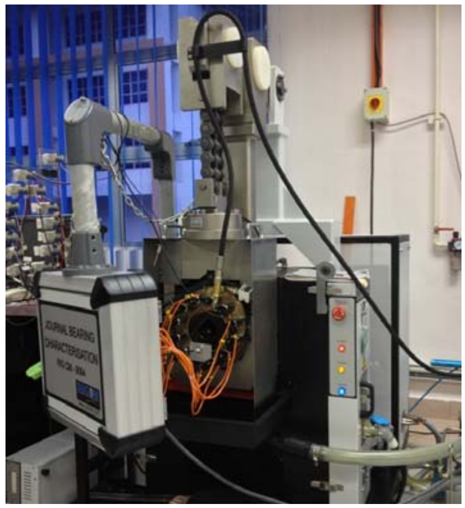


Fig. 1: Journal bearing test rig

The test rig consists of, a frame, bearing unit, loading, drive, lubrication, control and measuring systems. A Phosphorous bronze grade 1, centrifugally casted bearing having l/d ratio = 1 slides over journal with radial clearance of 0.05 mm. The inner surface of the bearing is ground and polished to surface finish of 1.6 Ra value with cylindrically and roundness below 3 microns (the inner diameter of the bearing 100.1 mm). The bearing part was modified to fix 12 pressure and temperature sensors on the front face and circumference of bearing at every 30 degrees interval as shown in Fig. 2. The sensors use ultra stable technology that provides stability over a wide temperature range. The oil inlet and outlet temperatures were also measured using another two sensors as seen in Fig. 2.

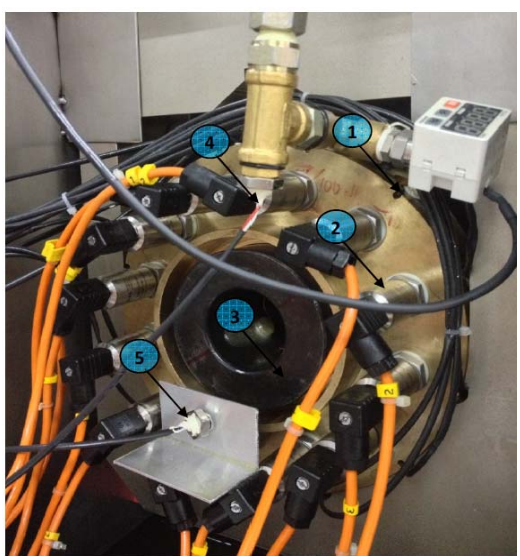


Fig. 2: Housing with pressure and temperature sensors. (1) Temperature sensor (2) Pressure sensor (3) Shaft (4) Temperature inlet (5) Temperature outlet

A machined, ground and polished 100 mm journal is tightened to spindle by a draw bolt, the spindle in mounted inside housing rotating on taper roller bearing; the heat generated on spindle during test is cooled by re-circulating oil from the lubrication unit (40lit). The oil to spindle is supplied from a 40 litre capacity lube tank, fixed beside the tester, the oil is pumped by a gear pump and passed through a 50 microns high pressure filter before being supplied to housing through high pressure tubing, the oil enters at 3 points from the top of housing; the used oil, flows back to tank from the bottom of housing. The oil flow is constant at 6 lpm flow rate, the flow rate can be increased by operating the pressure regulator viewing the pressure gauge provided on lube tank. The oil feed-pressure ranges from 0.1 to 1 MPa.

The experiments were performed over a range of loads and speeds levels. The nominal load range of the bearing test rig is from 5 to 100 kN and the rotational speed range of the shaft is limited to 1000 rpm, due to the flow rate capacity of the test bearing lubrication system. The nominal output of the motor is 7.6 kW. The oil feed- pressure is regulated using a power pack lubrication system. Table 1 illustrates the details of test bearing dimensions, lubricant properties and operating parameters.

Table 1: Dimensions of test bearing, lubricant properties, operating parameters and sensor specifications

1: Dimensions of test bearing, lubricant properties, operating parameters and sensor specifications

Part detail	Range
Bearing material	Phosphorous bronze
Inner bearing diameter D	100.1 mm
Bearing Length, L	50 mm
Surface roughness	0.8Ra on ID grounded & polished
Journal material	EN-353 steel
Outer journal diameter, D	100 mm
Surface roughness	0.8Ra grounded & polished
Radial clearance, c	52 µm (0.05mm)
c/r ratio	0.001
Load range, W	5-100 kN
Journal speed	100 – 1000 RPM
Lubricant viscosity	68 cSt @ 40°C 8.8 cSt @ 100°C
Lubricant	ISO VG 68
Pressure sensor	
Model	MEAS (M 5156)
Range	10 MPa
Accuracy	(0.001± 1% measured value) MPa

Design of Experiments (DOE):

Of late, the design of experiment (DOE) is very widely employed in various science domains because of its benefits, such as, minimizing the number of experiments that are required to be accomplished, whereby, the laboratory works are considerably reduced (Ferreira *et al*., 2007). The Box-Behnken Design (BBD), as one of RSM design, was introduced just by employing three levels of each factor and consequently with an acceptable number of experimental points (Hinkelmann and Kempthorne, 2007). The employment the BBD should be constrained to a condition, in which one is not keen in estimating intense responses. Moreover, this design is rotatable (or near rotatable), which means that the model constitutes a rationally constant circulation of scaled forecast variation right through the experimental design region (Montgomery, 2005). It needs three levels of each factor, which results in minimized experimental testing to assess multiple variables and their interactions (Ragonese, 2002).

Depending on a three-level-three-factor Box–Behnken design, the experiments have been designed. The key process parameters for journal bearing that determine the maximum oil-film pressure are: rotational speed (S), bearing load (L) and oil-feed pressure (O). Three levels of each input variable are used in Box–Behnken design technique so that design the experimental design before executes the experimentation. Each experiment was replicated thrice. The manipulated variables and their levels investigated in this work are given in Table 2.

Table 2: Process control parameters and their limits

Variables	Units	Notations	Factors Levels (coded)		
			-1	0	1
Speed	rpm	*S*	100	400	800
Load	KN	*L*	5	10	15
Oil-Feed Pressure	MPa	*O*	0.2	0.5	0.8

Fuzzy Logic Approach:

Fuzzy logic (FL) was initiated first by Zadeh (Zadeh, 1965; Zadeh, 1968; Zadeh, 1973) to manipulate and represent data and information possessing non-statistical uncertainties. FL was particularly introduced to mathematically represent uncertainty and vagueness and to provide formalized tools for dealing with the imprecision intrinsic to many problems. Essentially, FL uses the mathematical theory of fuzzy sets to mimic the process of human mind to effectively employ modes of reasoning by allowing the computer to behave less precisely and logically than conventional computer (Mohammad *et al*., 2012; Erfan *et al*., 2012). Significant components that characterise the fuzzy controller, viz; input, fuzzification, rule based, membership functions, interface engine, defuzzification and output are shown in Fig. 3.

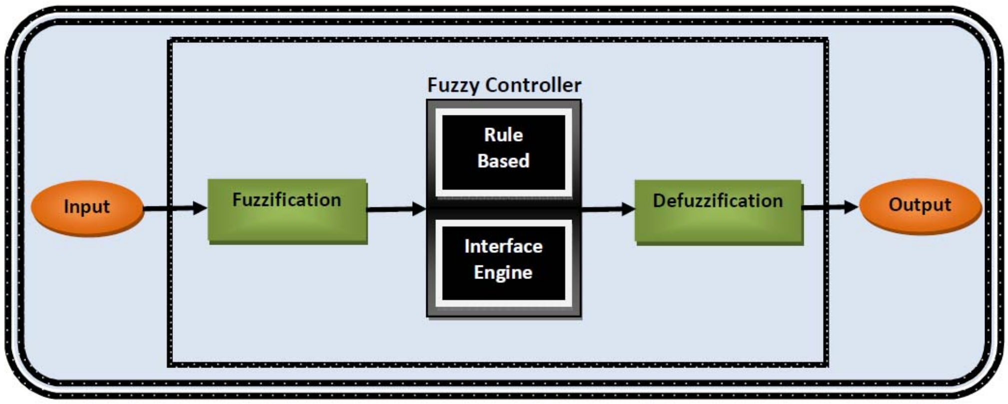


Fig. 3: Blocks of a fuzzy controller

The basic concept underlying fuzzy logic is that of a linguistic variable, that is, a variable whose values are words rather than numbers. Although words are often less precise than numbers, their use is closer to human perception. It can be described simply as control with sentences rather than equations, and it can include empirical rules that are especially useful in operator controlled plants. For instance a typical fuzzy controller "If journal speed is (Medium) and load is (Low) and oil-feed pressure is (Low) then oil-film pressure is (Very Low)". This sentence builds in the familiar if-then format, and formally the if-side is called the condition, and the then-side is called the conclusio. Linguistic variables such as low, medium and high can be included in the model without needing to be precisely defined. This is an essentially superior characteristic of fuzzy logic modeling as it permits for imprecise measurements. In general, fuzzy logic as a concept is easy to understand, because the mathematical aspects behind fuzzy reasoning are very simple.

Particle Swam Optimization:

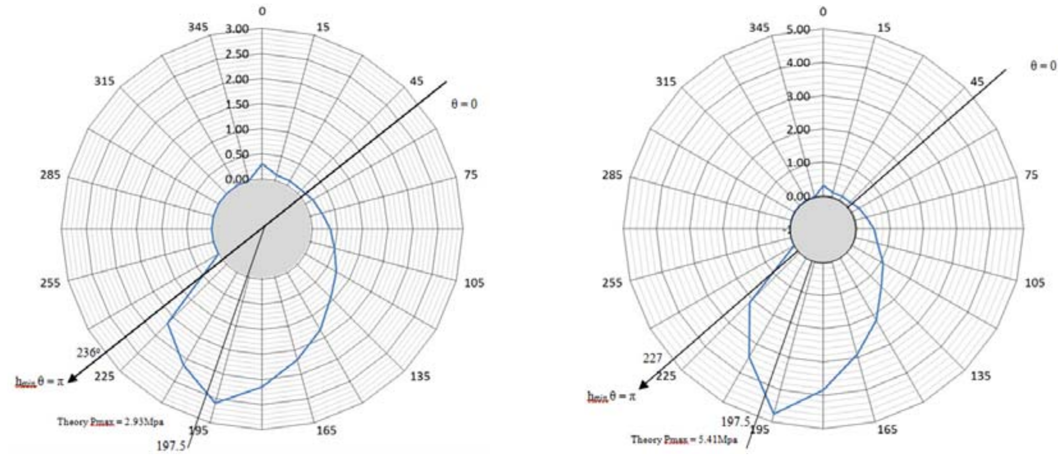
Particle Swarm Optimization (PSO) was originally proposed by Kennedy and Eberhart in 1995 as a simulation of social behaviour of organisms that live and interact within large groups. The essence of PSO is that particles move through the search space with velocities which are dynamically adjusted according to their historical behaviours. This mimics the social behaviour of animals such as bird flocking and fish schooling. With several alterations on the original model, the algorithm could optimize complex functions based on the concept of Swarm Intelligence method (Danial Yazdani *et al*., 2013; Wenxing Xu *et al*., 2013).

RESULTS AND DISCUSSION

Experimental Identification of Max-Pressure Location:

Pressure distribution around the hydrodynamic journal bearing circumference is experimentally determined. The aim of this step is to identify the region of interest (the maximum oil-film pressure location around the bearing circumference) so that to be modelled next stage. The lubricant pressure profile is measured by the 12 pressure sensors that are fixed on the front face bearing (see Fig. 2). The pressure sensors measure the fluid pressure developed through the holes bored to within 0.5 mm, from the bearing surface.

Experimental results of oil-film pressure distribution at rotational speed of 600 rpm with different loads are plotted in Fig. 4. The theoretical values obtained from charts of (Raimondi and Boyd, 1958) are also shown on the plotted profiles. For the same operating conditions in the test, the predicted maximum pressure location from Raimondi and Boyd chart is to be at 197.5 degrees (Figs. 4 a&b). This experiment has revealed that the maximum pressure position was recorded at 195 degrees. The experimental values nearly agree with the predicted values from (Raimondi and Boyd, 1958).



(a) At 6 KN load (b) At 10 kN load

Fig. 4: Experimental pressure distribution around the journal bearing circumference

Therefore in this study, the modeled region is particularly determined to be particularly at 195 degrees which equivalents to the pressure sensor no. 7 located on the front face of the true scale bearing circumference (see Fig. 2). Theoretically, when the load increases, the position of film thickness will shift to a new position. However, the position of maximum pressure remains the same as predicted from chart of (Raimondi and Boyd, 1958). Conventionally, the converging and diverging sections are defined by the minimum film thickness. In diverging section the pressure may drop to sub-atmospheric pressure (Desai and Patel, 2005). However, in this study, values of zero are assumed in this diverging section.

Proposed Fuzzy Sets Structure:

The fuzzy model that has been designed to predict the maximum oil-film pressure in hydrodynamic journal bearing uses three inputs obtained from Box- Behnken design and one output. Rotational speed, bearing load, and oil-feed pressure are the inputs and oil-film pressure is the output of the system. The first step in establishing the algorithm for selecting the lubrication condition is to choose the shape of fuzzy membership functions or fuzzy sets for the process variables based upon experimental data. The system is based on the interrelationship that exists for lubrication material between its speed (input 1), load (input 2), oil-feed pressure (input 3), and are distributed and triangle shape is used for the membership functions for the input and the output variables. The membership functions for each fuzzy set for input fuzzy variables and for output fuzzy variable are shown in Figs. 5-8, respectively. The experiment has been conducted based on the design matrix as given in Table 3. The average of at least three results of oil-film pressure are calculated and presented in Table 3. The experimental data were used as input of FL and PSO to predict the maximum oil-film pressure. The predicted values of the maximum oil-film pressure by the proposed model are presented in Table 3.

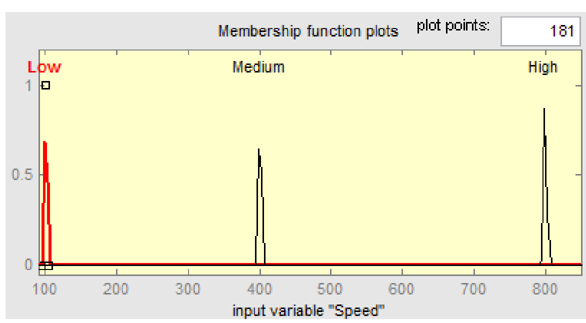


Fig. 5: Speed input membership function

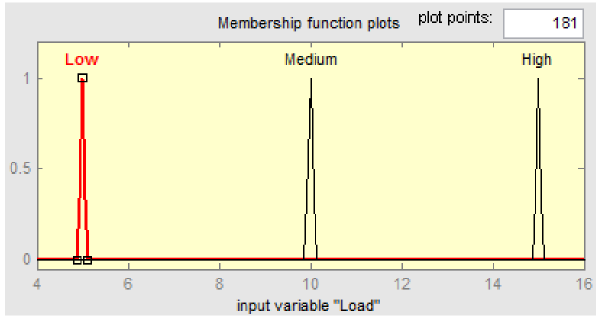


Fig. 6: Load input membership function

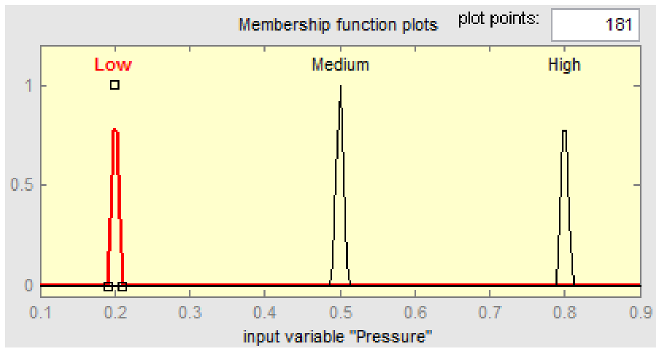


Fig. 7: Oil-feed pressure input membership function

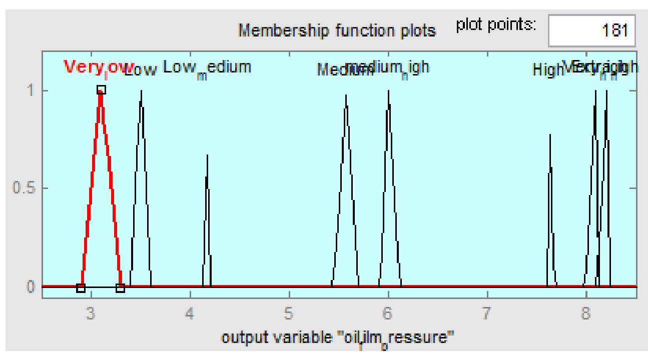


Fig. 8: Oil-film pressure output membership function

Table 3: The BBD matrix with observed and predicted values of maximum oil-film pressure (MPa)

Run order	Coded Factors			Experimental ^{a} (MPa)	Predicted by FL	Predicted by PSO
	S (rpm)	*L* (KN)	*F* (MPa)			
1	0	1	1	8	8.06	8.01
2	0	0	0	5.66	5.65	5.66
3	1	-1	0	3.29	3.25	3.27
4	1	0	-1	4.17	4.15	4.16
5	1	1	0	8.28	8.24	8.25
6	-1	0	1	6.23	6.20	6.22
7	0	-1	-1	2.96	3.10	2.98
8	-1	0	-1	5.63	5.5	5.6
9	1	0	1	5.47	5.46	5.48
10	0	0	0	6.11	5.96	5.99
11	0	1	-1	7.64	7.66	7.65
12	0	0	0	5.94	5.93	5.94
13	-1	-1	0	3.55	3.54	3.54
14	0	-1	1	3.21	3.20	3.22
15	-1	1	0	8.02	8.03	8.02

^{a} Average of three readings.

Proposed PSO Structure:

PSO algorithm starts with a group of random particles that searches for optima by updating each generation. Each particle is represented by a volume-less particle in the n-dimensional search space. The i^{th} particle is denoted as $X^i=(x_{i1},x_{i2},....,x_{in})$. At each generation, each particle is updated by ensuing two best values. They are the best solution that has been achieved *(mbest)* and the global best value *(gbest)* that is obtained so far by any particle in the population. The basic concept of PSO lies in accelerating each particle toward its *mbest* and the *gbest* locations, with a random weighted acceleration at each time step as shown in Fig.9.

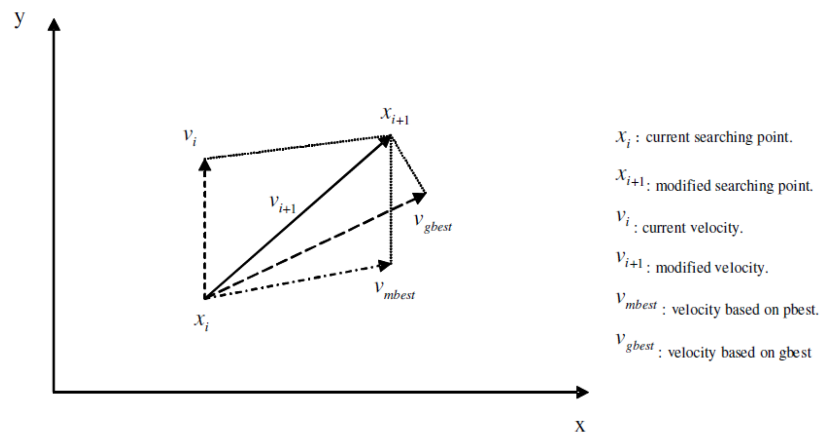


Fig. 9: Modification of a searching point by PSO

With the inclusion of the inertia factor, ω, the equations are (Hou *et al*., 2005; Park *et al*. 2006; Immanuel Selvakumar and Thanushkodi, 2007).

$$v_{i+1} = v_i\omega + \alpha_1 \cdot rnd() \cdot (mbest_i - x_i) + \alpha_2 \cdot rnd() \cdot (gbest_i - x_i) \quad (1)$$

$$x_{i+1} = x_i + v_i \quad (2)$$

where *rnd()* is a random number independently generated within the range [0,1] and; *α1* and *α2* are two learning factors which control the influence of the individual's knowledge (or personal influence) and that of the neighbourhood (or social influence) respectively. The PSO Pseudo-Code and PSO flow chart is shown in Fig. 10 and 11 respectively while the PSO optimization algorithm can be written as follows:

1. Generate a random initial swarm of particles, assigning each one a random position and velocity.
2. Compute the fitness values of the N particles.
3. Update the values of the best position of each particle and the best position found by the swarm.
4. Update the position and the velocity of every particle according to Eq. 1 and 2.
5. Steps 2 to 4 are repeated until a pre-defined stopping condition is reached.

```
begin PSO
  c:=0  { counter }
  Initialize particle
  Do:      {for each particle}
     Calculate fitness value
     If the fitness value is better than the best fitness value (mbest) in history
        set current value as the new mbest
     Choose the particle with the best fitness value of all the particles as the gbest
     Calculate particle velocity using Eq. 1
     Update particle position based on Eq. 2
     c:=c+1
  end
end PSO
```

Fig. 10: Pseudo-code of the Particle Swarm Optimization

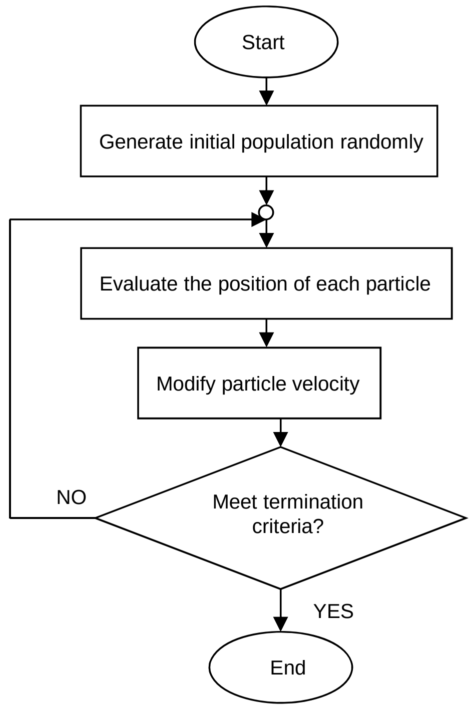


Fig. 11: Flow chart of PSO

Verification Test:

In this study, FL and PSO approaches were employed for predicting the maximum oil-film pressure in hydrodynamic journal bearing. At this stage, comparison criteria are needed to quantify the difference between the predicted values by both methods and the actual values. Three confirmation experiments of the observed and predicted values, which were randomly selected from the ranges illustrated in the Table 3, are shown in Table 4. The residuals (the error percentage) between FL and PSO with the observed data are given in Table 4.Thus, from Table 4, it is obvious that FL and PSO are capable of predicting the maximum oil-film pressure response values for any combination of the speed, load and oil-feed pressure values within the range of the experimentation conducted. In addition, Fig. 12 shows the distribution of oil-film pressure of the actual values versus predicted values by FL and PSO.

Table 4: Validation test results

Run No.	*S* (rpm)	*L* (KN)	*F* (MPa)	Experimental	FL predicted	Error %	PSO Predicted	Error %
1	800	5	0.5	3.29	3.25	1.2	3.27	0.61
2	800	15	0.5	8.28	8.24	0.48	8.25	0.36
3	800	10	0.8	5.47	5.46	0.18	5.48	0.18

Conclusions:

Fuzzy logic (FL) and particle swam optimization (PSO) approaches were employed to predict the desired response of maximum oil-film pressure in hydrodynamic plain journal bearing. The results show that the application of a FL and PSO based model for predicting oil-film pressure is possible for the independent variables rotational speed, bearing load and oil-feed pressure and produce the best match between predicted and experimental data. Predicted values were compared with the experimental values and their closeness was determined. Results revealed that PSO is more accurate than FL with average percentage deviation of 1% or 99% accuracy. The results presented in this paper are expected to be quite useful to the bearing designers as well as academic community.

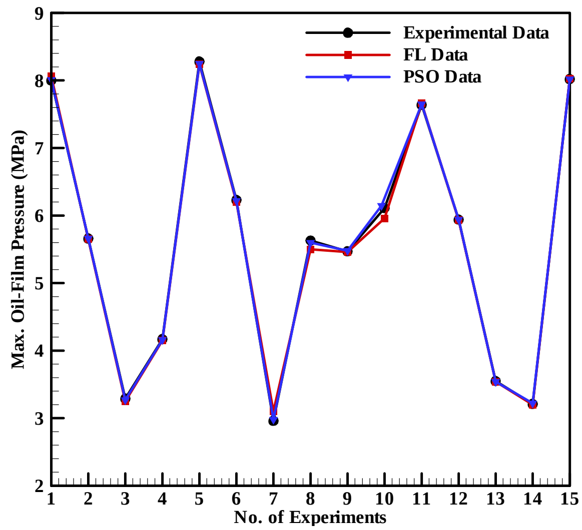


Fig. 12: Experimental data vs. predicted data by FL and PSO

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