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Simulation of Hydrodynamic Pressure Bearing in Forestry Engineering Based On Multi Objective Function Optimization and Artificial Neural Network

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Abstract:

In order to optimize the performance in the design process, simulation of hydrodynamic pressure bearing in forestry engineering is researched in this paper. The multi objective function optimization and artificial neural network is used in this paper to improve the accuracy and efficiency of simulation. This present study might be of special interests to designers who need a synchronized improvement of their sliding bearing performance as well as the reduction of the lubricant flow for their precision machines or high-speed devices and engines. However, the method described within this paper successfully bridges the gap between the experimental and the pragmatic and makes the optimization of journal bearings not only highly doable, but cost efficient as well, combining technological aspects and artificial intelligence tools for function minimization.

***Keywords**: Simulation; forestry engineering; hydrodynamic pressure bearing; multi objective function; optimization; artificial neural network.*

I. INTRODUCTION

Hydrodynamic journal bearings (HJBs) are excellent devices able to support rotating shafts under the action of loads with negligible friction and good damping properties. Furthermore they are: passive, maintenance free, cheap and easy to realize. HJB are widely used in ICE's facilities, such as crankshaft and turbocharger, and when, more in general, rotating shafts have to sustain loads (hydropower, power generation, naval facilities, process industry and chemical industry) [1-2].

In some applications, for their characteristics, HJB constitutes the only available choice for designers but in the majority of the cases the mix with all the properties is the key of the success of these mechanical components. Aspects like: manufacturability, reliability, cost and working precision are increasing their importance respect to performances nevertheless they rarely appear in the design procedures [3]. The global aim of this work is to solve the multi-objective and multivariable problem of HJB design in a fast and industrially feasible way. The solution flow has also to be flexible to accommodate future modification, take into account different materials, lubricants and geometrical designs. The local aims are: solve the RE PDE using numerical methods and Artificial Neural Networks, devise a series of objective and implement code for their minimization with Genetic Algorithms and Artificial Bee Colony Algorithm, design and build a test rig machine to collect data in order to validate 3D CFD model developed to predict thermal behavior of journal bearings and finally demonstrate with two different study case the effectiveness of the method. Just few investigations have been made to verify it is possible to use commercial computational fluid dynamic codes to analyses HJB. With the advent of fast processors a complete description of the flow phenomena inside the lubricant layer can be easily predicted. Furthermore, commercial CFD codes have the ability to integrate numerous effects in the analysis such has: deformation and shaft misalignments, visualization and post process, heat flow calculation, material properties variations with temperature and pressure and sleeve deformation. The first author who worked in this field was Gertzos et al., [4-6], in his paper the author proposed a CFD methodology to analyses HJB without the inclusion of any thermal effect. In the results of the paper a quite remarkable difference between finite volume solution (Thermal Hydro Dynamic solution, THD) and CFD is present, nevertheless the author point out some useful features needed to analyze HJB with CFD such as: boundary conditions, convergence problems and mesh discretization problems (not solved in that work). The difference and the improvements to this work is the introduction of the thermal solution of the fluid film and the modified geometry generated to simulate the inlet channel.

II. HJB FRAMEWORK AND STRUCTURE

The plethora of techniques available for the calculation of the performance vector P in various conditions is huge. The methods are divided into three categories: approximated methods, analytical solution of the Reynolds Partial Differential Equation (RE PDE) and numerical solution of the Reynolds PDE. The approximated methods are divided into two sub-categories: the first group interpolates the pressure profile and the second interpolates experimental data or exact PDE solutions. Nearly all the authors that have developed an optimization algorithm developed also an approximated method for performance calculations.

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In Fig. 1, a comparison of the work previously mentioned is presented. The red dashed double dot line is for the Raimondi Boyd solution, the black continuous line is for the approximated analytical solution and the green simple dashed is for a CFD work which is going to be described later. This comparison is of great importance and promotes the idea that, the analytical solution is not enough precise a Somerfield numbers lower than 0.1 which is the present field of interest the CFD simulations and the finite volume techniques are in good agreement; therefore these two methods have been selected to be used in the present work.

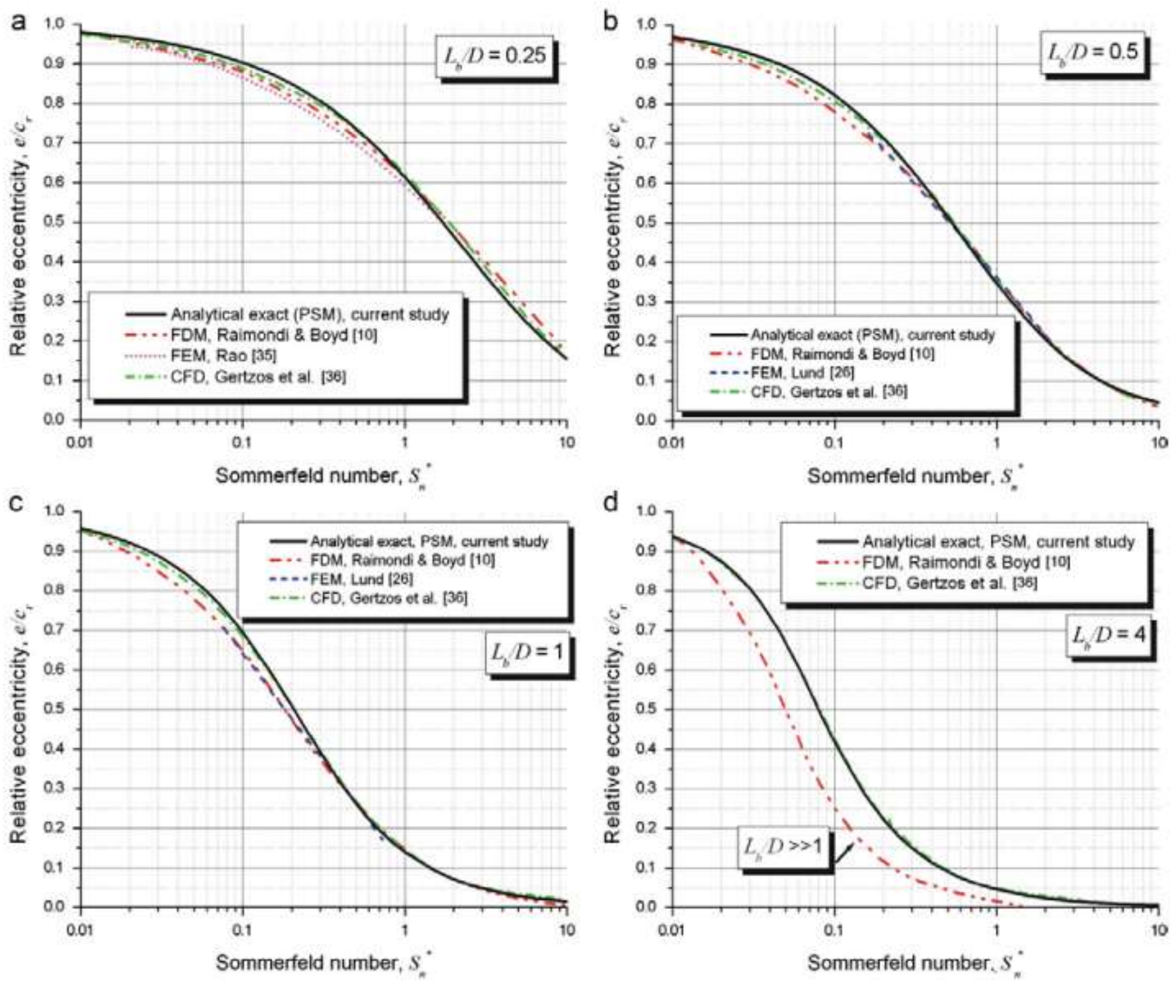

Fig 1: Main results under the form of characteristic figures from [2] where a comparison of the eccentricity ratio calculated with different techniques is presented

Another advantage is that the finite difference formulation is simple and allows a direct comparison with CFD solutions (which are also based on finite difference schemes with up-

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wind solution methods) [7-11].

The optimization of HJB has been analysed by several authors before. Is frequent in literature to find publications treating optimization problems as simple "improvement problems" in which the design of a product is implemented with new features. In this work with the term "optimization" the author wants to describe the rigorous mathematical process through which the performance of the product is implemented pursuing an objective minimization.

Just few investigations have been made to verify it is possible to use commercial computational fluid dynamic codes to analyze HJB. With the advent of fast processors a complete description of the flow phenomena inside the lubricant layer can be easily predicted. Furthermore, commercial CFD codes have the ability to integrate numerous effects in the analysis such has: deformation and shaft misalignments, visualization and post process, heat flow calculation, material properties variations with temperature and pressure and sleeve deformation. In the results of the paper a quite remarkable difference between finite volume solution (Thermal Hydro Dynamic solution, THD) and CFD is present, nevertheless the author point out some useful features needed to analyze HJB with CFD such as: boundary conditions, convergence problems and mesh discretization problems (not solved in that work).

The examples designed by the author in Fig. 2 show journal bearings employed in the automotive industry, the first on the left is a crank-shaft journal bearing and the second is HJB for turbocharges. In their nature this products are similar but their working condition is very different, the crank-shaft bearing works at moderate speed with a dynamic applied load, the second is an hydrostatic or quasi-hydrostatic bearing in which the shaft rotates a very high speed and the applied load is negligible. In the third example, Fig. 3, the structure of a HJB system for hydro-power shaft is presented. This kind of bearing has the aim to sustain a rotating shaft at moderate speed (1000-2000 rpm) and the inlet is of rectangular shape.

The structure of the sliding bearing is made by a shaft which is rotating inside housing, between the housing and the shaft there is a bronze sleeve. This last mentioned part is separated by the rotating surface by a thin film of lubricant. The fact that the shaft can rotate around an axis different from the sleeve axis generates a convergent-divergent duct where the pressure of the fluid is increased to overcome an applied load.

The principal performances of journal bearings are power loss (Pl) due to rotational friction, lubricant mass flow (Q) due to the pumping action of the bearing and to the pressure profile generated, temperature rise (ΔT) due to friction, maximum pressure (Pmax) and minimum lubricant film thickness (hmin). All these performances before mentioned form the vector P =

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(Pl, Q, ΔT, Pmax, hmin). The decision variable are: the sleeve diameter (D), the length to diameter ratio (λ=L/D), the clearance (C), the inlet channel inclination (θin) and the inlet channel diameter (din) forming the decision variable vector Dv = (D, λ, C, θin, din).

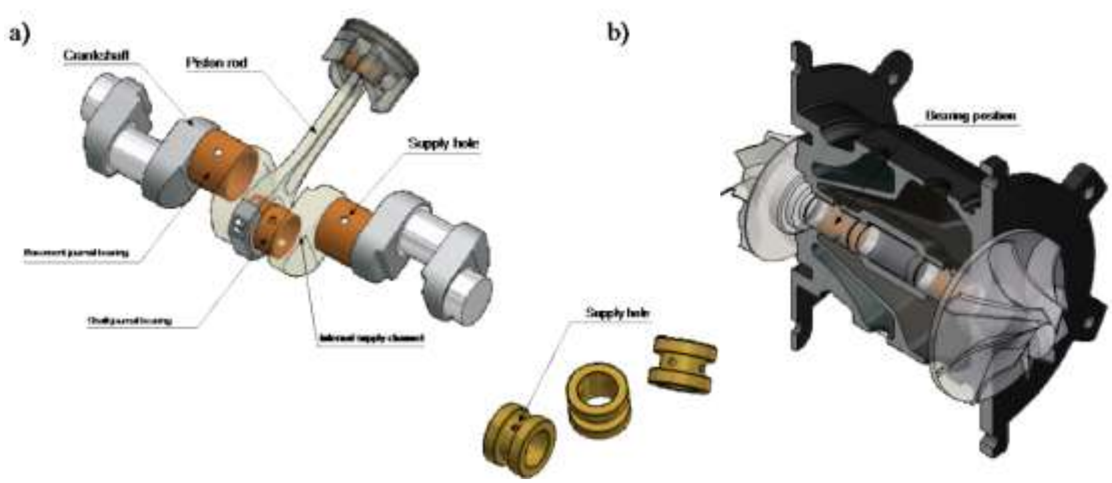

Fig 2: (a) the HJB for the crank-shaft and (b) the HJB for turbochargers

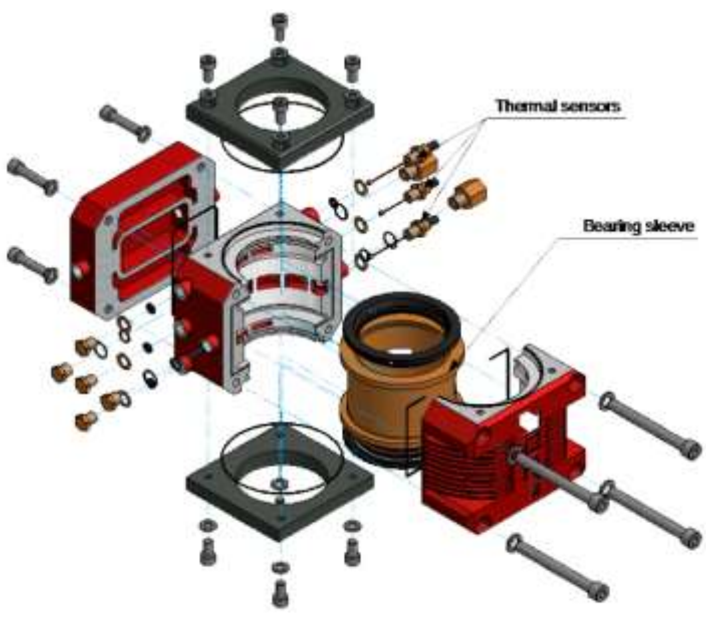

Fig 3: HJB for hydro-power with internal diameter 100 mm

III. THE ALGORITHM OF MULTI OBJECT FUNCTION AND ARTIFICIAL NEURAL NETWORK

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One of the big novelties and creative points of the whole paper is the use and the understanding of the Artificial Neural Network as reliable dynamic curve fitting tool. Some considerations [12-13]:

1) Develop a FD or FEM tool with complete capability of take into account temperature and inlet conditions of the flow is long in terms of time, needs a validation and requires a considerable programming skills.

2) The finite volume method is useful just for a single gamma of products, if the shape or the bearing type changes the program as also to change its features and a global review is needed (with further validation problems).

3) The approximated solutions have a large margin of error when employed on a big spread of length and diameters.

4) Neither approximated methods and finite volumes are flexible in ensure the solution of multiple problems.

5) The optimization process requires numerous evaluations of the objective function (10000 evaluations or more).

In contrast to this characteristic the optimization flow requires a short time of solution to be industrially feasible.

The basic equation for the routing algorithm is shown below:

$$\overline{x_i} = \frac{x_i - b_i}{a_i - b_i} \quad (1)$$

Experimental data to determine, we can also experience the value of the formula (2) the decision.

$$n = \log_2 m \quad (2)$$

Hidden node output is calculated as follows:

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$$h_j = f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) \quad (3)$$

The output of the output node is calculated as follows:

$$f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) = f\left(f\left(\theta_j\right)\right) \quad (4)$$

Where in θ is an output node threshold.

Put Equation (3) into Equation (4), then we can get the S-type function:

$$f\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right) = f\left(f\left(\theta_j\right)\right) \quad (5)$$

In the structure of GA algorithm, we can get the optimization equation as the following equation (6):

$$h_j = \exp\left(-\frac{\left\|X - C_j\right\|}{2b_j^2}\right), \quad j = 1, 2, \ldots, m \quad (6)$$

The output of the network is given as:

$$y_m(k) = wh = w_1 h_1 + w_2 h_2 + \ldots + w_m h_m \quad (7)$$

Assuming the ideal output is y (k), the performance index function is:

$$E(k) = \frac{1}{2}\left(y(k) - y_m(k)\right)^2 \quad (8)$$

The equation of basic function is as equation (9) as follows:

$$\partial_j (C_{ijkl} \partial_k u_l + e_{kij} \partial_k \varphi) - \rho \ddot{u}_i = 0 \quad (9)$$

Under the linear relationship, basic equation is shown in equation (2):

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$$\partial_j (e_{ijkl}\partial_k u_l - \eta_{kij}\partial_k \varphi) = 0 \quad (10)$$

The linear differential equation can be expressed into the following simplified forms:

$$L(\nabla,\omega) f(x,\omega) = 0 \ ,$$

$$L(\nabla,\omega) = T(\nabla) + \omega^2 \rho \mathrm{J} \quad (11)$$

In which,

$$T(\nabla) = \begin{Vmatrix} T_{ik}(\nabla) & t_i(\nabla) \\ t_k^T(\nabla) & -\tau(\nabla) \end{Vmatrix} , \quad \mathrm{J} = \begin{Vmatrix} \delta_{ik} & 0 \\ 0 & 0 \end{Vmatrix} ,$$

$$f(x,\omega) = \begin{Vmatrix} u_k(x,\omega) \\ \varphi(x,\omega) \end{Vmatrix} \quad (12)$$

$$T_{ik}(\nabla) = \partial_j C_{ijkl} \partial_l \ , \quad t_i(\nabla) = \partial_j e_{ijk} \partial_k \ , \quad \tau(\nabla) = \partial_i \eta_{ik} \partial_k$$

Consider an infinite situation, we have the equation (5) in the following:

$$L^0 = \begin{Vmatrix} C_{ijkl}^0 & e_{kij}^0 \\ e_{ikl}^{0T} & -\eta_{ik}^0 \end{Vmatrix} \quad (13)$$

Consider the propagation, instead the equation (13) with the following form:

$$C(\mathrm{x}) = C^0 + C^1(\mathrm{x}) \ , \quad e(\mathrm{x}) = e^0 + e^1(\mathrm{x}) \ , \quad \eta(\mathrm{x}) = \eta^0 + \eta^1(\mathrm{x}) \ , \quad \rho(\mathrm{x}) = \rho_0 + \rho_1(\mathrm{x}) \quad (14)$$

Then we have equation (15) to (18):

$$C^1 = C - C^0 \ , \quad e^1 = e - e^0 \ ,$$

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$$\eta^1 = \eta - \eta^0 \quad , \quad \rho_1 = \rho - \rho_0 \quad (15)$$

The containing inclusions can be simplified into the following integral equation set:

$$f(x,\omega) = f^0(x,\omega) + \int_V S(x-x')(\mathrm{L}^1 F(\mathrm{y}') + \rho_1\omega^2 \mathbf{g}(R)\mathrm{T}_1 f(\mathrm{y}')]S(\mathrm{y}')\mathrm{dy}' \quad (16)$$

In view of the following relationship

$$\frac{1}{2\pi}\int_{-\infty}^{\infty} e^{-ik_3x_3'}dx_3' = \delta(k_3) \quad (17)$$

Equation (8) can be converted into the following form:

$$f(y,\omega) = f^0(y,\omega) + \int_s S(y-y',\omega)\mathrm{L}^1 F(\mathrm{y}',\omega)\mathrm{d}y' + \rho_1\omega^2\int_s \mathbf{g}(y-y',\omega)\mathfrak{J}f(\mathrm{y}',\omega)\mathrm{d}y' \quad (18)$$

In which, S is cylinder cross section, $y = (x_1, x_2)$, and

$$\mathbf{g}(y-y',\omega) = \frac{1}{(2\pi)^2}\int_0^{\infty}\bar{k}d\bar{k} \int_0^{2\pi} \mathbf{g}(\bar{k},\omega)\exp(-i\mathrm{k}\cdot(\mathrm{y}-\mathrm{y}'))d\phi \quad \bar{k} = (k_1,k_2) \quad (19)$$

Then is fundamental for the success of all the optimization flow to find a way to predict HJB performance reducing the calculation time, this task can be accomplished by the Artificial Neural Networks (ANN). The ANNs are dynamic curve fitting tools able to include new results and predict complex function values. Their advantages are [14-15]:

• Fast response: The operations required to predict the function value for an ANN are simple additions or products (rarely trigonometric functions) and the response time is hence faster than any numerical method e.g. the calculation time of one finite volume solution presented in section 2 is 60 seconds while for the ANN is 5 milliseconds.

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• Accuracy: Accuracy is important to point out that the use of ANN as a fitting tool do not decrease the precision as much as the approximated solutions do. For all this above mentioned reasons the ANN is chosen as a performance tool in the first part of the optimization. Furthermore, several studies demonstrate that the use of ANN for tri-biological design problems can be done in numerous other fields.

IV. EXPERIMENT RESULT

Every output of the network is hence function of a vector Dvnet made of three components. Each component comes from a vector made of 12 values equally spaced between the minimum and the maximum value of the decision variable e.g. if Dmin=30.00 mm and Dmax=41.00 mm the Dnet vector is {30.00, 31.00, 32.00, 33.00, 34.00, 35.00, 36.00, 37.00, 38.00, 39.00, 40.00, 41.00} which is a (1x12) vector. The possible combinations are 123 =1728 which is the exact number of examples used for the training process, each combination of decision variables from the matrix cnet (1728x3) is solved with the finite volume tool and the matrix outnet (1728x6) is generated. Column per column results are used to train the network.

The optimization search is discrete, the minimum number of neurons is 5 and the maximum is 10, the minimum number of layers is 2 and the maximum is 20, the mutation rate is 0.05 the crossover factor is 0.8, the number of subjects is 20 and the maximum number of generations is 30. There is no practical reason to limit the number of neurons, virtually the dimension of the network can be large, in this case longer time for training is required and the benefits of ANN will vanish.

ANN training results are presented in Fig. 4 and Fig. 5. The table shows the characteristic of each ANN created for the single performance calculation and, has a reference, a global ANN to compare the results in terms of speed and error. The global network (that calculates all the performance at the same time) is larger nevertheless it does not have the precision of the single networks and the calculation time is 5 times the slowest single network.

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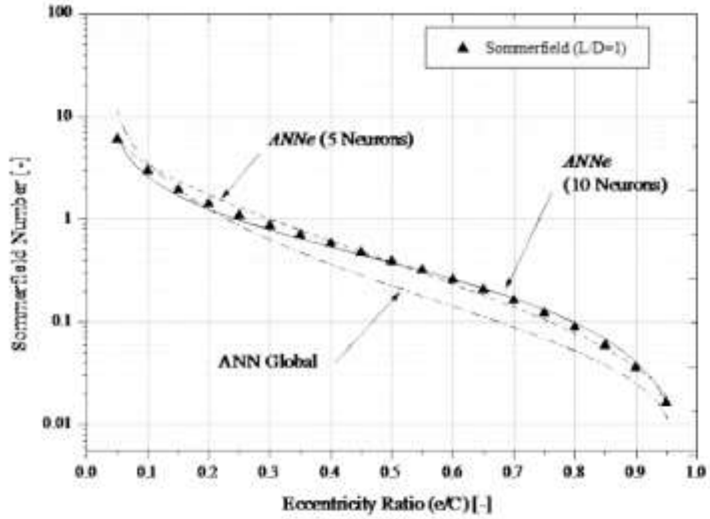

Fig 4: Prediction of the eccentricity with ANNe carried out with the used ANN (ANNe (10 Neurons)) and the comparison with the global network and another network with less neurons to see the effect of the optimization on the training

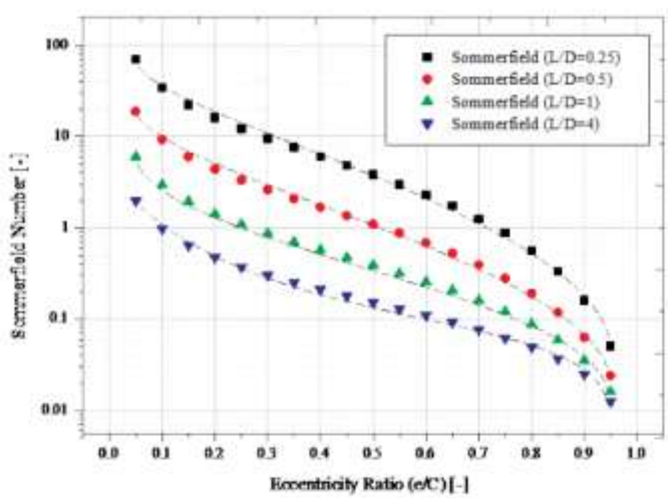

Fig 5: Eccentricity prediction of the single ANNe. The calculated values are presented with dots and the predicted ANN results are presented in dashed line

As presented in Fig. 5 the single networks are fast and precise, to calculate the performance vector P and the eccentricity a time of 0.024 s is needed which for the optimization process carried out in this work for 100 subjects/employed bees means 2.4 s. This is a negligible time

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for a method with an average error lower than 1%. Nevertheless, to complete the discussion about the ANN training each of the examples takes 124 s to be calculated which lead in a global time for calculation of 2 days, 11 hours and 31 minutes; the training process is faster just 5 minutes are needed for a training process with a precision of 10-5.

V. CONCLUSION

In this paper the three main AI tools used in the thesis work are illustrated. In order to optimize the performance in the design process, simulation of hydrodynamic pressure bearing is researched in this paper. The multi objective function optimization and artificial neural network is used in this paper to improve the accuracy and efficiency of simulation. The ANN are used to predict the journal bearing performances and the Genetic Algorithms and the ABC algorithm are used to minimize the objective functions. This present study might be of special interests to designers who need a synchronized improvement of their sliding bearing performance as well as the reduction of the lubricant flow for their precision machines or high-speed devices and engines.

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