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A methodology for cracks identification in large crankshafts

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A B S T R A C T

Diesel engines used in power plants and marine propulsion are especially sensitive to outage events. Any advance in the early detection of failure will increase the reliability of the electricity supply and improve its productivity by reducing costly power outages. Fault detection and diagnosis is important technology in condition-based maintenance for diesel engines. This article presents a classifier based on neural networks for identifying failure risk level in crankshafts, the engine component of greatest cost concern. The authors have developed a finite element model for crack growth that fits well with fracture appearance and produces the evolution of crankshaft stiffness with crack depth. A lumped system model of the engine uses this evolution as input, giving the instantaneous speed at the engine flywheel as a function of crack depth. All the results shown in the paper come from outputs of the simulation models which have been built from real engine data. Measurements of the instantaneous flywheel speed were not available due to the crankshaft failure. All data are extracted from this speed and are then classified using a Radial Basis Function neural network.

1. Introduction

Diesel engines are commonly used in power plants all around the world, particularly for on-site power generation in special locations such as islands, which are not connected to a mainland electrical grid. This kind of power plant is especially sensitive to outage events. Any advance in the early detection of failure will increase the reliability of the electricity supply and will improve its productivity by reducing costly power outages.

This is of particular interest in order to detect problems related to the engine crankshaft. In the case of crankshaft failure, repair costs include not only that of the crankshaft itself, but the cost of other parts of the engine that can be affected by crankshaft failure, such as connecting rods, pistons and cylinders, must be added. In addition, the length of time required for repairs has to be taken into account, mainly because of the crankshaft location inside the engine. This greatly increases the total repair cost.

Several reliability, availability and maintainability (RAM) studies of diesel generators have been conducted and in some of them [1], statistics on availability, failure cause, mean time between forced outages and so on have been shown. In relation to diesel engines, Arinc Research Corporation conducted a study for the US Army Engineering and Housing Support Centre (EHSC) [2] that showed results from diesel engines up to 2 MW. This study included a detailed classification of the parts involved in the failure of this power range and it revealed that, even though the failures per year related to engine crankshaft were low (0.02), it resulted in a higher mean time to perform corrective maintenance

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(MTTCM) for outages due to crankshaft, see Table 1 [2]. (MTBF=mean time between failures; MTBCM=mean time between corrective maintenance; MTTCM=mean time to perform corrective maintenance.) Similar conclusions are shown in Ref. [3].

The most common cause of crankshaft failure is fatigue. In order for fatigue to take place, a cyclic tensile stress and crack initiation site are necessary. The crankshafts of diesel engines of power plants run with harmonic torsion combined with cyclic bending stress due to the radial loads of the combustion chamber pressure transmitted from the pistons and connecting rods, to which inertia loads have to be added. Although crankshafts are generally designed with a high safety margin in order not to exceed the fatigue strength of the material, high cyclic loading and local stress concentration could lead to the growth of cracks even when fatigue strength is not exceeded by average values. Pandey [4] analyses failures in the crankshafts of 35 hp two-cylinder engines used in tractors, where the fracture plane was located between the main bearing and the journal. The crack was initiated at the crankpin web region in a plane about 45° in respect to the rotational axis, showing typical fatigue failure with beach marks. The stress related to the fatigue initiation was estimated at 175 MPa, significantly below the tensile stress of the nodular cast iron of these crankshafts which is close to 680 MPa. Taylor et al. [5] developed two fatigue experiments in a crankshaft of a four-cylinder engine made of spheroidal graphite cast iron, with a tensile strength of 440 MPa: one torsional and the other flexural. The crankshafts underwent torsional and flexural cyclic loading until failure and in both types of tests the same fracture angle of 45° in respect to the rotational axis was observed. Yu and Xu [6] investigated the fracture of the web between the 2nd journal and the 2nd crankpin of the crankshaft of a four-cylinder diesel engine of a truck plant. The failure occurred after 200 h in service and the fracture plane was about 45° inclined with respect to the shaft axis. The macroscopic view of the fracture surface indicated stable crack growth regions with beach marks in the middle. Baumik et al. [7] studied the fracture of the crankshaft of a four-cylinder aircraft engine made of case-hardened SAE 4340 grade forged steel. The fracture had taken place along the webs at the No. 2 and No. 3 journals after 1460 h in service and 262 h since the last overhaul. In both cases, the fracture was produced along the web radius, and transverse to the axis of the crankshaft. In journal 3 the fatigue crack had propagated to about 80% of the web cross-section before giving rise to the final overload fracture. In these cases it was possible to discover the origin of the fracture by tracing back the beach marks, which was found to be at the web radius region. Other investigations related to crankshaft failures gave similar results [8]: crankshaft failure is due to fatigue that is initiated by cracks located at the web fillet radius and progress to the journal inner radius leading to the final overload fracture.

In the case of cracks in rotating structures, one of the approaches used to identify them is based on the fact that the presence of a crack reduces the stiffness of the structure, hence reducing the natural frequencies of the original healthy shaft without cracks. The change in modal properties, natural frequencies and mode shapes, may be useful for the detection of a crack as well as its depth and location [9–16].

Currently, intelligent optimisation techniques have been included in fault recognition methodologies applied to engines, especially artificial neural networks (ANN) with very interesting results [17–21]. ANN techniques can handle incomplete data to deal with nonlinear problems and, once trained, can perform predictions and generalisations with important time savings. Among the different existing architectures and methodologies, Radial Basis Function (RBF) neural networks correspond to a very useful kind of ANN for classifying applications and function approaches [22,23].

The aim of this paper is to show a methodology for the identification of cracks and their depth in crankshafts, which will allow improvement in the predictive maintenance strategy of diesel power plants. The methodology is based on the development of a dynamic model of the crankshaft coupled to a 3D FEM model of the crack growth, applying a RBF neural network for classification purposes.

Table 1
Failures per year, MTBF, MTBCM and MTTCM for diesel engines up to 2 MW [2].

	Failures per year	MTBF (h)	MTBCM (h)	MTTCM (h)
Control and instrumentation	0.12	74070.5	40738.8	5.2
Cooling water system	0.12	74070.5	28095.7	3
Exhaust system	0.43	20369.4	10720.7	1.6
Bearings	0.09	101847	81477.6	8.9
Cylinder	0.3	29099.1	19399.4	4.3
Cylinder heads	0.77	11316.3	10445.8	10.7
Crankshafts	**0.02**	**40738.8**	**271592**	**30**
Pistons	0.22	40738.8	32591	2.9
Turbocharger	0.14	62675.1	35425	3.6
Valves	0.02	407388	203694	3.8
Rings	0.04	203694	81477.6	8.3
Intake manifold	0.05	162955.2	135796	9.9
Rods	0.02	407388	407388	21.5
Camshaft	0.08	116396.6	58198.3	14.1
Crankcase	0.1	90530.7	90530.7	5.6
Chain drive	0.01	407388	407388	21
Tappet	0.01	162955.2	162955.2	9.7
Other components	0.02	271592	271592	0.3