An Engine Oil Replacement Timeline

José Neves, Filipa Ferraz, Henrique Vicente and Paulo Novais

***Abstract*—**Engine oil conditions are crucial either for the proper engine function and to calculate the oil´s lifetime. Factors like rotation per minute, temperature, trip length, clarity of the oil is important to determine the level of contamination of the engine oil. Thus, the type of engine heating cycles, the power of the engine and the components of the oil used are also factors that determine whenever oil replacement should occur. Therefore, analyzing oil contaminations matters when it comes to replace it again. Consequently, manufactures and mechanics recommendations are not always the best, leading to consequences such as corrosion and sludge in the engine. So, this work focuses on engine oil parameters and environmental conditions to estimate the optimal oil replacement intervals, here given in terms of a replacement timeline, which may also contribute to a better environment that embodies all living and no living things on Earth.

***Keywords*—**Artificial Neuronal Networks, Energy and Environment, Engine Oil Replacements, Logic Programming.

I. Introduction

OIL chemistry and engine technology have evolved impressively in recent years, but nobody would ever know it from the behavioral changes of car owners, and its impact on the environment. Mostly driven by an outdated oil change commandment, they are needlessly dripping an ocean of contaminated waste oil.

On the one hand the majority of automakers today call for oil changes at either 10000 or 15000 kilometers, and the interval may go as high as 25000 kilometers in some cars. Yet, this wasteful cycle continues largely because the automotive service industry, while fully aware of the technological advances, continues to address the 5000-kilometre gospel as a way to keep the service bays busy. As a result, car owners are dumping their engine oil twice as often as their service manuals endorse.

On the other hand, the 5000-kilometre oil change is a fable that should be laid to cessation. Failing to heed the service interval in your owner's manual wastes oil and money, while compounding the environmental impact of illicit dumping. Part of the blame for this over-servicing lies in our insecurities about increasingly complicated engines that are all but inaccessible to the average driver.

Because busy car owners seldom read their owner's manuals, most have no idea of the actual oil change interval for their cars. Therefore, they blindly follow the windshield reminder sticker, whether it is an accurate indicator of the need for an oil change or not, i.e., the quality of oil has changed quite a bit, and the public in general is not aware of that [1]. Oil amendment interims are, mainly, due to:

- An improved robustness of today's oils;
- More and more automakers using synthetic oil;
- Tighter tolerances of modern engines; and
- The introduction of oil life monitoring systems, which tell the driver when an oil change is needed. However, existing systems do not address incomplete, contradictory or default information, which is their major drawback.

Indeed, the engine is like the heart of a car, i.e., it is an essential part of it. Thus, its components have to be in order and in accurately conditions, like human's vessels. And one of those components it is the engine oil that allows the engine's lubrication, so it can function properly.

Engine oil has some features that are relevant like viscosity high enough to maintain a greasing film, but, at the same time, low enough to let it flow throw the various parts of the engine at any condition. Therefore, the viscosity is seen as one of main parameters to check, especially when it is controlled by the temperatures variations at which the engine is subjected, by the oil composition, since the fact that it can be synthetic or not, petroleum-based or not, by atmospheric conditions, by the number of heating cycles of the engine, by the kind of use of the car, among others factors, that can lead to viscosity variations and oil contamination, making consequently repercussions in the engine and in its function [2], [3]. Still about oil contamination, there are issues like engine power, fuel type and trip average length that may according to its results, affect negatively the oil clarity, which means the presence of wastes in it [4].

Hence, it's advisable an engine oil replacement between certain time intervals or mileage, based on real and specific parameters instead on a generic prediction that suppliers and manufactures make [5]. Really, as it was already stated above, they recommend a change of oil about every 10000 to 15000 kilometers [6]. Of course it depends on the factors referred to above, but these are the more common replacement intervals suggested by the oil producers and mechanics.

Therefore, the change-interval question: When to perform an oil change?

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When one is working on oil monitoring, the challenging question with which car owners are met relies on the similarity between the signs and symptoms among the quality of oil.

Typically, the earliest acts for the diagnosis of oil quality proceed from the detection of a specific outbreak. An oil analysis will tell you the condition of your oil, and it also can reveal any problems that your engine may be experiencing. Some sample tests can show traces of fuel and coolant in the engine oil, which are early signs of engine problems. These tests may close the door to mistake and doubt.

Above any kind of dispute, the main problem with the diagnosis of oil change comes from the large number of different states that may mimic its signs. Also this pinpointing is usually done over a large period of time, therefore generating a huge amount of data, which has to be treated and interpreted by the car owner(s) [7]–[10].

Facing with such a large amount of facts, even experienced experts have difficulties to make a precise diagnosis and distinguishing between this and other car malfunctions. With this article we make a start on the development of an unusual or original diagnosis assistance system for oil change. We will center on a logic programming based approach to knowledge representation and reasoning, complemented with a computational framework based on Artificial Neural Networks.

II. Knowledge Representation and Reasoning

Many approaches for knowledge representation and reasoning have been proposed using the *Logic Programming* (*LP*) paradigm, namely in the area of Model Theory [11]–[13], and Proof Theory [14], [15]. We follow the proof theoretical approach and an extension to the *LP* language, to knowledge representation and reasoning. An *Extended Logic Program* (*ELP* for short) is a finite set of clauses in the form:

$$p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \tag{1}$$

$$?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m) \;\; (n, m \geq 0) \tag{2}$$

where *?* is a domain atom denoting falsity, the p_i , q_j , and p are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign $\neg$ [15]. Under this representation formalism, every program is associated with a set of abducibles [11], [13], given here in the form of exceptions to the extensions of the predicates that make the program. Once again, Logic Programming (LP) has emerged as an attractive formalism for knowledge representation and reasoning tasks, introducing an efficient search mechanism for problem solving.

Due to the growing need to offer user support in decision making processes some studies have been presented [16], [17], related to the qualitative models and qualitative reasoning in Database Theory and in Artificial Intelligence research. With respect to the problem of knowledge representation and reasoning in Logic Programming (LP), a measure of the *Quality-of-Information* (*QoI*) of such programs has been object of some work with promising results [18], [19]. The *QoI* with respect to the extension of a predicate *i* will be given by a truth-value in the interval [0,1], i.e., if the information is *known* (*positive*) or *false* (*negative*) the *QoI* for the extension of $predicate_i$ is 1. For situations where the information is unknown, the *QoI* is given by:

$$QoI_i = lim_{N \to \infty} \frac{1}{N} = 0 \qquad (N \gg 0) \tag{3}$$

where *N* denotes the cardinality of the set of terms or clauses of the extension of $predicate_i$ that stand for the incompleteness under consideration. For situations where the extension of $predicate_i$ is unknown but can be taken from a set of values, the *QoI* is given by:

$$QoI_i = {}^{1}/_{Card} \tag{4}$$

where *Card* denotes the cardinality of the *abducibles* set for *i*, if the *abducibles* set is disjoint. If the *abducibles* set is not disjoint, the *QoI* is given by:

$$QoI_i = \frac{1}{C_1^{Card} + \cdots + C_{Card}^{Card}} \tag{5}$$

where C_{Card}^{Card} is a card-combination subset, with *Card* elements. The next element of the model to be considered is the relative importance that a predicate assigns to each of its attributes under observation, i.e., w_i^k, which stands for the relevance of attribute k in the extension of $predicate_i$. It is also assumed that the weights of all the attribute predicates are normalized, i.e.:

$$\sum_{1 \leq k \leq n} w_i^k = 1, \forall_i \tag{6}$$

where $\forall$ denotes the universal quantifier. It is now possible to define a predicate's scoring function $V_i(x)$ so that, for a value $x = (x_1, \cdots, x_n)$, defined in terms of the attributes of $predicate_i$, one may have:

$$V_i(x) = \sum_{1 \leq k \leq n} w_i^k \times QoI_i\,(x)/n \tag{7}$$

It is now possible to engender all the possible scenarios of the universe of discourse, according to the information given in the logic programs that endorse the information depicted in Fig. 2, i.e., in terms of the extensions of the predicates *Manufacturer Specifications*, *Mechanic´s Observations*, *Oil Manufacturer Recommendations*, and *Engine Oil*.

It is now feasible to rewrite the extensions of the predicates referred to above, in terms of a set of possible scenarios according to productions of the type:

$$predicate_i\big((\, x_1, \cdots, x_n)\big) :: QoI \tag{8}$$

and evaluate the *Degree of Confidence* (*DoC*) given by $DoC = V_i(x_1, \cdots, x_n)/n$, which denotes one's confidence on a particular term of the extension of $predicate_i$. To be more general, let us suppose that the Universe of Discourse is described by the extension of the predicates:

$$a_1(\cdots), a_2(\cdots), \cdots, a_n(\cdots) \qquad (n \geq 0) \tag{9}$$

Therefore, for a given *scenario*$_i$, one may have (where $\perp$ denotes an argument value of the type unknown; the values of the others arguments stand for themselves):

$$\begin{cases} \neg a_1(x_1, y_1, z_1) \leftarrow not\ a_1(x_1, y_1, z_1) \\ \quad a_1(\perp, \quad [10, 20], 15) :: 0.5 \\ \quad \underbrace{[5, 10][5, 30][10, 20]}_{\text{attribute`s domains for } x_1, y_1, z_1} \\ \\ \neg a_2(x_2, y_2, z_2) \leftarrow not\ a_2(x_2, y_2, z_2) \\ \quad a_2([45, 54], [10, 12], \perp) :: 0.65 \\ \quad \underbrace{[30, 60] \quad [6, 14]\ [2000, 6000]}_{\text{attribute`s domains for } x_2, y_2, z_2} \\ \\ \qquad \vdots \end{cases}$$

1st interaction: transition to continuous intervals

$$\begin{cases} \neg a_1(x_1, y_1, z_1) \leftarrow not\ a_1(x_1, y_1, z_1) \\ \quad a_1([5, 10], [10, 20], [15, 15]) :: 0.5 \\ \quad \underbrace{[5, 10] \quad [5, 30] \quad [10, 20]}_{\text{attribute`s domains for } x_1, y_1, z_1} \\ \\ \neg a_2(x_2, y_2, z_2) \leftarrow not\ a_2(x_2, y_2, z_2) \\ \quad a_2([45, 54], [10, 12], [2000, 6000]) :: 0.65 \\ \quad \underbrace{[30, 60] \quad [6, 14] \quad [2000, 6000]}_{\text{attribute`s domains for } x_2, y_2, z_2} \\ \\ \qquad \vdots \end{cases}$$

2nd interaction: normalization $\frac{Y - Y_{min}}{Y_{max} - Y_{min}}$

$$\begin{cases} \neg a_1(x_1, y_1, z_1) \leftarrow not\ a_1(x_1, y_1, z_1) \\ \\ \quad a_1\left(\left[\frac{5-5}{10-5}, \frac{10-5}{10-5}\right], \left[\frac{10-5}{30-5}, \frac{20-5}{30-5}\right], \left[\frac{15-10}{20-10}, \frac{15-10}{20-10}\right]\right) \equiv \\ \\ \quad a_1([0, 1], [0.2, 0.6], [0.5, 0.5]) :: 0.5 \\ \quad \underbrace{[0, 1] \quad [0, 1] \quad [0, 1]}_{\text{attribute`s domains for } x_1, y_1, z_1} \\ \\ \neg a_2(x_2, y_2, z_2) \leftarrow not\ a_2(x_2, y_2, z_2) \\ \\ \quad a_2\left(\left[\frac{45-30}{60-30}, \frac{54-30}{60-30}\right], \left[\frac{10-6}{14-6}, \frac{12-6}{14-6}\right], \left[\frac{2000-2000}{6000-2000}, \frac{6000-2000}{6000-2000}\right]\right) \equiv \\ \\ \quad a_2([0.5, 0.8], [0.5, 0.75], [0, 1]) :: 0.65 \\ \quad \underbrace{[0, 1] \quad [0, 1] \quad [0, 1]}_{\text{attribute`s domains for } x_2, y_2, z_2} \\ \\ \qquad \vdots \end{cases}$$

The *Degree of Confidence* (*DoC*) was evaluated using the equation $DoC = \sqrt{1 - \Delta l^2}$, as it is illustrated in Fig. 1. Here Δl stands for the length of te arguments intervals, once normalized.

Below, one has the expected representation of the universe of discourse, where all the predicates´arguments are nominal. They speak for one´s confidence that the unknown values of the arguments fit into the correspondent intervals referred to above.

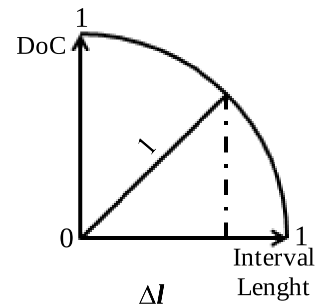

Fig. 1 Evaluation of *Degree of Confidence*

$$\begin{cases} \neg a_{1_{DoC}}(x_1, y_1, z_1) \leftarrow not\ a_{1_{DoC}}(x_1, y_1, z_1) \\ \quad a_{1_{DoC}}(0, \quad 0.916, \quad 1) \quad :: \quad 0.5 \\ \quad \underbrace{[0, 1]\ [0.2, 0.6]\ \ [0.5, 0.5]}_{\text{attribute`s values ranges for } x_1, y_1, z_1} \\ \quad \underbrace{[0, 1] \quad [0, 1] \quad [0, 1]}_{\text{attribute`s domains for } x_1, y_1, z_1} \\ \\ \neg a_{2_{DoC}}(x_2, y_2, z_2) \leftarrow not\ a_{2_{DoC}}(x_2, y_2, z_2) \\ \quad a_{2_{DoC}}(0.954, \quad 0.968, \quad 0) \quad :: \quad 0.6 \\ \quad \underbrace{[0.5, 0.8]\ [0.5, 0.75]\ [0, 1]}_{\text{attribute`s values ranges for } x_2, y_2, z_2} \\ \quad \underbrace{[0, 1] \quad [0, 1] \quad [0, 1]}_{\text{attribute`s domains for } x_2, y_2, z_2} \\ \\ \qquad \vdots \end{cases}$$

III. A CASE STUDY

Therefore, and in order to exemplify the applicability of our model, we will look at the relational database model, since it provides a basic framework that fits into our expectations [20], and is understood as the genesis of the LP approach to knowledge representation and reasoning.

Consider, for instance, the scenario where a relational database is given in terms of the extensions of the relations or predicates depicted in Fig. 2, which stands for a situation where one has to manage information about oil replacements intervals. Under this scenario some incomplete data is also available. For instance, in relation Mechanic´s Observation the value for Oil Replacement of model AXG11TRE is unknown, while in relation Oil Manufacturer Recommendations values for Mileage of model AXG11TRE range in the interval [10000, 15000].

Now, we may consider the extensions of the relations given in Fig. 2 to populate the extension of the *engine*$_{oil}$ predicate, given in the form:

$$engine_{oil}: RPM, HP, Oil\ Capacity, Fuel, Trip\ Lenght, Oil\ Replacement, Oil\ Clarity, Mileage \rightarrow \{0,1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth-values *false* and *true*. It is now possible to give the extension of the predicate $engine_{oil}$, in the form:

$\{$

$$\neg engine_{oil}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage}) \leftarrow not\ engine_{oil}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage})$$

$$engine_{oil}(4600, 94, 6.5, 0, 1, 10302, 1, 10000) :: 1$$
$$\underbrace{[4600,6500]\ [56,130]\ [3.5,8.5]\ [0,1]\ [0,1][10302,11686][0,1][8000,15000]}_{\text{attribute`s values ranges}}$$

$$engine_{oil}(5800, 56, 3.5, 1, 1, \perp, 0, [10000,15000]) :: 1$$
$$\underbrace{[4600,6500]\ [56,130]\ [3.5,8.5]\ [0,1]\ [0,1][10302,11686][0,1]\ [8000,15000]}_{\text{attribute`s values ranges}}$$

$\}$

In this program, the first clause denotes the closure of predicate $engine_{oil}$. The next clauses correspond to two terms taken from the extension of the $engine_{oil}$ relation. It is now possible to have the arguments of the predicates extensions normalized to the interval [0,1], in order to compute one's confidence that the nominal values of the arguments under considerations fit into the intervals depicted previously. One may have:

$\{$

$$\neg engine_{oil}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage}) \leftarrow not\ engine_{oil}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage})$$

$$engine_{oil}([0,0], [0.514,0.514], [0.6,0.6], [0,0], [1,1], [0,0], [1,1], [0.286,0.286]) :: 1$$
$$\underbrace{[0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]}_{\text{attribute`s domains}}$$

$$engine_{oil}([0.632,0.632], [0,0], [0,0], [1,1], [1,1], [0,1], [0,0][0.286,1]) :: 1$$
$$\underbrace{[0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]}_{\text{attribute`s domains}}$$

$\}$

The logic program referred to above, is now presented in the form:

$\{$

$$\neg engine_{oil_{DoC}}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage}) \leftarrow not\ engine_{oil_{DoC}}(RPM, HP, Cap_{acity}, F_{uel}, Trip_{lenght}, Repl_{acement}, Cla_{rity}, M_{ileage})$$

$$engine_{oil_{DoC}}(1, 1, 1, 1, 1, 1, 1, 1) :: 1$$
$$\underbrace{[0,0], [0.514,0.514], [0.6,0.6], [0,0], [1,1], [0,0], [1,1], [0.286,0.286]}_{\text{attribute`s values ranges}}$$
$$\underbrace{[0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]}_{\text{attribute`s domains}}$$

$$engine_{oil_{DoC}}(1, 1, 1, 1, 1, 0, 1, 0.7) :: 1$$
$$\underbrace{[0.632,0.632], [0,0], [0,0], [1,1], [1,1], [0,1], [0,0][0.286,1]}_{\text{attribute`s values ranges}}$$
$$\underbrace{[0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]\ [0,1]}_{\text{attribute`s domains}}$$

$\}$

where its terms make the training and test sets of the Artificial Neural Network given below (Fig. 3).

Manufacturer Specifications						
#	Brand	Model	RPM	HP	Oil Capacity (L)	Fuel
1	Citroen	Saxo 1.5D X	5000	57	4.7	D
2	Ford	Escort MK2	6500	83	3.5	G
3	Mercedes	250D	4600	94	6.5	D
4	Citroen	AX G11 TRE	5800	56	3.5	G
5	Ford	GT70	4750	130	8.5	G

Mechanic's Observations					
#	Brand	Model	Trip Length	Last Oil Replacement (km)	Oil Clarity
1	Citroen	Saxo 1.5D X	mix	11686	dark
2	Ford	Escort MK2	short	11387	light
3	Mercedes	250D	mix	10302	dark
4	Citroen	AX G11 TRE	mix	⊥	light
5	Ford	GT70	mix	⊥	⊥

Engine Oil								
#	RPM	HP	Oil Capacity	Fuel	Trip Length	Last Oil Replacement	Oil Clarity	Mileage
1	5000	57	4.7	0	1	11686	1	10000
2	6500	83	3.5	1	0	11387	0	10000
3	4600	94	6.5	0	1	10302	1	10000
4	5800	56	3.5	1	1	⊥	0	[10000,15000]
5	4750	130	8.5	1	1	⊥	⊥	8000

Oil Manufacturer Recommendations					
#	Brand	Model	Oil Recommendation	Alternative Lubricant	Mileage (km)
1	Citroen	Saxo 1.5D X	Magnatec 10W-40 A3/B4	GTX 15W-40 A3/B3	10000
2	Ford	Escort MK2	Magnatec 5W-30 A5	Edge 0W-40 A3/B4	10000
3	Mercedes	250D	Magnatec 10W-40 A3/B4	GTX 10W-40 A3/B4	10000
4	Citroen	AX G11 TRE	Magnatec 10W-40 A3/B4	GTX 10W-40 A3/B4	[10000,15000]
5	Ford	GT70	Edge 10W-60	Syntrans Transaxle 75W-90	8000

Fig. 2 An extension of the relational database model. 0 (zero) and 1 (one), in column Fuel stand for, respectively, for diesel and petrol. In column Trip Length 0 (zero) and 1 (one) denote, respectively, short and mix. In column oil clarity 0 (zero) denotes *light* and 1 (one) denotes *dark*.

IV. Artificial Neural Networks

Neves et al [21]–[23] demonstrated how Artificial Neural Networks (ANNs) could be successfully used to model data and capture complex relationships between inputs and outputs. ANNs simulate the structure of the human brain being populated by multiple layers of neurons. As an example, let us consider the case where one may have a situation that may lead to an oil change, which is given in the form:

$$\{$$

$$engine_{oil} attributes: RPM, HP, Cap, F, Trip, Repl, Cla, M$$

$$\Downarrow$$

$$engine_{oil}(\underbrace{\begin{array}{cccccccc}[4800,5000], & \perp, & 4.5, & 0, & 0, & 10564, & 1, & 10000) \\ [4600,6500] & [56,130] & [3.5,8.5] & [0,1] & [0,1] & [10302,11686] & [0,1] & [8000,15000]\end{array}}_{\text{attribute`s domains}} :: 1$$

$$\Downarrow \textit{1st interaction: transition to continuous intervals}$$

$$engine_{oil}(\underbrace{\begin{array}{cccccccc}[4800,5000], & [56,130], & [4.5,4.5], & [0,0], & [0,0], & [10564,10564], & [1,1], & [10000,10000]) \\ [4600,6500] & [56,130] & [3.5,8.5] & [0,1] & [0,1] & [10302,11686] & [0,1] & [8000,15000]\end{array}}_{\text{attribute`s domains}} :: 1$$

$$\Downarrow \textit{2nd interaction: normalization } \frac{Y - Y_{min}}{Y_{max} - Y_{min}}$$

$$engine_{oil}(\underbrace{\begin{array}{cccccccc}[0.105,0.211], & [0,1], & [0.2,0.2], & [0,0], & [0,0], & [0.189,0.189], & [1,1], & [0.286,0.286]) \\ [0,1] & [0,1] & [0,1] & [0,1] & [0,1] & [0,1] & [0,1] & [0,1]\end{array}}_{\text{attribute`s domains}} :: 1$$

$$\Downarrow \textit{DoC calculation: } DoC = \sqrt{1 - \Delta l^2}$$

$$engine_{oil_{DoC}}(0.994,\quad 0,\quad 1,\quad 1,\quad 1,\quad 1,\quad 1,\quad 1) \quad :: 1$$

$$\underbrace{[0.105,0.211], [0,1], [0.2,0.2], [0,0], [0,0], [0.189,0.189], [1,1], [0.286,0.286]}_{\text{attribute`s values ranges}}$$

$$\underbrace{[0,1] \quad [0,1] \quad [0,1] \quad [0,1] \quad [0,1] \quad [0,1] \quad [0,1] \quad [0,1]}_{\text{attribute`s domains}}$$

$\}$

In Fig. 3 it is shown how the normalized values of the interval boundaries and their *DoC* and *QoI* values work as inputs to the ANN. The output translates the chance of being necessary to go ahead with an oil change, and $engine_{DoC}$ the confidence that one has on such a happening. In addition, it also contributes to build a database of study cases that may be used to train and test the ANNs.

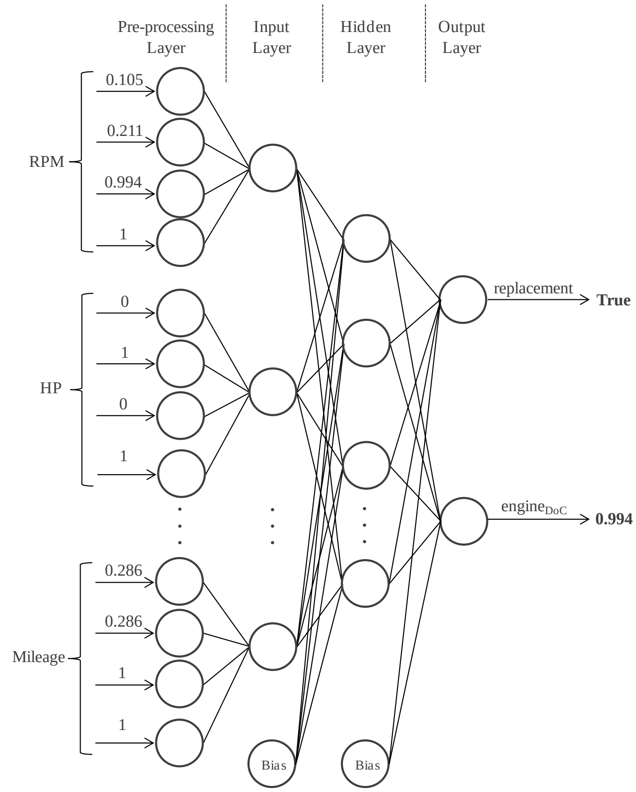

Fig. 3 The Artificial Neural Network topology

V. Future Work and Conclusions

To set a timeline to oil change is a hard and complex task, which needs to consider many different conditions with intricate relations among them. These characteristics put this problem into the area of problems that may be tackled by AI based methodologies and techniques to problem solving. Despite that, little to no work has been done in that direction. In this work it is presented the founding of a computational framework that uses powerful knowledge representation and reasoning techniques to set the structure of the information and the associate inference mechanisms based in ANNs. This finding has several reasons, namely:

- Data do not equal to information;
- The translation of the raw measurements into interpretable and actionable read-outs is challenging; and
- Read-outs can deliver markers and targets candidates without pre-conception, i.e., knowing how motor conditions and risk factors may affect oil change.

Indeed, one´s approach to decision making is above everything else, very versatile and capable of covering every possible problem instance by considering incomplete, contradictory, and even unknown data. Future work may recommend that the same hitches has to be approached using others computational frameworks like Case Based Reasoning or Particle Swarm, just to name a few.

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