Key factor identification for energy consumption analysis

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ABSTRACT

Nowadays the economic, environmental and societal issues concerning energy consumption require a deeper understanding of the factors influencing it. The influencing factors could concern the technical characteristics of the systems, the operational conditions and usage of equipment, the environmental conditions, etc. To understand the main contributing factors a knowledge model with the influencing factors is formalized in the form of an ontology. This ontology model allows to distinguish in a general way the main concepts (i.e. factors) that show higher consumption trends. This way, a preliminary analysis reflecting the key influencing factors could be perform in order to focus later on a deeper analysis with data mining techniques. This paper focuses on the formalization of an ontology model in the marine domain for energy consumption purposes. Then, the approach is illustrated with an example of a fleet of diesel engines.

1. INTRODUCTION

Managing energy consumption has become a key factor in enterprise concerns (Saidur, 2010), (Abdelaziz, Saidur, & Mekhilef, 2011). Indeed, it impacts not only from an economical point of view but from societal and sustainable development point of view as well (Hepbasli & Ozalp, 2003). Indeed, energy consumption:

- Increases in the price of energy,
- Carbon impact taxes,
- Environmental impact...

Hence when designing new systems, engineers aim at optimizing and decreasing energy consumption. However, many "old" systems are still in used and require attention for decreasing their energy consumption. Toward this aim, one solution is to bring new technologies to "old" systems. For instance, in the building domain, one has seen outer insulation, heat pump as new technologies available for upgrading old buildings. Nevertheless, such way is slowed down because of:

- The upgrading cost may be too high regarding the price of the "old" system or the economical capabilities of the owner;
- The ratio number of old systems by upgrade providers is always very high when a new technology emerge and makes the time to upgrade all "old" system very long.

When regarding quality management in enterprise, it preaches to learn from mistakes and to pool and share best practices. From this last idea, one can think to apply it to energy consumption reduction. Indeed, such a way does not suffer from both drawbacks outlined earlier. It cost almost nothing to apply new procedures since they do not require hardware upgrade and they can be widely spread using information technologies. However, it requires tools in order to support the determination of the best practices. Such tools have to deal with large/huge amount of data, multi-dimensional data, heterogeneous data, business knowledge structuring". One way is to use data mining techniques in order to highlight those best practices. However, data could be heterogeneous since it can come from different units with different characteristics. Then the use of data mining techniques alone may provide poor results, since they are only based on data. Moreover, data mining always requires pre-analysis in order to structure data and ease the search. Another way lies in using data structuring techniques through knowledge modeling in order to help expert to detect those best practices. The paper proposes to explore this second way. It shows how an expert can use an ontology to analyze from several points of view the energy consumption "trajectory" in order to detect what are the key factors impacting the reduction or increase of energy consumption. The purpose of this approach is not to replace data mining techniques, but to provide an overview of the factors affecting power consumption in order to help data miners and statisticians identifying the relevant data that require deeper analysis. This paper focuses on the formalization of an ontology model in the marine domain for energy consumption purposes. Then, we show on an example how the analysis can be conducted.

2. TOWARDS A SEMANTIC MODEL FORMALIZATION

To identify the factors that impact energy consumption one common approach is data mining where artificial intelligence, statistics and machine learning techniques helps to explore and discover knowledge from data. However, some drawbacks of data mining techniques is the time and efforts required to treat real process data due to:

- the noise and outliers values in the signals,
- the synchronization between the multiple data sources,
- the heterogeneity of signals since systems evolve in different environments, with different missions and thus monitored signals show significant variations (Voisin, Medina-Oliva, Monnin, Léger, & Iung, 2013).

To facilitate the work of data miners and statisticians and to overcome some oh these drawbacks, we propose to use semantic models that integrate the knowledge from experts of a domain and provide common semantic to data. In that sense, semantic models, such as ontologies, structure information from a common understanding of experts. The structured knowledge is based on the definition of the main concepts related to a domain and on the relationships among those concepts.

This paper focuses on the formalization of knowledge in the marine domain for energy consumption purposes. To provide the structure to the energy consumption of diesel engines in the marine domain, an ontology model is used. An ontology determines formal specifications of knowledge in a domain by defining the terms (vocabulary) and relations among them (Gruber, 2009). Ontologies are composed of classes, properties of the classes and instances:

- Classes describe concepts in the domain. In the marine domain, examples of classes are "components" or "diesel engines". Subclasses represent concepts that are more specific than the superclass (mother class). When a superclass has a subclass, it means that they are linked by a subsumption relation, i.e. "is a" relation, allowing a taxonomy to be defined. Hence, a hierarchy of classes is established, from general classes to specific ones.
- Properties are contained in a class definition and describe relationships among the classes. For example, the class "component" has property called "is monitored by" with the class "performance indicator". The property "is monitored by" links the individuals of the class "component" with the individuals of the class "performance indicator".
- Instances are the set of specific individuals of classes. For example, the engine "Baudouin 12M26.2P2-002" is a specific individual that is part of the class "diesel engine".

Ontologies define through concepts or classes, the characteristics of similarities among units and contexts, for instance, by defining common characteristics in the operational and contextual domains. The ontology gathers knowledge which is shared on one hand by the Condition Monitoring/ Prognostics and Health Management (PHM) community and on the other hand by the naval community. Some of the capabilities provided consist in (Noy and McGuinness, 2001): sharing common understanding of the structure of information among people or software agents, making domain assumptions explicit, defining concepts and knowledge and making domain inferences to obtain non-explicit knowledge.

The ontology model was built through experts interviews leading to the identification of the concepts to be considered and of the relationships among those concepts.

3. ENERGY ORIENTED SEMANTIC MODEL

The main factors that impact energy consumption are classified in:

- Maintenance factors
- Operation factors
- Environmental factors

An ontology model is formalized in order to structure knowledge and relationships among concepts coming from experts. The semantic model allows grouping data, building clusters and making them comparable. The different clusters will allow to detect differences between the groups and to identify specific directions for deeper investigation. A brief explanation of the factors that were integrated in the ontology model is presented in the following.

For the maintenance factors, it is well known that some degradation modes imply higher energy consumption. So a classification of degradation modes is included in the ontology model. The classification is built from the norm IEC 60812 (*Analysis techniques for system reliability – Procedure for failure mode and effects analysis (FMEA)*, 2006) (Figure 1). The type of maintenance that is performed affects the energy consumption trends of equipments as well. Hence, it is included and built from the norm EN 13306 (*Maintenance terminology*, 2001) (Figure 1).

The operational context integrates the operational conditions to which the units are exposed to. Operational conditions usually lead to different units' behaviors (Medina-Oliva, Voisin, Monnin, & Léger, 2014). In the naval domain, operational context is break up into (Figure 2):

- *The operation conditions* (Figure 3): which include the speed of the engine, torque as well as the engine operation temperatures, such as the engine outlet water temperature. Moreover, engine speed are classified according to expert's rules into "low", "medium" and "high" speed engines. This rule is coded in the ontology; for instance, the "low speed" engine are those whose speed is lower than 200 rpm.

- *The operation modes* enumerate the working modes of the machine. For instance, steady state during constant speed or transient state during the acceleration/braking phases, etc.

- *The production conditions* include how the user maintains and uses the equipment. For this reason, the type of machine-operator is included (e.g. rough, smooth and regular driving), as well as the number of stops made. The lubrication and coolant consumption and types are included as well, since they affect the engine performances.

- *Machine configurations* corresponds to the arrangement or structure of the equipment. It can be in series or in parallel. This factor is formalized in order to differentiate behaviors of the power consumption evolution. Material and performances will depend if the machine is used in series with high demand (constantly) or if they are used with a lower load in a parallel configuration.

- *Mission* of the engine depends on its usage. This factor is quantified either by the distance travelled or by the working time. Also the usage of the engine will depend on the mission of the ship. This is why different types of ships were included (non-exhaustive list).

The environmental context describes the surrounding environment of the engines as a third class of influencing factors. The environment takes into account the weather conditions, the chemical composition of water (pH, salinity), the environmental temperature, water turbulence, etc. (Figure 4) which might impact units functioning behavior.

Hence, the main classes of factors that influence power consumption are formalized. This formalized knowledge is used with the gathered data in order to understand the power consumption behavior.

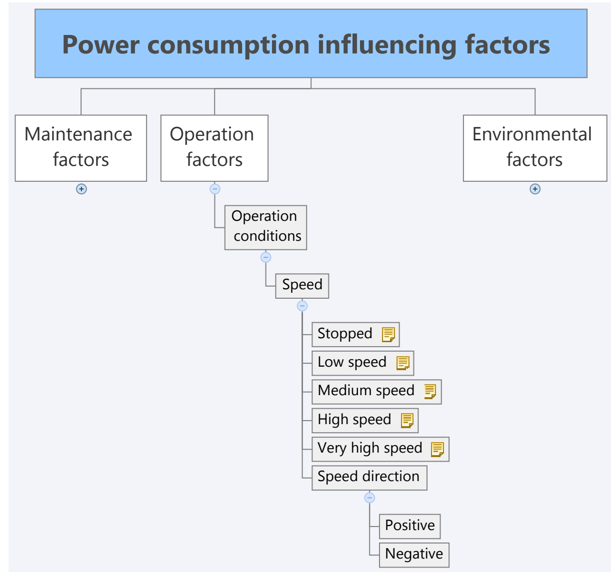

Figure 3. Part of operation conditions: speed classes.

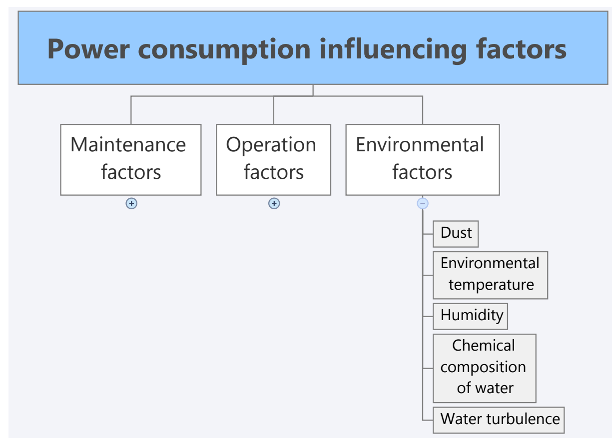

Figure 4. Part of environmental factors.

4. ENERGY ORIENTED CAUSALITY RELATIONSHIPS

Once an ontology model is built, it allows querying on the data stored in the database. The user (e.g. statistician) is able to have a first approach suggesting plausible explanations of some behaviors. To do that, one must first classify the studied scenarios in two clusters: Low Consumption (*LC*) or High Consumtion (*HC*) individuals. As a first approach the median value of the power consumption indicator was used allowing to divide the scenarios in two clusters. In Figure 5 the *LC* individuals are colored in green and the *HC* individuals in red.

After, the number of occurrences found for each concept are counted. For example, if an instance has ran 50% of the working time in "low speed", then 0.5 of individual is counted for that concept. Once the occurrences of every individual are counted for all the concepts in the ontology, bar charts repre-

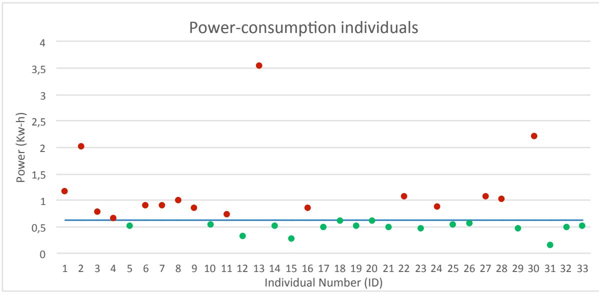

Figure 5. Definition of two clusters of individuals.

senting the differences trends of *LC* and *HC* individuals are shown (Figure 6). These bar charts reflect the most important factors influencing energy consumption at a first sight. This way a pre-analysis tool to data mining is proposed. Such tool helps to:

- search meaningful comparisons though the definition of clusters,
- identify possible causality relationships through comparisons,
- identify where to investigate further.

To illustrate the added-value of this approach a case study of a diesel engine used in the marine domain is studied.

5. CASE STUDY

To illustrate the feasibility of the proposed approach as well as the added-value, a scenario is proposed. This scenario shows how the ontology model is useful for statisticians before a deeper analysis for energy consumption purposes. The scenario contains 33 identical individuals exposed to different operational conditions. As a first step, the two clusters of individuals are presented in Figure 5: *LC* and *HC* individuals. The objective is to identify the key factors that influence the most the power consumption. To do such analysis, the impact of the concepts described in the ontology are investigated.

5.1. Speed classes (Figure 3)

According to the different speed classes defined by the experts, a bar chart is built showing the number of individuals belonging to each class (Figure 6). The chart uses the ratio of time spent in each speed class. For example if one individual spent 50% of time in the class “stopped”, 25% in the class “low speed” and 25% in the class “medium speed”, then the corresponding fraction of the individual is associated to each class. Finally all the fractions of individuals are summed for each class.

As a result we can see that the *HC* individuals spent more time in the medium and high speed classes (Figure 6). Deeper analysis is needed in that sense.

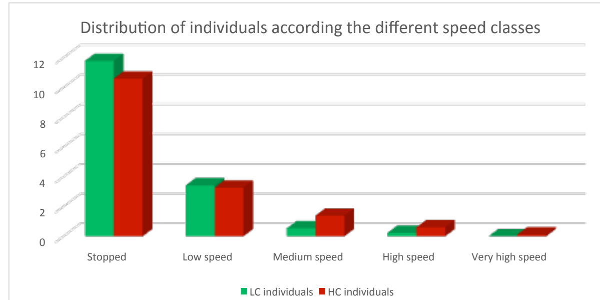

Figure 6. Bar chart with the distribution of individuals according the different speed classes.

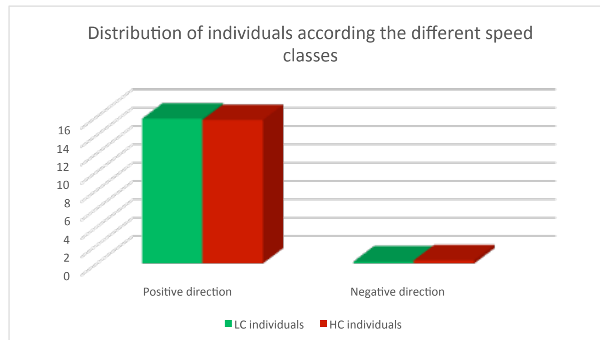

Figure 7. Bar chart with the distribution of individuals according the different speed direction classes.

5.2. Speed direction classes (Figure 3)

The speed direction was also considered. In Figure 7, it can be seen that there is a slight difference between the *LC* individuals running in the positive direction and the *HC* ones. The same behavior is found for the negative direction concept. However there is few difference so it can be possible to conclude that this concept is not interesting for further analysis.

5.3. Torque classes (Figure 2)

From the torque classes’ analysis, it can be noticed that the individuals that belongs to the very high torque classes have a higher power consumption (Figure 8). Deeper analysis is needed to understand the relation between the increment of torque and power consumption.

5.4. Machine-Operator classes (Figure 2)

There are two types of machine-operators for the engines. With this approach it is possible to notice a significant difference between both machine-operators (Figure 9): Machine-operator Y produces higher power consumption. This factor is interesting for further analysis.

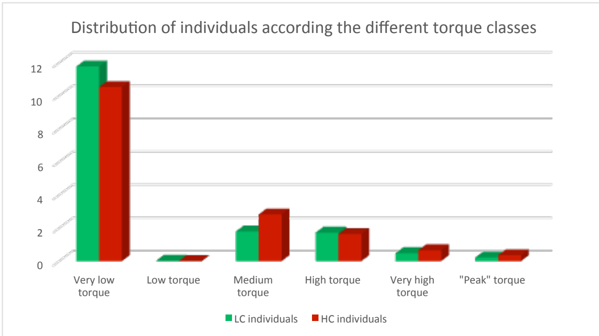

Figure 8. Bar chart with the distribution of individuals according the different torque classes.

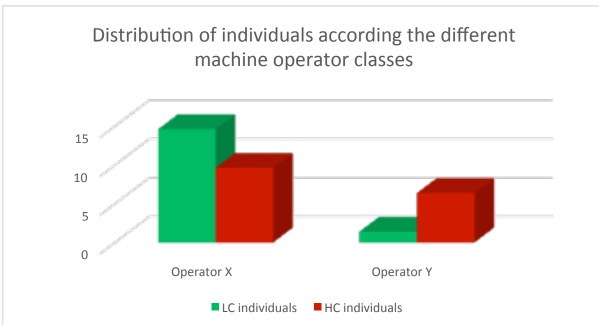

Figure 9. Bar chart with the distribution of individuals according the different operator classes.

5.5. Operation modes (Figure 2)

The effect of the engine operation mode is also addressed. As expected, individuals that are more in operation mode (and thus more loaded) require more power (Figure 10).

5.6. Transient mode classes (Figure 2)

The analysis of the time spent in transient modes (acceleration and braking) was also studied (Figure 11). Such operations modes are listed in the ontology (Figure 2). It is possible to observe that *LC* individuals spent more time in acceleration and braking modes. It is also known that the acceleration and braking phases demand more load (regarding the inertia). So such result is surprising. For this reason and in order to understand better the effect of the acceleration/braking modes, this factor needs to be further studied. For example the number of acceleration/braking, the speed delta among the accelerations/braking, etc. Maybe some correlated factors exist and should be investigated such as the waiting/moving factors.

5.7. Operation condition - engine exhaust gases temperature (Figure 2)

Concerning engine exhaust gases temperature, it can be seen a slight trend of more power consumption when the exhaust gases temperature is very high (class 380-400°C) (Figure 12).

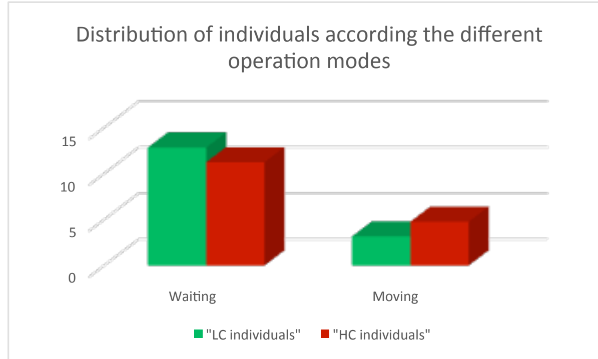

Figure 10. Bar chart with the distribution of individuals according the different operation modes classes.

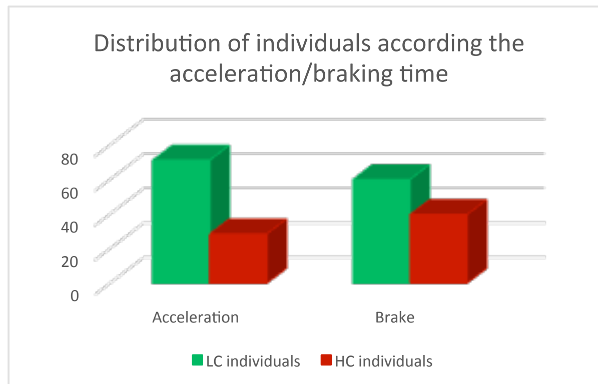

Figure 11. Bar chart distribution with the distribution of individuals according the acceleration/braking time.

However, this trend is not clearly established and thus with the existing information, it is not possible to draw conclusions.

5.8. Environmental temperature class (Figure 4)

A final factor that was study was the effect of the environmental temperature on the power consumption (Figure 13). It can be noticed that for lower temperature classes (¿25”éC and 25-28 “éC), the power consumption is higher and for the higher temperature classes, the power consumption is reduced.

With this preliminary analysis based on a semantic model it is possible to focus the attention on the more relevant factors that affect the power consumption. In this case-study some factors were irrelevant such as the speed direction, the operation modes classes, and the exhaust gases temperature. On the other side, factors that require deeper analysis are: the speed and torque classes, the operator, the transient mode classes and the environment temperature.

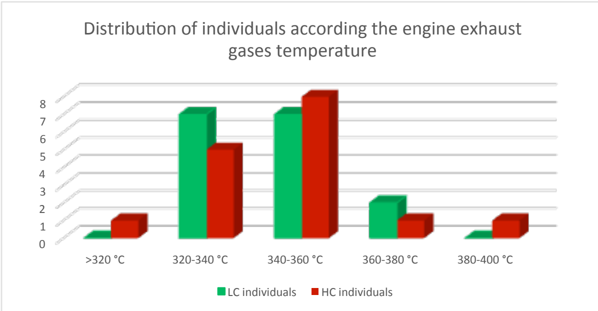

Figure 12. Bar chart with the distribution of individuals according the engine exhaust gases temperature.

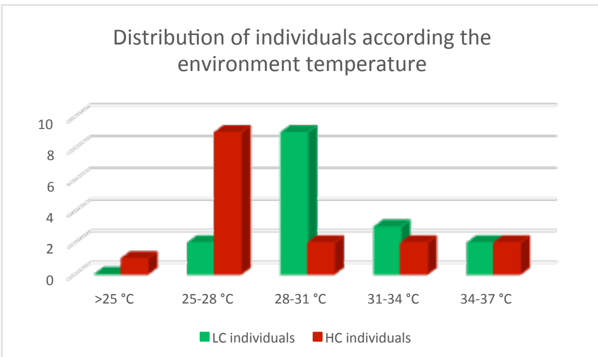

Figure 13. Bar chart with the distribution of individuals according the environment temperature.

6. CONCLUSIONS

The proposed approach provides the basis for the analysis of the influencing factors on performances. In this paper the target performance is the power-consumption. To do such analysis, an ontology model is formalized. The ontology contains expert knowledge which is introduced as a part of the classes (concepts) in the model. The classes allows to make cluster to bring information for engineers/statisticians. Moreover, the ontology model contains contextual information about the operational and environmental conditions of the engines, allowing to understand better some behaviors.

The influence of each cluster (represented as classes in the ontology) on the power consumption can then be visualized. This way, data-mining time and efforts are reduced. Moreover, the semantic model could integrate causality links that could not always be explained with data.

Some experimentations have already been done as shown in this paper. However, further experimentations have to be conducted to show the feasibility and the added value of this methodology. Moreover embedded knowledge could be refined while implementing this solution to different industrial systems.

As a future work, the analysis must take into account several factors at the same time. Hence, we propose to use 3D bar chart to show correlated influences of 2 factors. Moreover, a semantic model to deal with the technical characteristics of different units will be integrated, in order to use it from a fleet-wide perspective (Medina-Oliva et al., 2014).

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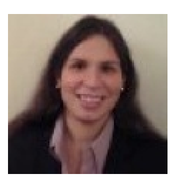
BIOGRAPHIES



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Dr. Maxime MONNIN is a Research Engineer at PREDICT Company where he is responsible of the R&D Team. In 2007, he received his PhD from the University of Valenciennes. This research founded by the French Procurement Agency (DGA), was conducted in collaboration with NEXTER and the Nancy Research Center for Automatic Control (CRAN), and addressed system of systems availability modelling and simulation. His research interests focus on fleet-wide health management. He is member of the French DIAG 21 Association (www.diag21.com) and of the PHM Society.

Dr. Jean-Baptiste LEGER is CEO and co-founder, in 1999, of the PREDICT company, France. He is graduated from Lorraine University, France and his PhD thesis, presented in 1999, was on Formal Modelling Framework for Proactive Maintenance Systems mainly based on Monitoring, Predictive Diagnosis and Prognosis. He has close to 20 years of experience on CBM and PHM systems. His experience includes fault detection and isolation, condition monitoring, fault tolerant control, prognostic, health management, intelligent maintenance and e-maintenance. He is currently working on formal approach of CBM, PHM, HUMS, IVHM and Therapy Systems. He is VP of the French DIAG 21 Association (www.diag21.com) and member of the PHM Society. He participates to standardization working groups in relation to PHM/IVHM (SAE, IEEE, BNAE).

Pr. Benot IUNG is full Professor of Prognostics and Health Management (PHM) at Lorraine University (France). He conducts research at the CRAN lab where he is managing today a research group on Sustainable Industrial System Engineering. His research and teaching areas are related to dependability, prognostics, heath management, maintenance engineering and e-maintenance. In relation to these topics he took scientific responsibility for the participation of CRAN in a lot of national, European (i.e. REMAFEX, DYNAMITE) and international projects with China and Chile. He has numerous collaborations with industry and serve on the advisory board for PREDICT company. He is now the chairman of the IFAC WG A-MEST on advanced maintenance, the chairman of the ESRA TC on Manufacturing, a fellow of the IFAC TC 5.1., a French Associate Member to CIRP Federation and a founding Fellow to the ISEAM. Benot Iung has (co)-authored over 150 scientific papers and several books including the first e-maintenance book in Springer. He has supervised until now 15 MA, 14 Ph. D. Students and 2 Post-Doctorate students. Benot IUNG received his B.S., M.S. and Ph.D. in Automatic Control, Manufacturing Engineering and Automation Engineering, respectively, from Lorraine University, and an accreditation to be research supervisor (2002) from this same University.

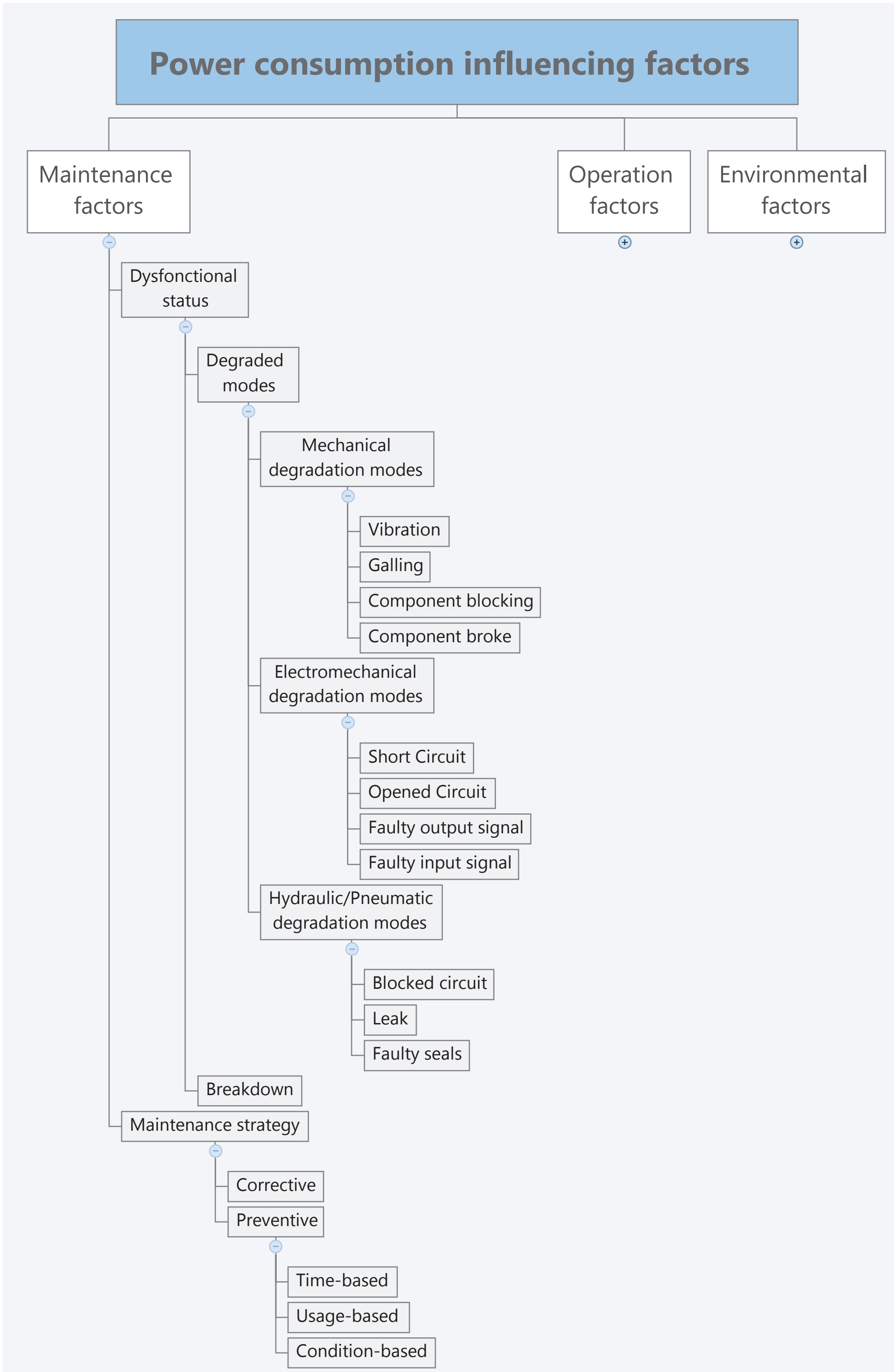

Figure 1. Part of the maintenance factors.

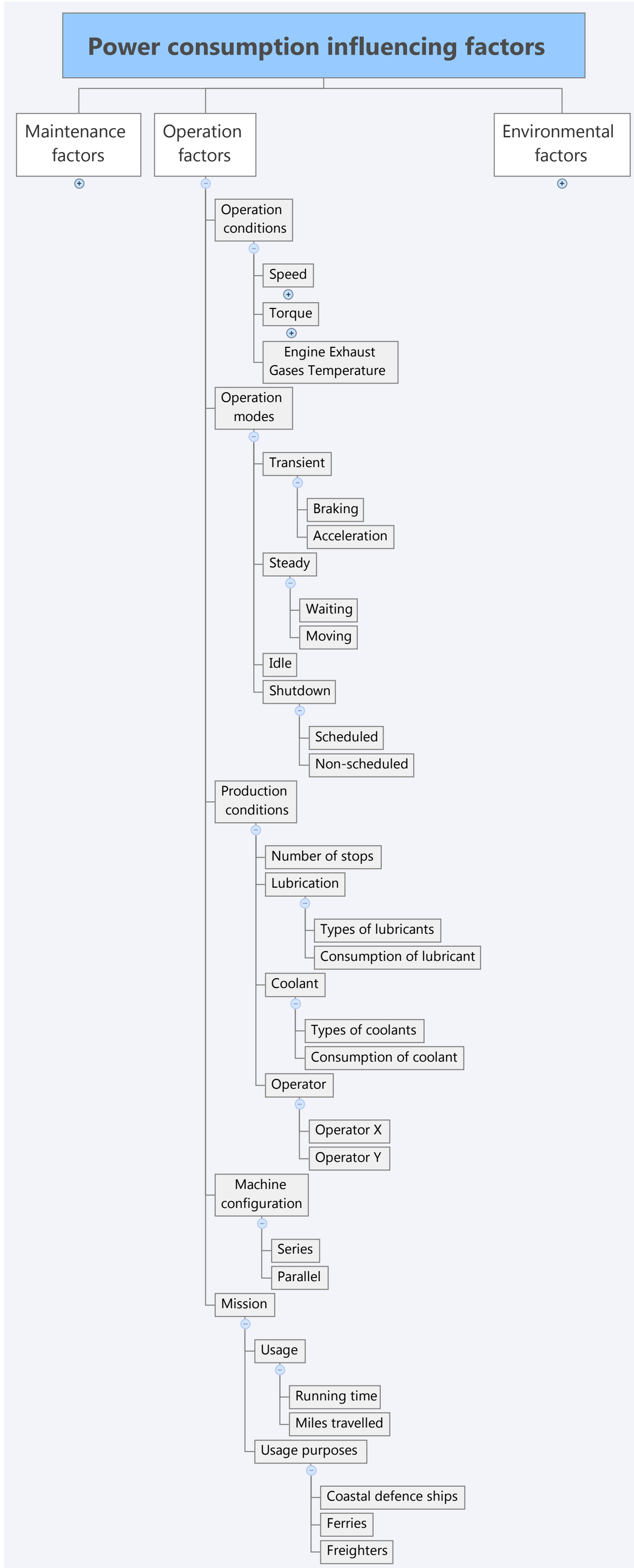

Figure 2. Part of the operational factors.