E-Debitum: Software Debt Management

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Abstract— This paper condenses previous work in the concept of a new software Energy metric: Energy Debt. This metric is an expression of meaning costs in relation to the use of force over time, of preference in the implementation of faulty software over strong power as an effective but time-consuming process. This paper describes how to use a SonarQube tool called E-Debitum to calculate power credit for Android apps in all versions. This plugin employs powerful, well-defined capabilities, as well as an expandable scent catalogue based on the current bright green system erature, with each fragrance describing potential energy savings. Finally, the E-Debitum test was confirmed in three popular Android apps with different releases, displaying how their energy debt fluctuates across all emissions. IDEAS FOR CCS: Software and its engineering; independent analysis; software performance. WORDS ARE ESSENTIAL: Green Software, Energy Credits, and Code Analysis. THE ACM REFERENCE FORMAT IS: Daniel Maia, Marco Couto, Joo Saraiva, and Rui Pereira contributed to the ACM reference format. Debitum: Software Debt Management, 2020. At the 35th IEEE / ACM International Conference on Automated Software Engineering Workshops (ASEW '20), Visual Event, Australia, September 21-25, 2020. 8 pages, ACM, New York, NY, USA. https:\s//doi.org/10.1145/3417113.3422999.

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I. INTRODUCTION

Debt Technology (TD) describes the difference between the current situation and the good state of the software system. An important technical credit concept is that software systems can incur complexity / storage / storage incorporates art objects, resulting in higher costs for future development and maintenance activities. This additional expense can be viewed as a form of credit owed by developers to the software system.

Although technology credit is still a hot research topic, the work we've done has garnered a lot of attention over the years: The most recent programme, the study of the atic map [27], identified ten distinct types of technology credit, necessities, properties, design, code, test, construction, documentation, infrastructure, translation, and technical credit crunch.

TD, in fact, is a problem for both researchers and software developers. Because of the current widespread use of non-wired computing evil, power consumption is an important consideration not only for computer hardware manufacturers, but also for researchers and software engineers [42]. Several programmes, in fact, do not function properly.

Procedures, such as energy patterns of mobile applications [8, 12], the potential effect of code scent [4,], energy-greedy API application patterns [29], efficient (to) energy data structures [33, 38], programming languages [39], and so on, have been reported in the literature, and they have a significant impact on the power consumption of the software.

All of these research activities show that dynamic habits, also known as energy odours, are common in software programmes. This could be due to a lack of current information for software developers to use when developing energy-efficient software, as well as a lack of supporting tools [43].

This paper is based on work on energy debt [9], the metaphor for estimating the cost of making a software system due to the occurrence of a strong odour in the software source code, where compared to the average cost of energy for non-energy performance a smelly version (i.e., the right power) of that same software.

The following is how this paper is organised: Section 2 completely removes- writes an idea of the energy bill and how it should be expressed / - calculated and presented our catalogue of energy bills; Section 3 introduces our SonarQube tool, E-Debitum, and the active trial- using E-Debitum in three popular Android apps to analyse their own energy debt; Section 4 introduces related work; and Section 5 concludes with our future ideas and activities.

II. INTRODUCES THE STRENGTH CREDIT STRUCTURES:

This section will define the current definition of energy debt in order to introduce a general concept behind the concept in Section 2.1. Following that, we will present such concepts, elaborating on each one in detail. First, we describe how to present our newly presented fragrance catalogue, i.e., I consider the issues that need to be addressed and the associated energy costs, as well as present an example of the currently translated catalogue the concept of energy debt (Section 2.2). Following that, in Section 2.3, we explain how energy debt can be calculated using a specific software release version and the appearance of a detected odour free. Finally, we will look at how this debt can be converted into equity.

A. A Synopsis of the Concept:

Technical debt represents the cost of doing more work on a software system as a result of engineers who take "shortcuts devoid of good manners"[1]. In other words, this cost can be defined as the technical effort, in working hours, required to fix all problems in a software release caused by poor planning processes. Costs continue to rise as newer versions (and newer versions) are released, and if initial problems can be mistreated, interest accumulates [5]. Based on the fundamental concept of technological debt, Energy Debt is defined as the amount of unnecessary power that the software system consumes the most of the time as a result of long-term energy coding scent. Figure 1 depicts a striking comparison of the two concepts.

The image on the left shows a pre-technical credit submission, which includes redundancy concepts, the corrective effort, and the definition of interest. The definition of energy debt is presented on the right side, in which we consider that modifying software (i.e., adding new features to new releases) will eventually lead to new additions (power) code stinks, which is why Power Debt (ED) increases with each version.

The cost of saving power code stinks from software releases because it remains the same at the same time release is valid. For example, if two software programmes, S1 and S2, have the same energy code, the pass rate of power used by S1 may be higher than S2 if both are intended for long-term use.

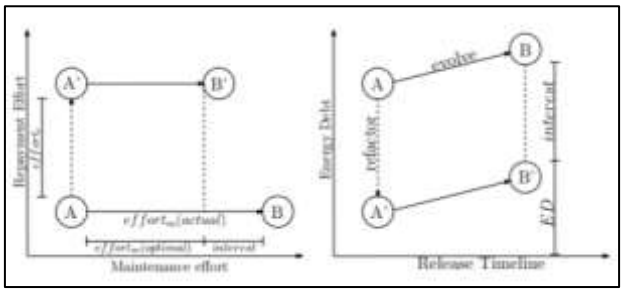

Fig. 1: Credit Card Names vs. Technical Debt

As stated in previous comments, the soft energy credit ED- disposal should be expressed as an expense function that receives two variables: software release r and time to use t. Equation 1 describes such a function, and it also allows us to calculate its ED power debt after time to use t with the exemption granted r:

cost (r) t ed (r, t) ed (r, t) ed (r, t) ed (r, t) (1)

The cost function (r) used in the calculations represents the cost of releasing energy r per unit of time. In other words, it is related to the current number of power code smells in that version, as well as energy costs (per unit of time) per unit. The following is an explanation of the function specified in Equation 2:

cost (r) = N I + 1 wi (r) E (i) (2)

In this case, N is the number of odours incorporated into the fictitious odour catalogue, and wi (r) returns the value of the odour weight I affecting the number of fragrances found in the release r and the context in which they are found. E I compensates for the expected energy debt per unit of fragrance I as described in the fragrance catalogue.

The presented formula assumes that each observer of the smell of energy has a corresponding energy credit value, which is expressed in performance over time units (e.g., per minute). However, when reading about the impact of energy consumption on odour, researchers generally present potential benefits / savings as a period (i.e., maximum and saving very low visual acuity). This is due to the fact that measuring power is not a completely decisive task; for example, CPU / room temperature has a significant impact on power consumption.

Following a high/low maintenance method provides valuable information about potential energy savings. A specific odour has a storage limit, such as 3000 mJ per minute, as well as a minimum of 150 mJ per minute. When compared to another scent with maximum and minimum savings of 900 mJ and 300 mJ per minute, we know that the first can lead to a high gain in the best-case scenario, but the second scent produces better savings in the worst-case scenario. As a result, depending on the project's objectives, an engineer can use this information to determine how well they focus their attention when the code reproduces the scent [8].

In accordance with the preceding considerations, energy debt should be considered. Based on the smell of each code, two energy values were identified as energy saving: very high (Emax) and low (Emin). Expect the energy bill to be included in the time-to-use function. As shown in Figure 2, it is expected that Emax will increase significantly with increasing use time.

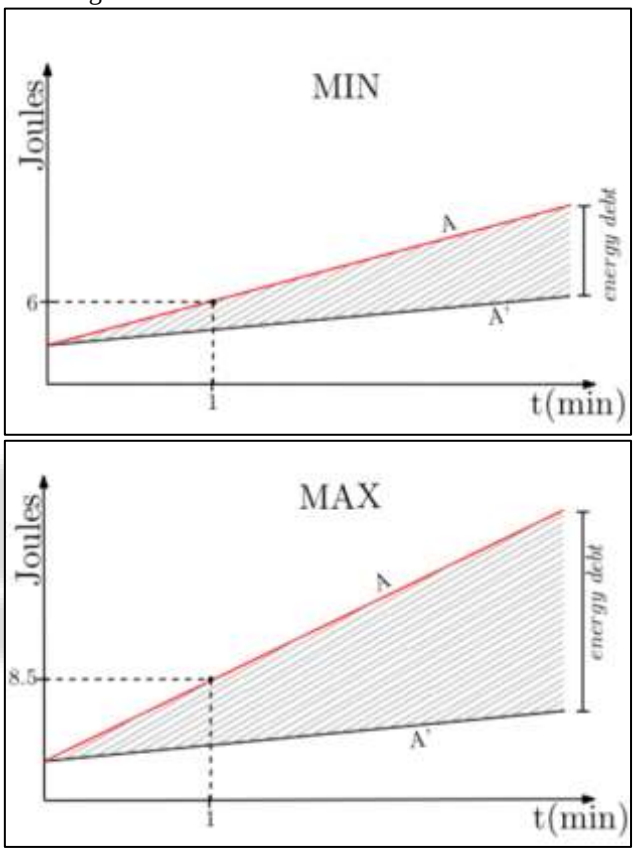

Fig. 2: shows how mortgage debt grows over time.

There are two versions to be released from this image: the correct version (A'), which has all odours removed, and the power smelly version (A). As would be expected, the correct version already has a constant increase in energy consumption. The area between line A', once (red) A-line, which is much larger when processing high prices, can be used to summarise debt power. This will alter Equation 1, which will process two cost costs in the form of two functions:

(r, t) ed =costmax (r) t; costmin (r) t. (3)

As a result, the energy bill will be presented on a regular basis. As a result, each cost function will necessitate a reference to the appropriate energy credit per unit of time. Alternatively, the Equation 2, the E I job will be Emin I for the lowest savings and Emax I for very high savings.

B. Debt Costing and Estimation:

The next step, using the defined energy scent catalogue, is to define a strategy for analysing the emergence of such a scent

in a given release.The normal source code will be used in the beginning of this work, along with an analysis tool that can detect the smell of code. There are several approaches that can be taken to accomplish this. SonarQube3, for example, has a wide range of applications.The technology used to calculate technical debt provides descriptive API rules for obtaining news / smells in various languages.

Detecting the appearance of the odour, on the other hand, is required but not the only requirement for analysing its impact on power debt. The smell can be found, for example, inside an inaccessible death block or code, or it can be inserted within a possible process that is performed only once in the software's life cycle (e.g. initial setup).On the other hand, the smell of code can be a part of a machine that is intended to be reused multiple times, such as a rope, a rope.

Assistance (most common on Android). These types of situations must be considered when calculating energy debt and from an energy standpoint.

Debt settlement entails employing mathematical analysis methods; we can use the previously defined strategies for analysing static energy.

Several strategies for this project have been proposed, all of which have been accepted by the public with promising results. As previously advised in previous work on energy debt [9], we will consider a simplified version of the strategy proposed by Jabbarvand et al. [21]:

w I r) = C j = 1 methods (j) (4)

According to these figures:

- C is the number of odours discovered in release r;
- methods (j) is the number of paths in the telephone graph.thanks to j
- The odor's appearance is visible;
- If j, LB will be 1.However, the odour is not contained within the loop a permanent loop that indicates the loop is tied; can be considered if conceivable or predetermined

More information and examples can be found in the Power Debt Calculation, Please see [9] for all versions.

C. *Making Payments on Interest:*

The concept of technical credit interest has already been formatted [5], and its application has been investigated [2, 3, 49]. When technical debt is not available, the cost / effort of adding features to new releases increases as the software changes targeted. Maintaining a credit card debt necessitates more effort rather than retaining one without it; the difference in effort between, Both are examples of so-called technical debt interest.

Figure 1's left side depicts an interest. There is a version of the software, A, that contains the scent of the code, which is why the technology debt exists. At this point, a decision can be made about what is most important. If the priority is to release the version as is, without having to deal with smell, and the last attempt / conversion to a new release B, it would be higher if the priority was to invest in repairing smells and releasing an appropriate version of that release, A', without technical debt. This is similar to the idea of debt collection in that the debt must be repaid.

Chatzigeorgiou et al. [5] proposed a prediction strategy I The point of technical debt violation, that is, when the accumulated tax is greater than the initial attempt to remove the technical debt (i.e., from the first release, so-called principal). With this approach, engineers can be introduced in a different way: if technical debt is not resolved now, they will most likely have to wait until the N number is issued to deal with it properly; otherwise, since and thereafter, an extra effort to fix it from the non-confrontational debt of technology will always be greater than the effort to deal with it principally. This ultimately means that they will be wasting development time for the time being.

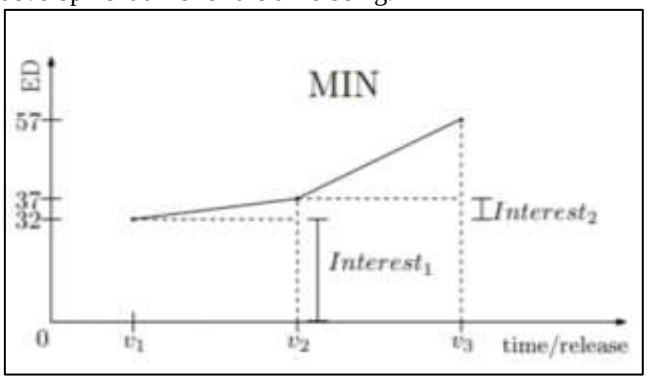

Fig. 3: Seedling growth

Figure 3 depicts an interest view within a power liability. Three software releases are included, and the prices shown are for a limited amount of debt. In this case, we believe that issues from previous versions have not been resolved in any way, resulting in an ever-increasing energy debt. We believe that no profit has been collected thus far with the first release, v1, for the sake of truth that power liability is measured in terms of operating time, which will be void as soon as the version is released.

We can calculate the profit using v2. Another possible solution is to calculate the ratio of all previous releases' energy bills. In this case, the minimum amount of interest that can be collected is 32. Similarly, for release v3, the minimum profit collected is (32 + 37)/2= 34.5.

The method presented may appear to be very simple, but it is proper debt repayment disclosure. Because interest is exactly equal to energy debt, if the interest rate falls, the original debt is repayable. It is critical to define interest in the same way that an energy bill is defined: an interval that describes the minimum / maximum immunisation of excess energy used during use. As a result, we argue that the expected use time for each new release should be greater than for any previous release. As a result, while energy debt can be reduced during the middle discharge, accrued interest will be increased for later release.

III. E-DEBITUM: ANALYSIS OF POWER CREDIT:

Despite the fact that a strong scent can occur in any system language, the number of specific language odours present is limited. This proof of concept is written in Java with this in mind.

To achieve our objectives, we used the E-Debitum5 tool with two different SonarQube plugins, and tem plates will be used to manage the required logic involved in assembling a tool built into the platform. The first plugin creates a set of rules that correspond to the smell's power. As a result, it is referred to as a rule plugin. A platform is required for the process of analysing the acquisition and writing of any

energy odour present in the code, as well as any other existing content.

The metrics plugin, which takes effect immediately after the code scan is completed, is in charge of measuring the minimum / maximum Power Credit system. Includes the number of events for each given code smells once more, using the estimated cost of the volume per minute they use cause, it retains the total amount of debt in its most advanced / worst cases.

These activities are kept separate to improve plugin code readability and to allow SonarLint users to apply the rules as they write the code, rather than receiving only the power of odour during analysis. It is worth noting that in this case, they would only see rules but would not fully comprehend their overall impact.

A. Plugin for Rules:

To save development time, a Java legal rules template6 was used to create the first SonarQube plugin. As a result, for each fragrance law enacted, five files will be created.

To begin, a test file will be created. This will include the code that will be used for law enforcement. It has a set of routes that record your circumstances for both compliant and non-compliant code to show SonarQube what patterns to look for when exploring what a given scent is and what you should emit. Following that, a section of the rules will be upgraded, with logic when SonarQube detects a potential occurrence of the non-compliance code. It will confirm that it is not a falsehood and, if it exists, will report the issue. Finally, a test class will be created that only allows one unit of testing to rule.

In addition, an HTML and JSON file will be created to display legal information to end users within SonarQube. This includes a brief description of the law, as well as an example of a non-compliance code and its amendment, as well as legal debt and tags.

Once applied, each rule, in addition to the RulesList class baked into the plugin template, must be activated within the plugin.

B. Plugin for Metrics:

Another template, Sonar API7, was used in this plugin. Three Java classes must be upgraded to accomplish this. First, those who use the Sonar API's Plugin interface. This section serves as the starting point for all SonarQube extensions. In this case, two extensions will be added, resulting in the addition of two more classes.

The first extension is the MeasureCom puter interface implementation. This section is in charge of defining system output and learning what and how much smelling energy was discovered and summarised corresponding size and smallness limited liability. Finally, an additional extension is the use of the Metrics interface interface, which is the last required and second class. This class simply defines metadata in SonarQube's minimum and maximum power credit as flexibility.

C. Job Related:

Cunningham [15] defined debt technology as the pitfalls of creating sub-optimal software to fit in the short term. This is a common practise used to meet a temporary development deadline with the intention of ending it later. As soft materials evolve, there is an obligation to borrow from a variety of sources, including "technological obsolescence, evolution, rapid trade success, the introduction of new and improved technology, and more - to put it another way, the invisible features of natural software ageing as well as evolution." [23]. However, the most common problems can be attributed to software development, which arises as a result of malicious or general coding process ignorance, emphasizing various aspects of technological debt [48].

Allowing technology debt to grow indefinitely outside of debt management raises the risk of producing unruly and ineffective code, which could impede the addition of new or updated functions. As a result, if such code is ignored for an extended period of time, resources will be required to repair it, resulting in a lower return [5].

Another flaw in the software is the use of excessive power. Indeed, the profiling, analysis, and optimization of energy efficiency software has evolved into a highly effective field of study.

It has been demonstrated that developers are aware of the issue of energy consumption and frequently seek assistance in resolving such issues [30, 42, 43]. There is currently a wide range of work being done to understand what features in programming languages, such as different data structures [17, 28, 38, 41], languages [10, 39], memorization [44], design patterns [46], code refac toring [47, 51], and even the test phase [26], can have a high impact on energy costs.

Clearly, there has been research in the Android ecosystem on topics such as the classification of Android applications as more or less energy efficient [21], identifying green energy APIs [29], estimating the use of force on parts of the code [11, 19], and so on. In fact, research on reducing power consumption in the Android system has probably been the most tested area in the last ten years [4, 12–14, 22, 24, 32, 34, 45, 50]. The results of the majority of these courses can be quickly translated into our strengths a scent catalogue to be used in energy credit calculation.

Furthermore, much research has been conducted on the provision of a few methods to measure energy consumption. Because eCalc [16], vLens [25], eProf [35], Trepn [18, 19, 21], GreenOracle [7], GreenScaler [6], and COB WEB [20] are examples of Android power analysis. There is also a function in the default tools to assist in discovering the power of greedy colour codes [36, 37], automatically refactoring for the most economical data framework [31, 40], or by default revitalising the greedy Android patterns [4, 8, 13].

D. Summary and Future Activities (Conclusions):

This paper introduced the concept of energy debt as a way to supplement energy costs during the software development process due to the occurrence of the power code has the same odour as its source code. We introduced the fragrance catalogue of modern energy code, whose power is known costs at the time of each use, and expressed the energy bill as a function taking into account I the number of smells, (ii) the context received, and (iii) the expected time to process the application. Interest rates on energy debt are also expressed as energy collections debt for each exemption, which can be avoided by exhaustion odour on previous releases.

Our E-Debitum tool was used to automate the discovery of the presentation power code as well as the calculation of energy and interest debt. With the help of two plugins, this tool can be used within the framework of Sonar Qube. We were able to perform test authentication on the well-known 3rd Android applications in all different releases by using E-Debitum.

We are currently working on expanding the scent catalogue, which we believe includes reviews and the smell of energy code. In addition, we are working on a large study on energy bills, which will include hundreds of open source Android apps.

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