What makes a task difficult? An Empirical Study of Perceptions of Task Difficulty

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***Abstract*— Estimating the difficulty of tasks is imperative for project planning, task assignment, and cost calculation. However, little is known about how and for what purpose software practitioners estimate task difficulty in their day-to-day work. In this paper, we interviewed 15 professionals to understand their needs and perceptions when estimating task difficulty. We find that practitioners do estimate the difficulty of tasks for scheduling and prioritizing their work. Additionally, performing such estimation requires more than one metric, and across more than one domain (i.e. code metrics, process metrics, and task metrics). The use of metrics that encapsulate different aspects of a task allows developers to gain a holistic view of the task and its potential difficulty.**

Keywords—task difficulty, effort estimation, empirical study, software metrics.

I. INTRODUCTION

A large majority of projects (about 60-80%) face budget or schedule overruns [1], costing the software industry significant losses. Effort estimation is, therefore, imperative to the success of software projects. This estimation in a (software) project comprises three steps: identifying the constituent tasks, estimating the effort required for each task, and scheduling the tasks to minimize overall costs. Therefore, research has investigated different techniques to estimate development costs and effort based on formal models and expert developers, with the latter providing better predictions. Nonetheless, both approaches focus on full projects, not individual tasks.

Moløkken and Jørgensen [1] found that most developers (80%) rely on their intuitions when estimating task effort. This explains why expert-based estimations are more accurate than their formal counterparts, but a key question arises: what do developers know about their tasks or project that allows them to estimate better? It is not clear where and why current estimation models in the field underperform those of expert developers.

Our goal in this paper is to understand what is happening in the field: *when and why do developers estimate task effort, and if they use metrics (and which)*. In the realm of human behavior, these practices can explain why some project metrics succeed at supporting the estimation needs of software developers, and why others that were expected to succeed did not. To this end, we conducted a mixed-method study comprising an exploratory survey, followed by semi-structured interviews of survey participants, so that we could discuss their survey responses.

This paper answers the following research questions:

- RQ1: Why do developers perform task estimation?
- RQ2: How comfortable are developers when performing estimations?
- RQ3: What project metrics do developers find useful when estimating task difficulty?

In our study we use the term "difficulty" of a task as a proxy for the effort in "person-hours" needed to complete a task. We do so for two reasons. First, estimating the difficulty of a task is a more natural practice than computing person-hours – every developer needs to gain an undersanding of the kind of task that they are going to perform before starting on it. Second, in agile development [2], [3] effort is measured as difficulty of individual tasks, which are then used to determine which tasks gets completed in which sprints.

Our study results show that developers use a variety of metrics, including code, task, and process metrics. They often use these metrics in combination. Of these, they find task metrics to be the most useful. It is noteworthy that current effort estimation models do not consider task metrics in their calculations. This therefore, reveals a gap between what is needed by developers to perform estimation and what is currently available to them.

II. RELATED WORK

A. Effort Estimation

Effort estimation helps project managers make informed decisions on how to handle resources to deliver projects on time and budget. The two main estimation approaches used are model-based and expert-based [1]. Note that these are performed for the entire project and not for individual tasks.

Model estimation techniques use a pre-set equation (model) that require project-specific data to be given as parameters: COCOMO (I/II) [4]–[6], Price-S [7], SLIM [8], and SEER-SEM [9], among others. Expert-based estimation, on the other hand, is much less formal where an expert foresees how much effort a project needs. It is the preferred method of estimation among companies as it is more accurate [1].

B. Task Difficulty

There are some works that aim to measure the difficulty of software development tasks. De Alwis et al. [10] created a cognitive metric that uses graph-based analysis of the solution. Fritz et al. [11] uses psycho-physiological measurements (e.g., eye tracking, electro-dermal activity) to calculate the mental effort of an ongoing task. Similarly, the Modified Cooper Harper Scale (MCH), the Overall Workload scale (OW) [12], and the

Work is partially supported by NSF IIS-1559657 and CCF-1560526

978-1-5386-0443-4/17/$31.00 ©2017 IEEE

NASA Task Load Index (NASA-TLX) [13] evaluate the cognitive load of a task during its resolution or afterwards.

TABLE I. METRIC EVALUATION SCALE

Metric	Usefulness description of the metric
Essential (E)	It is essential for determining the difficulty of a task
Worthwhile (W)	It provides some help to infer the difficulty of a task
Unimportant (UI)	It does not help in determining the difficulty of a task
Unwise (UW)	It should not be used. It misleads the difficulty of a task

However, these measures can only be computed when a task is being performed or after it has been completed; and not before. Therefore, while they do measure the difficulty of a taks, they are not useful for prediction or estimation. In this paper, we try to understand how (and why) software practitioners estimate the difficulty of a task before they attempt to solve it, and the metrics that help them perform this estimation.

III. METHODOLOGY

We conducted a mixed-method study comprising an exploratory survey, followed by semi-structured interviews of the survey participants, where they elaborated on their survey responses. We follow the sequential explanatory strategy, characterized by the collection and analysis of quantitative data followed by the collection and analysis of qualitative data [14]–[17]. The survey helped us in three ways: (1) validated the problem and motivated further exploration through interviews, (2) helped us reach participants for the interviews in industry and open source, and (3) shaped our interview questions.

We targeted two different domains for our study: A large open source project (Drupal), and a large software development company. We selected these two because we had access to the team and their codebase.

Survey: The initial exploratory survey was conducted to gather data about practitioners' perception of what makes tasks difficult. We asked them to classify the usefulness of several metrics when estimating the difficulty of a task. We used Begel and Zimmermann's scale [16], which is detailed in Table I. This classification gave us an idea of what information developers do –or do not– consider in their estimation process.

For the survey, we selected ten metrics with the intention to capture different characteristics of the code, the process, and the task. We used current literature in defect prediction [18] to guide our metric selection. We focused on the following aspects of software tasks when selecting metrics: *code metrics (C)* represent volume, complexity, and documentation of the code; *process metrics (P)* stand for the collaboration, code churn, and file centrality in the development process; *task metrics (T)* were chosen from the ones available in issue trackers such as JIRA[1] and Bugzilla[2]. The complete list of metrics is shown in Table II.

TABLE II. METRICS USED IN THE SURVEY

	Metric	*Description*
C	LOC	Number of lines of code in a file
C	CCOM	Cyclomatic complexity of the code in a file
C	CTCR	Number of comments in a file
T	CMTT	Number of comments in a task
T	FILT	Number of files to modify to complete a task
T	REOP	Number of times the task has been reopened
T	DEVT	Number of developers associated previously with the task
P	FCOM	Number of edits previously done to the files in the repository
P	CENT	Centrality of a file based on co-commited files
P	DEVF	Number of developers associated previously with the file

TABLE III. TOPICS AND CARDS FROM CARD SORTING

	Metric	*Topic*	*Cards*	*Part.*
Metric-Related topics	LOC	Lines of Code	28	11
	CCOM	Cyclomatic Complexity	23	13
	CENT	Commit Centrality	17	9
	CMTT	Number of comments (task)	36	11
	CTCR	Number of comments (file)	21	13
	REOP	Number of Reopens	27	11
	FILT	Files to modify	18	10
	FCOM	Number of edits	14	10
	DEVF	Associated developers (files)	24	12
	DEVT	Associated developers (task)	22	10
	CFSC	Code from scratch	11	7
	DEPN	Dependencies	13	8
	COOR	Communication / Coordination	33	10
	OMET	Other metrics	17	7
Other topics	***Abbrv.***	***Topic***	***Cards***	***Part.***
	TASG	Task assignment	35	14
	TINC	Task incorrectly assigned	35	14
	REST	Resolution time	10	6
	TCXT	Task context	11	4
	TPRI	Task prioritization	23	11
	DEMO	Demographic information	31	15
	MCMB	Combination of metrics	23	15
	DEST	Difficulty estimation	33	11
	EXP	Experience	57	15

The survey consisted of twelve questions: demographics (2), practitioners' perceptions of the usefulness of the metrics (7), work habits (2), interview opt-in (1). The survey took 10–15 minutes to complete. We distributed the survey using the public forum for developers of a large open source blog project, and a private IM channel in a large software development company. We received 33 responses: 25 from the commercial company and 8 from Drupal.

To aggregate the perceived usefulness of estimation metrics we used the same process as Begel and Zimmermann [16]: The percentage of each usefulness value was calculated as:

$$E\% = \frac{E}{E+W+UI+UW};\ W^{+}\% = \frac{E+W}{E+W+UI+UW};\ UI\% = \frac{UI}{E+W+UI+UW}$$

Interview: Fifteen participants volunteered for the follow-up interviews. Participants varied in their roles, gender, experience, and team size. On an average, the interviews lasted for 34 minutes and focused on how participants perceived the difficulty of their tasks, and how the metrics from the survey were useful in that endeavor. Additionally, we asked participants how task assignment was done in their work, and how they started working on their assigned tasks.

Card Sorting: The first two authors transcribed and unitized the interviews, which produced a total of 557 cards [14], [19]. Responses were divided into smaller pieces (i.e. cards) with a single idea and enough context to be self-contained. In our case, this often translated to question-answer pairs, but splitting large responses as needed. Later, cards were grouped into topics based on the idea conveyed by the card through negotiated agreement. Our topics were open. In a first pass the authors individually analyzed the cards to identify initial topics, which later were

discussed and combined or divided to better grasp the contents of th cards. A second pass was done following a similar process.

Table III presents the final 23 topics divided into two sets: (1) Metrics discussed by participants (non-survey metrics are shaded); and (2) information about the task and the project that allowed participants to determine whether a task was difficult.

TABLE IV. TOPICS AND CARDS FROM CARD SORTING

	Count				Percentages (%)			Ranks (#)		
Metric	*E*	*W*	*UI*	*UW*	*E*	*W+*	*UW*	*E*	*W+*	*UW*
DEVT *(T)*	9	17	2	5	27.3	**78.8**	15.2	1	**1**	4
FILT *(T)*	6	18	2	7	18.2	**72.7**	21.2	4	**2**	3
DEVF *(P)*	8	15	3	7	24.2	**69.7**	21.2	2	**3**	3
FCOM *(P)*	6	17	8	2	18.2	**69.7**	6.1	4	**3**	5
LOC *(C)*	3	1-	4	7	9.1	**66.7**	21.2	6	**4**	3
CCOM *(C)*	7	14	4	8	21.2	**63.6**	24.2	3	**5**	2
REOP *(T)*	4	17	5	7	12.1	**63.6**	21.2	5	**5**	3
CENT *(P)*	4	17	5	7	12.1	**63.6**	21.2	5	**5**	3
CMTT *(T)*	6	14	6	7	18.2	**60.6**	21.2	4	**6**	3
CTCR *(C)*	6	10	7	10	18.2	**48.5**	30.3	4	**7**	1

IV. RESULTS

We seek to understand, from the practitioner's perspective, whether, and in what ways do developers estimate task difficulty in their day-to-day work. An understanding of such practices can explain why some proposed metrics in project estimation models have not been widely adopted, and what support do developers really need. To do so, we must first learn about the different motivations behind task estimations.

RQ1: Why do developers perform task estimation?

Our interviews reveal that the majority of our participants consider estimating the difficulty of tasks to be an important part of the development workflow: 11 out of 15 participants use some form of estimation. There are two main reasons for estimating task difficulty, as stated by our participants:

Prioritizing tasks: Seven participants (P3–7, P14–15) mentioned that they classify a task according to its difficulty to prioritize them. For example, P14 prioritizes difficult tasks: "*I choose the difficult task first, since I do not know [it], and I have to do research on that task ... Other tasks I leave for the end because I know I am familiar with those tasks*". Whereas, P7 has an opposite strategy and focuses on the easy tasks: "*I kind of follow the process and start doing the one which has least dependency on other files ... when there's hardly any dependency ... I follow the one which are easier to solve first*". This shows that different developers have different preferences in how they tackle their workload. In either case, estimating the difficulty of a task is important to them.

Ensuring optimal task assignments: Eleven participants (P1, P3–7, P9–10, P12, P14–15) said that estimating task difficulty helps to identify mismatches between the task assignments and their expertise. For example, P15 said that estimating the difficulty of a task helps the participant recognize (and raise the flag with the team) when they do not have the right expertise. P15 also uses this information to determine whether a task should be reassigned and to whom, to ensure that the team has an overall optimal task assignment. P15 highlights this by saying: "*if the unknown sphere [skill-set] is that high, then the [task] is difficult. So I let my manager know that it's difficult...*". Similarly, P12 stated that if the task assigned to him was too simple, the team was performing sub-optimally, not taking advantage of his specialized skill set: *"[if] I am given a task which is relatively simple to me, then the team is losing out on my experience ... [re]assign [the task] to someone else*".

> Every developer needed to perform estimation of task difficulty in some form as part of their development process.

RQ2: How comfortable are developers when performing estimations?

All 15 participants confirmed that they performed difficulty estimations of tasks assigned to them. To better understand why estimation techniques are not heavily used, we asked the participants how comfortable were they when performing difficulty estimations that they considered essential.

Six participants (P2–3, P6, P9, P10, P13) said that they were comfortable and performed some form of difficulty estimation before they started working on a task; P3 mentioned: "*Usually by the time you get [the task] you have a good idea of how difficult it is going to be, sometimes it can change ..., but usually [you have] a pretty good idea before you start*".

Nine participants (P1, P4–5, P7–8, P11–12, P14–15) felt that they were unsure about, or could not perform, task difficulty estimation since there are no specific or clear rules. P5 said: "*there is no rule ... to say that if [this happens] ... then [the task] is difficult*". Some participants said they do not use any (particular) metrics for task difficulty estimation. This means that either they are unaware of the various software project estimation metrics (and their benefits) or that performing such estimation is difficult, which makes them uncomfortable (e.g. P7 says "*But at higher level it is very difficult to get to know how challenging that [task] would be, at least algorithmically*").

We note that of the nine participants who were unsure of performing task estimation, six participants performed some form of informal guesstimation of task difficulty in their daily activities. For example, P5 (quoted above) later said in the interview that he sorts tasks based on their triviality as: "*... and after [the dependent tasks], just kind of things that are trivial and need to be done*".

> More than one-third of our participants were unsure in performing task estimation, yet they had to do it, albeit informally. Another third of the participants were unability to perform estimation due to lack of clear rules. This suggests a gap between current estimation models and the developers' needs.

RQ3: What metrics do developers find useful when estimating task difficulty?

We further investigate how, or with what metrics, do developers perform estimation (or guesstimation). To get a real feeling of the task, the participants said they need to look at the code directly. P11 mentions that "*there is definitely an assessment of how difficult is this [task]*" when referring to how he prioritizes his work which "*... requires looking at the code*". This sentiment was also shared by others like P5 and P13. It is no surprise that code-related metrics are widely used in different estimation models. Rahman et. al [18] studied a total of 54 code-related metrics and 14 process-related metrics that are useful for project estimation, but which of these are useful to developers?

Useful Metrics: Table IV presents developers' perceptions of usefulness of metrics from the survey (using eq. E%, W+%, UI%). Metrics are sorted by W+% (shaded), and ties are

resolved using E%. Count refers to the number of participants who chose each category of usefulness for that metric.

The top two metrics are task-related: DEVT and FILT, which refer to the number of developers and files associated with the task, respectively. These reflect the amount of effort required to complete the task. Next are process metrics. FCOM and DEVF (tied at #3). Both metrics reflect the evolution of the file,

TABLE V. ADDITIONAL METRICS

	Metric	*Description*
Collaboration Metrics	Communication COMM	The amount of needed to complete the task. As Brook's postulates [20] the amount of communication can become a bottleneck in task performance.
	Coordination COOR	How dependent the task is on other tasks, or developers. This is non-trivial and it is why agile teams need daily scrum meetings.
	Clients CLIE	The number of stakeholders (external clients, other teams, developers) who depend on the task.
	Access ACES	Whether the task required obtaining new permissions (access rights, pull-requests).
Project History	Task Lifetime LIFE	The time a task has been in the issue tracker. Long-living bugs are those that typically have some problems and haven't been resolved it [21].
	Defects DEFS	The number of defects that the file has had. Past literature [21] has found that past defects in a file are a good indicator of how buggy it will be.
Character	Priority PRIO	The urgency of a task as either noted in the issue tracker or because of an impending deadline.
	Dependencies DEPN	The number of components that are associated with the task. It is harder to consider the forward and backward impact of changes with more dependencies [22].
Task Type	Bug Reproduction BURP	Whether the bug is easy to reproduce or not. Hard-to-reproduce bugs are difficult to verify if they have been fixed, which can confuse developers who close an issue even though it is not fixed.
	Framework FRMW	Tasks might involve building frameworks to use external API or to implement other modules in the codebase. Research has found that identifying the right API and using it correctly is non-trivial.
	Testing TEST	The amount of testing needed. Tasks that are not well tested require additional time and effort. Currently, it is unclear how to know the "testedness" of code.

which is an important concern for developers [15]. Metrics #4 and #5 are code metrics: LOC and CCOM, both of which allude to the amount of effort needed to understand the code. Followed by REOP (task metric), suggesting that the number or reopens can indicate a complex issue that was incorrectly resolved several times; CENT (process metric) is also #5, where central files (that have been changed frequently with others); may indicate difficult task because of their effect on (neighboring) files, making the task difficult. Finally, participants were in disagreement wheter file comments are helpful or not.

However, our findings indicate that there is a distinct gap in the metrics that formal-based estimation models use and what is considered useful by practitioners. This is probably a key reason behind the better performance of expert-based models.

Traditionally, code-related metrics have been used as primary indicators in effort estimation models. However, our work suggests that developers consider process and task metrics to be more useful than "just the source code".

Additional Metrics: Our interviews reveal that practitioners also use other metrics (see Table V) that we classify into four categories. These metrics are not used in effort estimation models, nor are they among Rahman and Devanbu's [18] 68 code- and process-related project metrics. These additional metrics might be why expert-based models are preferred (and more effective) than traditional estimation models.

We find that majority of the additional metrics are project and task related. While past research has identified collaboration to be important in distributed software development, current effort estimation models do not consider aspects of coordination. Similarly, Codoban et al. [15] have shown that the history of a project is important for developers. Again, none of the estimation models consider any history metrics.

Developers recommended additional metrics related to collaboration in the team and history of the project, both of which are important aspects in distributed development; but thus far ignored by effort estimation models.

V. THREATS TO VALIDITY

Metrics: We based our metric selection on extensive defect prediction literature [18]. We used a subset of metrics that are core and heterogeneous to capture different aspects of the code, the process, and the task. We also opted for familiar metrics like LOC as opposed to "statement count", to make it simpler for participants. A comprehensive model that validates the use of one metric over a similar one is still needed to refine metrics.

Participants: Our interview participants were diverse in terms of roles, years of experience, and type of projects. Due to this variation, we witnessed many themes of perceptions; some of which, due to their uniqueness, occurred only once or twice. We hope other researchers with access to different projects would replicate our study to validate our findings.

VI. CONCLUSIONS

We found that practitioners ***do*** perform some form of estimation about the difficulty of the task, albeit informally, as part of their daily activities. Only a small subset of metrics that practitioners found to be useful were code-related, with the remaining of the metrics referring to the task or the process. There is no single metric that encapsulated difficulty, metrics need to be considered together with others to estimate difficulty.

The metrics currently used in formal estimation models, as well as in other related fields such as defect prediction, include those that are difficult to obtain manually from the source code, version control system, or issue trackers. Moreover, these metrics can be hard to interpret by the "lay" developer. Our study participants preferred to use simpler metrics (e.g. LOC as opposed to FPA, semicolon count, or statement count); none of the complicated metrics that are used in literature were referred to by participants in the survey or the interview. Therefore, there is a need to provide developers with mechanisms to gather metrics that are easy to understand.

Participants also recommended additional metrics related to collaboration, the history of the project, the nature of the tasks, and the task type. These dimensions reflect the new distributed development paradigm, where developers need to coordinate across teams, use external frameworks, and have to work on specialized tasks. Effort estimation models currently do not accommodate these aspects of development. A caveat is that

there is already a plethora of metrics that have been introduced, but are not being used by developers in the field. Researchers need to be careful to identify those metrics that are easy to gather and interpret, otherwise they will not be adopted by developers.

ACKNOWLEDGEMENTS

We thank all our survey and interview participants. We also thank Sruti Srinivasan Raghavan for her feedback on drafts of the paper.

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