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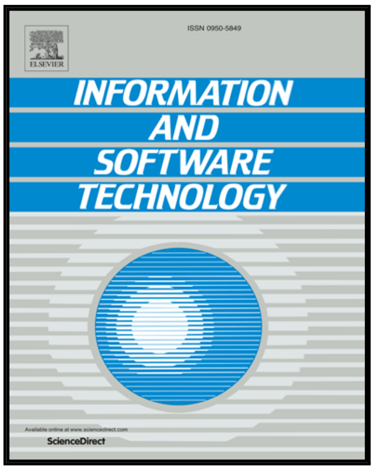

Research Patterns and Trends in Software Effort Estimation

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Highlights

- This study identified research trends prevailing in software effort estimation literature.
- Latent Dirichlet Allocation (LDA) was applied to the corpus of 1178 articles.
- This study established the semantic mapping between research patterns and trends.

Research Patterns and Trends in Software Effort Estimation

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Abstract

Context. Software effort estimation (SEE) is most crucial activity in the field of software engineering. Vast research has been conducted in SEE resulting into a tremendous increase in literature. Thus it is of utmost importance to identify the core research areas and trends in SEE which may lead the researchers to understand and discern the research patterns in large literature dataset.

Objective. To identify unobserved research patterns through natural language processing from a large set of research articles on SEE published during the period 1996 to 2016.

Method. A generative statistical method, called Latent Dirichlet Allocation (LDA), applied on a literature dataset of 1178 articles published on SEE.

Results. As many as twelve core research areas and sixty research trends have been revealed; and the identified research trends have been semantically mapped to associate core research areas.

Conclusion. This study summarises the research trends in SEE based upon a corpus of 1178 articles. The patterns and trends identified through this research can help in finding the potential research areas.

Keywords:
Software Effort Estimation, Latent Dirichlet Allocation, Research Trends

1. Introduction

Software Engineering (SE) discipline has evolved since 1960s and has garnered significant knowledge [1]. Over the years, there has been a strong criticism of SE research as it advocates more than it evaluates [2]. Many researchers have attempted to characterize software engineering research, but they failed to present a comprehensive picture [3, 4].

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SEE predicts the effort to accomplish development or maintenance tasks based on data which is generally incomplete, uncertain and noisy. Problems and issues in SEE have been addressed by researchers and practitioners from time to time. But much of the research has its focus on construction of formal SEE models [5]. The models designed by researchers have known advantages and disadvantages. The vast available literature on the subject posed a challenge before the researchers to review and identify the right path for their research.

The literature can be reviewed manually or algorithmically. The manual review provides an insight into the literature, but it is never free from biasness as researchers remain inclined towards more cited papers [6]. Natural language processing provides a powerful algorithm that extracts unobserved trends from a large collection of documents. Unlike manual tagging, which is effort intensive and requires expertise in the documents' subject-matter, algorithmic-based analysis is an automated process [7, 8, 9] called topic modelling. It takes a corpus, identifies the patterns and adds semantic meaning to the vocabulary. Both clustering and topic analysis approaches can be used with topic modelling. But as suggested by Evangelopoulos et al. [10], topic analysis is more appropriate relative to clustering for identification of research trends underlying the dataset. In topic analysis, a document is assigned to a mixture of topics, whereas in the case of clustering, each document is forced to join exactly one cluster. In this review, topic analysis and labelling have been incorporated to identify the latent patterns and trends in dataset. Two leading topic modelling techniques are Latent Semantic Indexing (LSI) [11] and Latent Dirichlet Allocation (LDA) [12]. In SE, LDA has been applied for mining software repositories [13], bug localization [14], defect prediction [15], software categorisation [16], classification of change messages [17] and software evolution [18].

Research patterns in SEE have been systematically identified and represented in this study by applying LDA to a corpus of 1178 articles published during the period 1996 to 2016. As many as twelve core SEE research areas and sixty research trends have emerged after the analysis of titles and abstracts of research articles. Semantic linking between sixty specific research trends and twelve core areas has been identified and presented. The review has been undertaken systematically keeping in view the guidelines proposed by [19, 20]. This review is intended to find the answer to following research questions:

- RQ1. Which research areas have been explored mostly by the researchers?
- RQ2. What research methods have been used for SEE?
- RQ3. Which research areas demand greater attention of researchers?

The paper has been divided into eight sections. The following section describes software effort estimation and related work in detail. The third section explains the process for data collection. The fourth section discusses the pre-processing and application of LDA to the corpus. The results and findings are presented in the fifth section. The sixth section provides the answers to research questions. The seventh section explains the threats to validity of the study. The final section concludes the paper.

2. Software effort estimation

SEE is one of the most challenging and important aspects in project management. Numerous estimation methods have been proposed by the researchers since the inception of SE as a research area [5, 21, 22]. Some of the studies on SEE have been reviewed in Table 1. There are several factors which influence the task of SEE. One of them is lack of information from the past including both experts' knowledge and experience. Another important problem, which is probably the origin of all other problems, is the nature of SE projects which are largely human-based, not repeatable, and affected by change. These aspects, in particular, make SEE difficult.

Other critical issue in SEE is project data, which is often incomplete, inconsistent, uncertain and unclear [23]. Since effort estimates act as base point for many project management activities including planning, budgeting and scheduling, it is very crucial to obtain almost accurate estimates. Moløkken-Østvold et al. [24] have reported in their study that there is overestimation by 30-40% on average in software projects. Simmons and Korrapati [25] have also supported this claim by explaining that 52.7 % of projects cost 189 % of their original estimates, which means that there is approximately 89% overrun in these projects. Estimation of effort in software systems is a challenging and substantial job for project managers. The challenge arises due to various factors, including the human factor, the complexity of the product, different development platforms, etc. [26]. Estimators use different methods for estimation. They employ a single technique (formal model or expert judgement) or both the techniques for estimation.

Numerous studies are available on software effort estimation. These have been listed and reviewed in Table 1. But none of the studies has discussed the patterns and trends in SEE by applying topic modelling technique. The review has been undertaken to identify different core research areas and trends prevailing in SEE.

3. Collection of data

The research data was collected from various online databases, journals, and conference proceedings. The data collection process comprises of the following steps:

Identifying information sources. The databases related to the research were identified. They included the esteemed software engineering journals and proceedings of various conferences.

Defining search criteria. The search keywords were decided based upon the research questions of the current study and adapted from the study of [37]. The search phrases identified were "software effort estimation", "software cost estimation", "project management" and "size metrics". The search string used for searching was "software effort estimation" OR "software cost estimation" OR "size metrics" OR "software project management". Search terms "software project management" and "size metrics" were included to broaden the search space for required articles on SEE. The search criteria conformed to relevancy and recency.

Search bibliographic databases. An automatic search was made through relevant sources of information using defined search criteria by open source tool JabRef [38] and search engines of specific publishers. The bibliographic databases of ScienceDirect, IEEExplore, Wiley and DBLP were searched; and identified articles were added to BibTeX database of JabRef. The bibliographic database search was meant for searching specific keywords in the publication title, abstract and keywords. As many as 1420 articles were collected in the BibTeX database. However, 1298 articles remained in the database after removal of duplicate entries.

Initial review. The literature dataset collected was reviewed by analysing the titles and abstracts using JabRef's search query for inclusion in the corpus. The papers were included in the corpus based upon inclusion and exclusion criteria given as here under:

Inclusion criteria. Under this criteria, the articles must be published in English. These must have their focus on software effort, cost or size estimation in any context from the year 1996 to 2016.

Exclusion criteria. The articles published before the year 1996 or not reporting on development related to the search keywords discussed in search criteria were excluded from the literature dataset. However, the papers describing the same study in more than one publication were not excluded.

Full review. The publications not conforming to the defined inclusion criteria were reviewed manually by analysing the metadata of their BibTeX entries in JabRef. After this step, 1178 publications considered relevant for the purpose of current research were identified.

The process followed for document collection is exhibited in Table 2. Figure 1 depicts the year-wise publications of collected SEE research literature dataset for the period 1996-2016. Further, Figures 2 and 3 highlight the necessary data about top ten authors and journals respectively.

4. Methodological analysis

4.1. Latent Dirichlet Allocation

LDA is applied to the literature dataset (corpus) to facilitate retrieving and querying a large corpus of data to identify latent ideas that describe the corpus as a whole [12]. In LDA, a document is considered as a mixture of a limited number of latent topics, and each keyword in the document is associated with one of these topics. Using latent clues, topic model connects similar meaning words and differentiates different meaning words [6, 39]. So, latent topics represent multiple observed entities having similar patterns identified from the corpus. Table 4 depicts the relevant entities represented through twelve latent topics. Loadings for

Table 1: Review of literature

Author	Findings of the study
Wen et al. [27]	The authors have investigated 84 primary studies of machine learning (ML) techniques in SEE for finding out different ML techniques, their estimation accuracy, the comparison between different models and estimation contexts. Based upon this study, they found out that in SEE, eight types of ML techniques have been applied; and concluded that ML models provide more accurate estimates as compared to non-ML models.
Jørgensen [28]	Jorgensen has reviewed 15 studies on expert estimation for validating the conformance to twelve expert estimation 'best practices' and found expert estimation as the dominant approach for SEE and no evidence in favour of model estimates over expert estimates.
Idri et al. [29]	The authors have performed a systematic review of 24 ensemble effort estimation (EEE) studies published between the period 2000 to 2016. They have identified two types of EEE, namely, homogeneous and heterogeneous. They also found that the estimation accuracy of EEE techniques is better than single models.
Trendowicz et al. [5]	This study has reviewed surveys for finding out the industrial objectives, the ability of software organizations to use estimation methods, and practically applied practices of SEE in organisations.
Idri et al. [30]	The authors have identified and reviewed 65 studies published on analogy-based Software Effort Estimation (ASEE) from the year 1990 to 2012; and revealed that the main focus of the research is on feature and case subset selection. They concluded that ASEE methods surmount when compared with eight techniques and can provide more accurate results in combination with fuzzy logic (FL) or genetic algorithms (GA).
Kitchenham et al. [31]	In this study, circumstances have been identified under which organisations should use cross-company dataset. The authors have reviewed 10 primary studies reporting comparative analysis of within and cross-company effort predictions. Three studies suggested that cross-company predictions perform equally good as within-company predictions, and four studies revealed the dominance of within-company predictions over cross-company predictions.
Sigweni and Shepperd [32]	The authors have conducted a review of published primary studies on feature weighting techniques (FWT) from the year 2000 to 2014 to determine whether FWTs lead to improved predictions based upon four parameters, namely, approach, strengths and weaknesses, performance and experimental evaluation. They have recommended the adoption of FWTs in the research.
Grimstad et al. [33]	The authors have argued that the missing software effort estimation terminology is a critical hindrance in estimation accuracy. They have reviewed software textbooks, SEE research papers and found limitations in use of estimation terminology. They also suggested guidelines to overcome this limitation.
Britto et al. [34]	This study has reviewed SEE in the context of global software development. The authors have used eight available studies; and concluded that there is a good scope for research in the global context.
Andrew and Selamat [35]	The authors have systematically analysed research works done on missing data imputation techniques from 2000-2012 to estimate software effort.They have presented the leading researchers, the current state of research and amount of work done in the area of missing data techniques in software effort estimation.
Usman et al. [36]	In this study, a review of effort estimation in agile software development (ASD) based on 20 papers has been presented. The study has concluded that most of the techniques are based on expert judgement, and use XP and Scrum only.

Table 2: Document collection process

Round #	Search criteria	Number of articles
1	Search phrases/Within databases/In Title OR Abstract OR Keywords	1420
2	Elimination of duplicate and irrelevant articles	242
Literature dataset		1178

terms and documents were generated by applying LDA to the corpus. The loading value for each topic indicates the extent of relation of the related term/document with certain topic solution. Core research areas and trends are represented by lower level and high level topic solutions respectively [40].

4.2. Pre-processing of data

Pre-processing phase involves the elimination of noisy words/characters from the dataset. The following steps have been incorporated for pre-processing the literature dataset:

1. Loading text
2. Lexical analysis of the text
3. Removing stop words
4. Stemming.

Loading text. The corpus in JabRef is imported into a .csv file; and required information from the bibliographic database is filtered by using JabRef export filter, designed exclusively for this purpose [41].

Lexical analysis. In lexical analysis, 1178 titles and abstracts of the articles were tokenised into 85,157 tokens. Generated tokens were converted into lowercase letters for each document. The elimination of punctuation characters, exclamation points, commas, apostrophe, question marks, quotation marks and hyphen was performed. Further, numeric values were removed to get only the textual tokens.

Stop-word removal. The common English words as given in nltk python package [42] and the phrases used to develop the literature dataset were removed.

Stemming. For preparing an effective literature dataset word forms are stemmed to their original root form. SnowballC stemmer algorithm [43] was used to stem the tokens for each document, and converted the inflected words to their base stem.

4.3. Applying LDA

LDA is applied to pre-processed corpus data as suggested by [12, 44, 45]. It produces topic models based on the three input parameters, namely, number of topics, the hyper-parameters α and β, and the number of the iterations needed for the model to converge. α is the magnitude of the Dirichlet prior over the topic distribution of a document. This parameter is considered as a number of “pseudo-words”, divided evenly between all topics that are present in every document, no matter how the other words are allocated to topics. β is per-word-weight of Dirichlet prior over topic-word distributions. The magnitude of the distribution (the sum over all words) is ascertained by number of words in the vocabulary. For identifying two, five, eight, twelve and sixty topic solutions as suggested by [46], the number of iterations considered are 200. The hyper-parameters α and β are smoothing parameters that change the distribution over the topics and words respectively; and initialising these parameters correctly can result in high quality topic distribution. The value of α has been kept as 50/T, where T is number of topics; and β has been fixed as 0.01 for all topic solutions.

In unstructured document set, where number of relevant trends is not known in advance; and it is a tedious task to identify the optimal number of topics. Coarse LDA model is generated if number of topics is insufficient, whereas excessive number of topics can result in a complex model making interpretation difficult [47]. There is no established measure to defend the optimal number of solutions, however, heuristic parameters suggested by Cao et al. [48] and Arun et al. [46] were applied to find the optimal range of topic solutions, which lies in the range from 54-66 as both approaches converge at this range as shown in Figure 4. Based on these heuristics and findings of the study [49], the optimal number of topic solutions for identifying research trends is chosen as sixty. The twelve topic solution has been considered as optimal low level solution as discussed in study by Sidorova et al. [40]. Two,

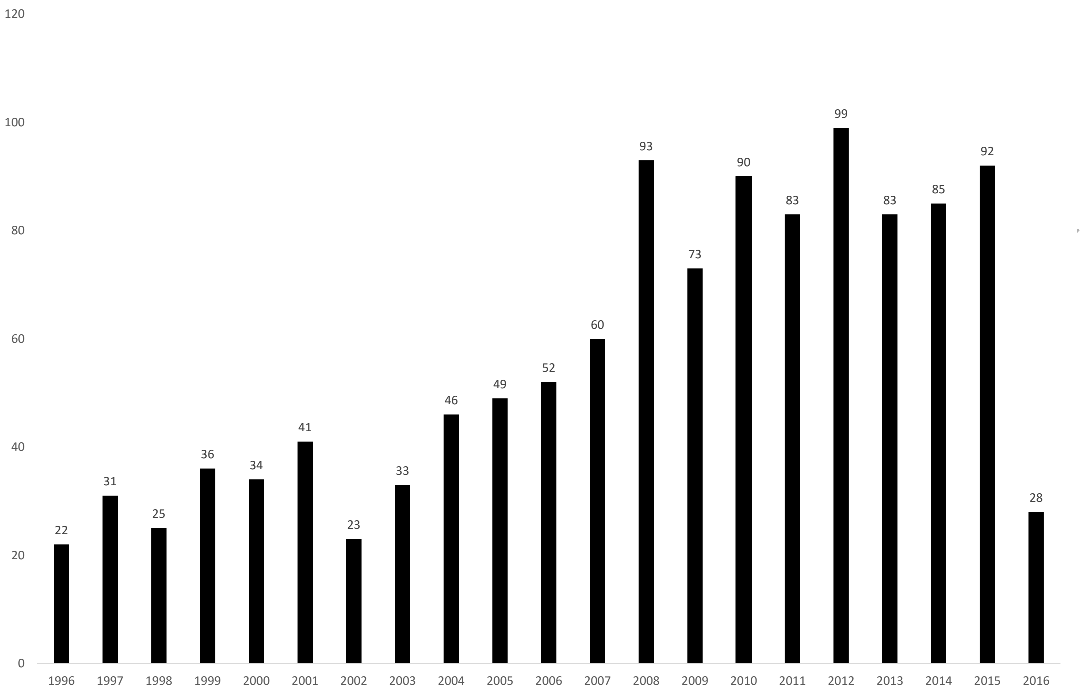

Figure 1: Paper publication year-wise

five and eight topic solutions are used to present the abstract view of large text corpus.

4.4. Topic labelling

For the purpose of current study, high-loading articles of all topic solutions have been reviewed. Further, the topics have been labelled individually to reach a conclusive topic label. Different topic solutions and count of high-loading articles are represented in a chronological order (Table 3 and 5).

5. Results and findings

Summary of topic solutions. The loadings for two, five, eight, twelve and sixty topics have been obtained through LDA. Table 3 summarises two, five and eight topic solutions as core research areas with corresponding labels and paper loadings. Twelve topic solution is considered to be the most appropriate for interpreting the core research areas. The number of articles loaded with each topic portrays the corresponding dominance of topic solution. Different topic solutions can correspond to the same research areas as "expert judgement" appears across (T5.5), (T8.6) and (T12.4), but there is a reduction in the number of high-loading articles.

5.1. Core research areas

The two topic solution presents abstract view of literature dataset and divides it into, "analysis of estimation process" (T2.1) and "estimation methods" (T2.2) as shown in Table 3. These areas cover analysis of different techniques, proposed models and methods to estimate effort.

In five topic solution, the emerged research areas are "size metrics" (T5.1), "estimation by analogy" (T5.2), "tools for estimation" (T5.3), "soft computing techniques" (T5.4) and "expert judgement" (T5.5).

The research areas have been further widened in eight topic solution with new areas emerging as

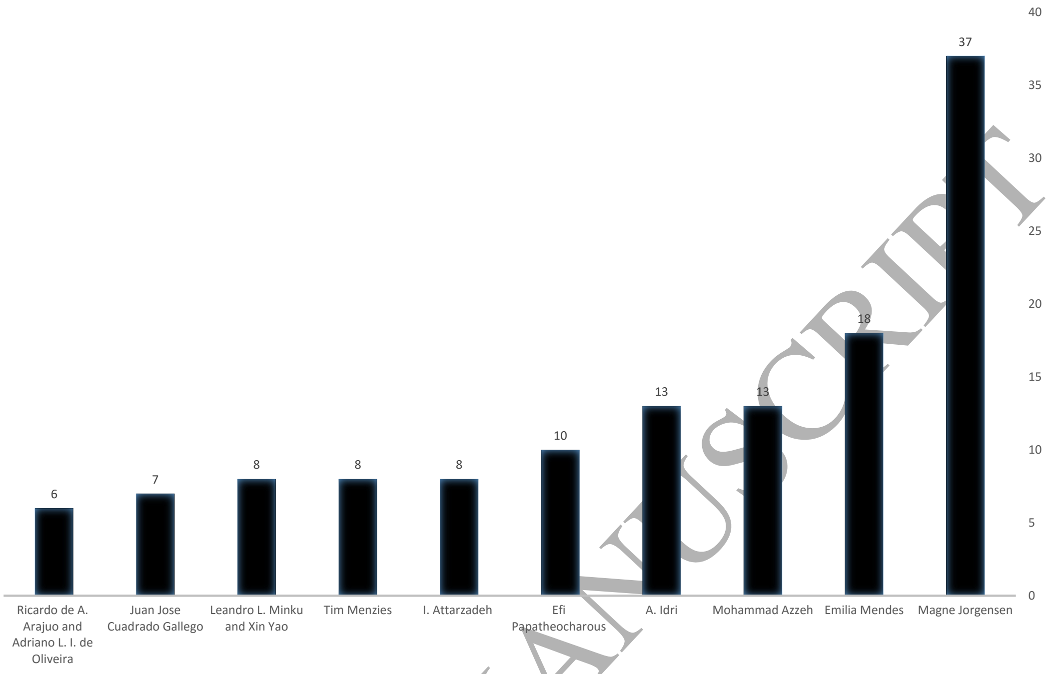

Figure 2: Top ten authors

"phase-wise effort distribution" (T8.3), "estimation for reusable components" (T8.4), "soft computing techniques" (T8.5), "neural networks" (T8.7), and "factors affecting cost" (T8.8). The remaining areas are the same as uncovered in five topic solution, including "estimation by analogy" (T8.1), "size metrics" (T8.2) and "expert judgement" (T8.6) with fewer loadings.

In twelve topic solution, more research areas appeared, namely, "application specific estimation" (T12.3), "estimation for web applications" (T12.5), "project data selection" (T12.7), "machine learning techniques" (T12.10) and "ensemble models" (T12.11). Other areas in twelve topic solution are "reviews and mapping studies" (T12.2), "expert judgement" (T12.4), "factors affecting estimation" (T12.6), "size metrics" (T12.8) and "estimation by analogy" (T12.9). High-loading terms and top five articles for twelve topic solution are depicted in Table 4. Figure 5 depicts research trends of twelve topic solution.

5.2. Research trends

The sixty topic solution resulted into detailed research trends in SEE as depicted in Table 5 with the count of published articles in chronological order. In sixty topic solution, some prominent research trends appeared, including "neural networks" (T60.31) with 60 articles and "fuzzy logic" (T60.45) with 41 articles. These relate to the "machine learning techniques" (T12.10) research area in twelve topic solution having substantial 158 high-loading papers. High loading articles include 'radial basis function neural network' [108], 'neuro-fuzzy model' [109], 'factors affecting fuzzy model' [110] and 'comparison of neural networks for SEE' [111]. "Size estimation" (T60.33), another important research trend with 40 articles, reports the articles on 'size estimation for object-oriented approach' [112], 'measurement of COSMIC' [87] and 'association of different function point methods' [113].

Another emerging trend in sixty topic solution

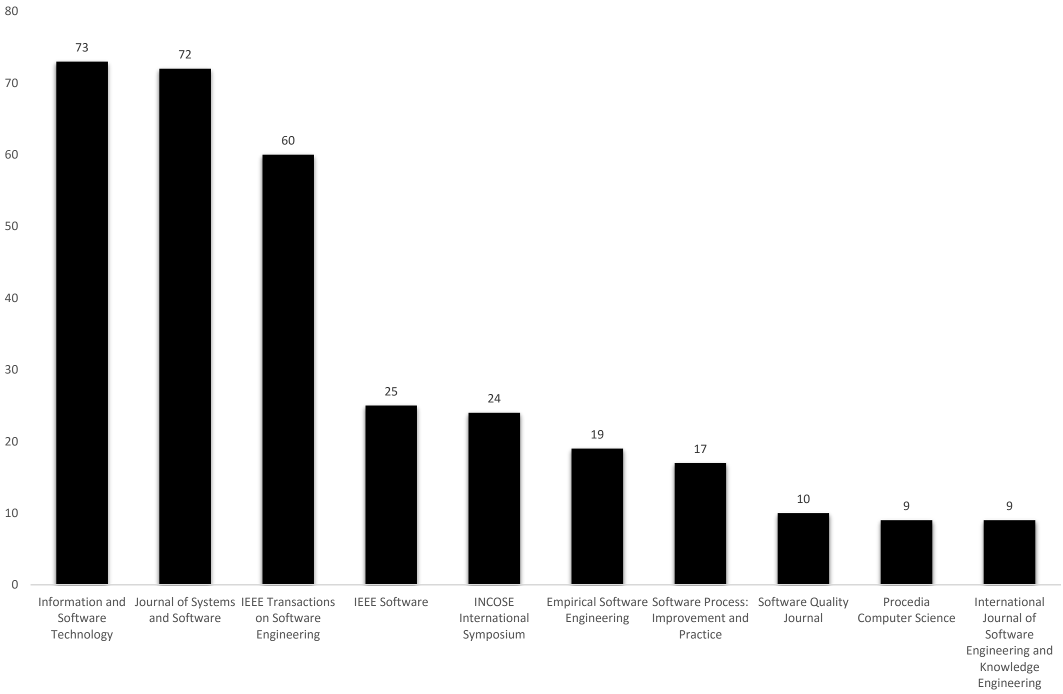

Figure 3: Top ten journals

is "ensemble models" (T60.58) which focuses on diverse approaches to estimate the effort rather than using a single approach. High loading papers focus on 'multi-objective ensemble generation for SEE' [102, 114] and 'review of ensemble models' [29].

Several other trends are also revealed across a number of articles in sixty topic solution including "missing data effects" (T60.10), "estimation by analogy" (T60.4), "factors affecting effort estimation" (T60.13), "estimation for web applications" (T60.37), "test effort estimation" (T60.42), "evaluation criteria and metrics" (T60.56), "nature inspired algorithms" (T60.38), "estimation tools" (T60.19) and "literature reviews" (T60.22).

6. Discussion

This study summarises the research trends in SEE based upon a corpus of 1178 articles. The present research includes articles from bibliographic databases from the period 1996-2016. Analysis of corpus for n topic solution has been performed by using LDA to find out the latent research patterns and trends. In SEE research, there have been only a few researchers who have long-term focus on SEE research. Figures 2 and 3 display top ten identified researchers and journals appearing respectively during the study period of 1996-2016. In this section, each research question has been discussed in view of the findings from the literature dataset and further research opportunities.

6.1. RQ1. Which research areas have been explored mostly by the researchers?

The brief answer is that various research areas have been explored by researchers since the inception of research in SEE. The focus of researchers in the SEE field changes over time as per the industry requirements. Figure 5 depicts that SEE research has gained momentum from the year 2004. The research areas can be explored by examining

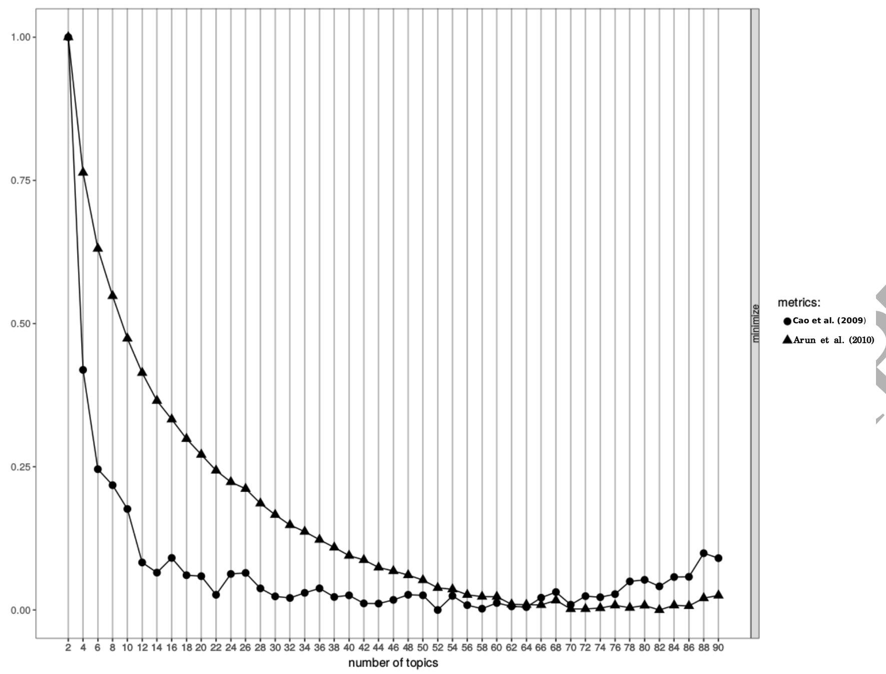

Figure 4: Selection of optimal number of topic solution

the dynamic changes in twelve core research areas and sixty research trends as identified in the last section. Further, the interesting results obtained from semantic mapping of core research areas and trends are presented in Table 7. The topics having loading value of 0.32 and above have been considered for semantic mapping [368]. But this does not validate the academic value of selected papers as loading values are the result of the number of occurrences of terms in the corpus. Also, the value of the threshold does not mean that the articles below threshold are not related to that factor.

The dynamics of twelve topic solution has brought out that "estimation for web applications" (T12.5), "size metrics" (T12.8), "ensemble models" (T12.11) and "dynamic effort estimation" (T12.12) have been considered for research more vigorously during the last two decades. The results of each research area help to find the dynamic characteristics. The results indicate that although many topics have remained stable over the time, yet "machine learning techniques" (T12.10), "expert judgement" (T12.4), and "estimation by analogy" (T12.9) have attracted the attention of more and more researchers. It has also been found that most of the research trends have shown an upward trend because the researchers have failed to reach consensus of developing and validating the generic model to predict effort for all types of projects. The researchers keep on experimenting with new methods, environments and metrics to evaluate and predict effort on the basis of review studies. Table 1 presents literature review at a glance on the sub-themes of SEE.

"Reviews and mapping studies" (T12.2) core research areas brings out "surveys" (T60.15) [55, 56, 176, 178] and "reviews" (T60.22) [21, 27, 33, 209] reporting on mapping studies and systematic literature reviews in SEE. The research trend "ensemble models" (T60.58) semantically mapped to this core area presents high-loaded paper that reports on systematic literature review on ensemble models [359]. These studies provide the road-map for naive researchers to identify the problem domains.

Since the inception of SEE research, size metrics (e.g. lines of code) has been a vital parameter for effort estimation, the researchers have proposed various new size metrics along with established size metrics and their suitability to predict in specific environment [84, 255, 354, 355]. "Size metrics" (T12.8) has uncovered two research trends "size estimation" (T60.33) and "function point analysis" (T60.57) in which research has been conducted since the year 1997 and is still an area

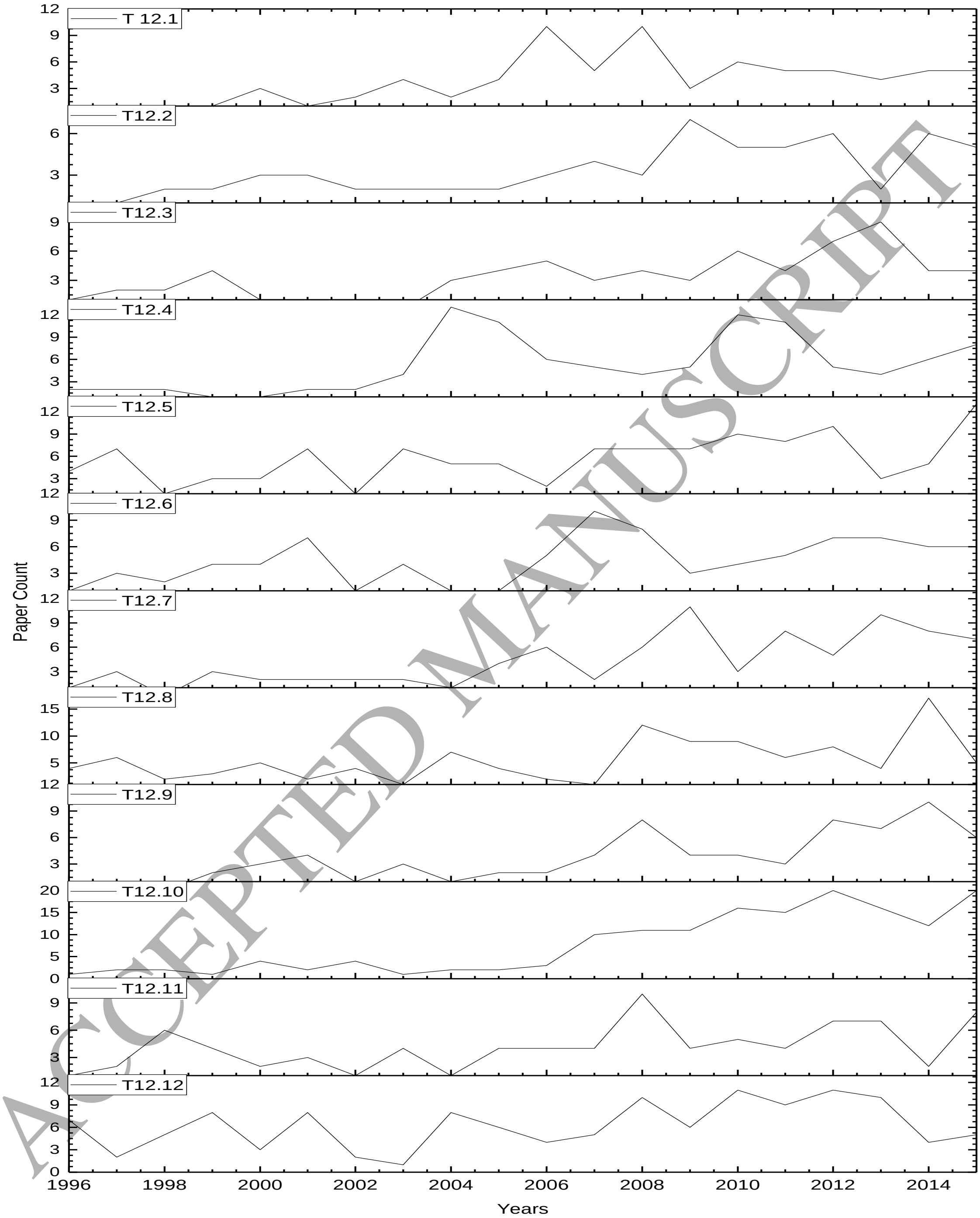

Figure 5: Research trends of twelve topic solution

Table 3: Year-wise paper count for two, five and eight topic solution

Topic id	Topic label	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
T2.1	Analysis of estimation process	18	12	17	19	14	20	7	15	29	29	27	31	36	36	42	37	47	39	37	41	12	565
T2.2	Estimation methods	4	19	8	17	20	21	16	18	17	20	25	29	57	37	48	46	52	44	48	51	16	613
T5.1	Size metrics	2	5	2	6	5	5	6	6	14	3	6	5	18	10	12	12	17	6	19	14	5	178
T5.2	Estimation by analogy	1	4	2	6	7	12	4	6	1	7	10	17	26	18	18	19	24	30	23	23	7	265
T5.3	Tools for estimation	13	8	13	12	7	14	2	9	12	16	11	15	19	14	21	22	27	18	16	13	6	288
T5.4	Soft computing techniques	2	8	3	7	8	3	4	6	7	10	13	11	20	17	23	15	18	14	16	24	5	234
T5.5	Expert judgement	4	6	5	5	7	7	7	6	12	13	12	12	10	14	16	15	13	15	11	18	5	213
T8.1	Estimation by analogy	2	2	0	2	1	1	1	3	3	2	4	9	12	9	9	8	11	12	16	11	5	123
T8.2	Size metrics	4	6	4	8	8	8	3	4	9	5	2	2	15	13	12	12	12	7	16	4	2	156
T8.3	Phase-wise effort distribution	1	5	1	1	2	5	0	1	3	5	4	6	12	9	7	8	12	7	10	9	0	108
T8.4	Estimation for reusable components	9	4	7	6	0	4	2	5	5	6	8	9	9	9	12	10	9	10	11	10	6	151
T8.5	Soft computing techniques	0	3	2	2	1	2	4	1	3	3	7	1	8	9	19	14	14	7	6	17	5	128
T8.6	Expert judgement	3	6	2	5	5	5	2	12	13	10	8	6	11	8	10	10	12	8	10	11	3	160
T8.7	Neural networks	1	3	3	10	7	10	5	4	2	8	10	17	17	9	13	15	19	21	9	19	6	208
T 8.8	Factors affecting cost	2	2	6	2	10	6	6	3	8	10	9	10	9	7	8	6	10	11	7	11	1	144

of interest for researchers. The trends have been focused on the estimation of different size metrics [88, 255, 256, 257, 369], function point for SEE, and conversion of FP to COSMIC and other size metrics [84, 354, 355, 356, 357]. Different size metrics including function points and web objects have been proposed to predict effort of web applications [71, 73, 124, 370, 371, 372, 373]. The "estimation for web applications" (T12.5) core research area reveals trends, namely,"estimation for web applications" (T60.37) focusing on web objects metric and models [272, 273], "system engineering" (T60.36) focusing on estimation models in system engineering and "estimation tools" (T60.19) supporting the use of estimation tools [193, 194]. Researchers have also used machine learning techniques for estimating the effort in web applications [349, 374, 375].

The application of "machine learning techniques" (T12.10) to predict effort has gained significant momentum from the year 2006 and uncovered seven research trends. The most explored algorithmic approaches "fuzzy logic" (T60.45) [376, 377], "neural networks" (T60.31) [26, 108, 117, 378, 379, 380], genetic algorithms [277, 381, 382] have been consistently used in every aspect of software effort estimation. Other trends identified are "nature inspired algorithms" (T60.38) which focus on the use of algorithms based upon various natural phenomena [23, 247, 248, 249, 276, 277, 279]. "feature selection in problem domain" (T60.17) [101, 383], "support vector regression" (T60.55) [348, 349], and "case-based reasoning" (T60.35) [263]. "Morphological approach" (T60.12), a hybrid approach researched by de A. Araújo et al. [166], is a morphological-rank-linear approach to estimate SEE in a better way [93, 94, 166, 167] which has been revealed by "machine learning techniques" (T12.10) core research area.

Jørgensen et al. [3] advocated that formal models should be developed as support to expert judgement and proposed guidelines for "expert judgement" (T12.4) [209, 316, 330]. "Expert judgement" (T12.4) reveals the research trends including "factors influencing expert judgement" (T60.48) discussing various factors in expert judgement [64, 65, 318, 320], "strategy selection" (T60.51) reporting selection factors and techniques [28, 330]. "Fuzzy logic" (T60.45) with a focus on handling imprecision and uncertainty in expert judgement [305, 306, 307] has been emerged from this core area. Researchers explored the techniques such as pairwise-comparisons, baysian belief networks, neural networks and regression in conjunction with expert judgement [384, 385, 386, 387] for accurate predictions.

The high-loaded papers for research area "project data selection" (T12.7) focused on the selection of data for training the model using "windowing approach" (T60.60) to improve the software estimation [79, 80, 81, 82, 388]. The "data specific estimation" (T60.44) trend investigated the cross-company and within-company data to achieve more accurate results [50, 52, 389]. Different selection strategies for project selection have been reported in "estimation by analogy" (T60.4) [390, 391]. In "factors affecting estimation" (T12.6), the trend called "missing data effects" (T60.10) has

Table 4: High-loading research papers for twelve topic solution

Topic id	Key terms	Topic label	High-loading papers	Loading
T12.1	model predict base cocomo construct compani valid relationship build compar	Validation of estimation models	[50]	0.519
			[51]	0.5
			[52]	0.472
			[53]	0.458
			[54]	0.4
T12.2	research studi evalu framework exist organ type support includ analyz	Reviews and mapping studies	[55]	0.51
			[21]	0.486
			[56]	0.476
			[57]	0.421
			[58]	0.41
T12.3	approach base process complex practic integr decis provid develop resourc	Application specific estimation	[59]	0.509
			[60]	0.507
			[61]	0.367
			[62]	0.36
			[63]	0.357
T12.4	estim fuzzi experi task expert inform process assess accur uncertainti	Expert judgement	[64]	0.75
			[65]	0.634
			[66]	0.592
			[67]	0.588
			[68]	0.566
T12.5	system applic engin develop manag web methodologi appli risk reliabl	Estimation for web applications	[69]	0.568
			[70]	0.546
			[71]	0.533
			[72]	0.515
			[73]	0.5
T12.6	data project set factor analysi effect investig domain collect level	Factors affecting estimation	[74]	0.667
			[75]	0.609
			[76]	0.522
			[77]	0.495
			[78]	0.489
T12.7	project accuraci bas improv studi plan weight manag analogy combin	Project data selection	[79]	0.768
			[80]	0.717
			[81]	0.716
			[82]	0.64
			[83]	0.598
T12.8	function measur size requir tool propos analysi specif standard compon	Size metrics	[84]	0.634
			[85]	0.612
			[86]	0.607
			[87]	0.603
			[88]	0.577
T12.9	method techniqu propos select obtain analogi dataset appli attribut produc	Estimation by analogy	[89]	0.529
			[30]	0.518
			[90]	0.435
			[91]	0.391
			[92]	0.385
T12.10	regress algorithm network perform neural featur learn optim compar propos	Machine learning techniques	[93]	0.667
			[94]	0.627
			[95]	0.618
			[96]	0.568
			[97]	0.566
T12.11	test approach perform error object gener effect statist empir relat	Ensemble models	[98]	0.519
			[99]	0.485
			[100]	0.449
			[101]	0.44
			[102]	0.435
T12.12	product time cost metric process phase qualiti activ mainten requir	Dynamic effort estimation	[103]	0.554
			[104]	0.456
			[105]	0.442
			[106]	0.441
			[107]	0.434

Table 5: Year-wise paper count for sixty topic solution

Topic id	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
T60.1	-	1	-	-	2	-	-	-	-	-	1	-	-	-	-	1	1	1	1	-	1	9
T60.2	-	2	-	1	1	1	1	1	1	-	-	1	2	1	1	-	1	-	1	-	-	15
T60.3	-	-	-	1	-	1	-	1	1	-	-	-	1	-	-	-	-	-	-	1	-	6
T60.4	-	-	-	1	-	-	-	1	1	-	1	-	5	2	-	1	1	1	1	2	-	17
T60.5	-	-	-	1	-	-	-	1	1	-	1	-	5	2	-	1	1	1	1	2	-	17
T60.6	-	-	-	1	1	1	-	2	-	-	-	1	-	-	2	-	-	1	-	-	-	9
760.7	2	-	1	-	-	-	-	-	-	-	1	3	1	1	-	2	1	1	-	1	1	15
T60.8	-	-	-	-	-	-	-	-	-	-	-	1	2	1	1	1	3	-	1	1	1	12
T60.9	-	-	-	-	-	1	-	1	-	-	1	-	1	1	2	-	2	1	-	-	-	10
T60.10	-	-	-	1	-	4	-	-	-	-	2	4	1	1	-	-	-	3	1	-	2	19
T60.11	1	1	1	1	2	3	1	-	1	-	1	1	-	1	-	3	2	1	3	1	-	24
T60.12	-	1	-	-	-	-	-	-	-	-	-	-	1	1	3	2	3	-	1	-	-	12
T60.13	-	-	-	-	-	-	-	-	-	-	-	-	1	-	3	1	2	2	1	3	-	13
T60.14	-	-	1	-	1	-	-	-	-	-	1	1	-	1	3	-	2	2	1	1	1	15
T60.15	-	-	-	-	-	1	-	-	-	2	-	-	-	1	-	1	2	1	2	2	-	12
T60.16	-	2	-	1	-	-	-	1	-	2	1	4	1	2	-	-	1	1	-	3	1	20
T60.17	-	-	-	-	-	-	-	1	-	-	-	1	1	1	1	2	1	-	1	-	1	10
T60.18	-	-	-	1	1	-	-	2	1	-	-	1	1	3	2	-	-	2	-	1	-	15
T60.19	1	-	1	1	1	-	-	-	1	-	1	1	1	1	3	3	3	-	1	1	1	21
T60.20	-	1	-	1	-	-	-	-	-	1	1	-	1	2	3	-	1	-	1	1	-	13
T60.21	-	1	-	-	-	-	-	1	-	1	1	-	1	-	-	2	-	-	2	1	-	10
T60.22	-	1	-	-	-	-	-	2	2	3	3	1	-	-	1	1	1	-	1	2	-	18
T60.23	-	-	1	2	-	1	-	1	-	2	-	1	-	-	2	1	1	1	-	-	1	14
T60.24	-	-	-	2	3	2	-	1	1	-	1	1	-	2	1	1	1	1	-	2	-	19
T60.25	-	-	-	-	-	2	1	-	-	-	-	-	-	1	-	3	4	1	3	2	1	18
T60.26	1	1	3	3	3	3	-	-	1	3	2	-	3	2	4	1	1	1	2	-	-	34
T60.27	-	-	1	1	2	2	3	1	3	2	-	1	-	2	-	1	4	2	1	2	1	29
T60.28	-	-	-	2	-	-	-	-	1	1	1	1	3	-	-	-	2	-	-	-	1	12
T60.29	-	-	-	-	-	-	-	-	1	-	-	-	-	-	2	-	1	1	2	1	-	8
T60.30	1	-	-	-	-	-	1	-	-	-	2	-	-	-	1	-	4	-	2	1	2	14
T60.31	1	2	1	1	1	1	2	-	-	1	1	4	5	4	8	4	9	5	5	5	-	60
T60.32	-	1	1	1	-	-	-	1	-	2	-	1	3	-	1	2	-	1	-	-	1	15
T60.33	-	2	1	-	2	2	2	-	2	1	-	-	4	4	5	3	2	2	6	2	-	40
T60.34	-	-	1	-	-	-	-	-	1	-	-	-	-	1	-	-	1	2	2	1	-	9
T60.35	-	-	1	2	1	2	1	-	-	3	1	1	4	-	2	-	1	1	-	-	-	20
T60.36	3	-	2	-	-	2	-	1	1	1	2	4	1	3	2	3	2	2	1	3	1	34
T60.37	1	-	1	-	3	1	1	6	2	1	-	-	3	1	1	-	2	1	1	3	-	28
T60.38	-	-	-	1	-	-	-	-	-	-	-	-	2	-	5	5	2	2	4	7	-	28
T60.39	-	2	-	-	-	1	1	-	-	1	1	1	1	2	2	1	1	4	4	1	-	23
T60.40	-	-	-	-	-	-	-	1	-	-	3	2	3	3	1	1	1	1	1	-	-	17
T60.41	1	-	1	-	-	2	-	1	-	2	3	2	1	4	-	3	1	1	3	2	-	27
T60.42	1	1	-	-	1	-	-	-	3	2	2	1	4	-	1	-	3	1	-	2	1	23
T60.43	-	-	-	-	-	-	1	-	2	2	-	-	2	-	1	-	1	1	-	2	-	12
T60.44	-	-	-	1	3	1	1	1	1	1	-	2	1	-	1	2	-	-	1	1	1	18
T60.45	-	2	1	-	-	-	1	1	3	2	4	1	2	3	5	7	1	1	3	4	-	41
T60.46	-	-	-	-	-	-	1	-	-	3	-	3	2	2	1	3	3	4	2	3	-	27
T60.47	2	-	-	1	-	-	-	2	-	1	-	1	1	1	1	2	3	3	3	1	-	22
T60.48	-	1	1	-	1	2	-	4	3	2	-	-	-	4	-	3	1	2	1	1	-	26
T60.49	-	1	-	-	-	-	1	-	-	-	1	3	1	4	3	1	1	5	4	-	-	25
T60.50	1	1	1	2	1	-	-	-	-	-	1	-	3	-	-	-	-	-	2	2	-	14
T60.51	-	-	1	-	1	-	-	-	1	1	-	-	-	-	5	2	1	1	-	-	-	13
T60.52	-	1	-	-	1	1	-	-	-	-	2	1	2	2	3	1	1	2	2	1	-	20
T60.53	2	1	-	-	-	-	-	-	3	1	-	1	1	1	1	-	3	-	-	-	1	15
T60.54	-	-	-	1	-	1	-	-	-	1	-	-	4	-	2	2	2	1	-	4	1	19
T60.55	-	-	-	-	1	-	-	-	-	-	1	2	2	2	1	2	2	4	-	5	-	22
T60.56	-	1	1	-	-	1	1	1	1	-	1	2	2	1	-	3	1	1	2	6	-	25
T60.57	1	2	-	3	1	1	1	-	1	1	-	-	3	2	1	2	5	1	5	-	1	31
T60.58	-	1	1	-	1	2	-	-	1	-	1	1	2	-	1	1	2	5	2	2	3	26
T60.59	1	-	-	1	-	-	-	-	1	1	3	3	6	-	1	1	-	1	1	-	1	21
T60.60	-	-	-	-	-	-	-	-	3	-	-	-	-	1	-	2	2	2	2	3	2	17

Table 6: Five high-loading papers for sixty topic solution

Topic id	Topic label	High-loading papers
T60.1	Early estimation	[115, 116, 117, 118, 119]
T60.2	Dynamic estimation	[120, 121, 72, 122, 123]
T60.3	Object oriented components estimation	[100, 124, 125, 126, 127]
T60.4	Estimation by analogy	[128, 129, 130, 131, 132]
T60.5	Productivity measurement	[133, 134, 135, 136, 137]
T60.6	Statistical filtering	[138, 139, 140, 141, 142]
T60.7	Project scheduling	[107, 143, 144, 145, 146]
T60.8	SRS based estimation	[147, 148, 149, 150, 151]
T60.9	Cost uncertainty	[152, 153, 154, 155, 156]
T60.10	Missing data effects	[157, 158, 159, 160, 161]
T60.11	Cost estimation models	[103, 162, 163, 164, 165]
T60.12	Morphological approach	[166, 167, 95, 94, 93]
T60.13	Factors affecting estimation	[168, 78, 169, 170, 171]
T60.14	Quality management	[172, 60, 173, 174, 175]
T60.15	Surveys	[176, 55, 177, 56, 178]
T60.16	Risk assessment	[179, 180, 181, 182, 183]
T60.17	Feature selection in problem domain	[184, 154, 185, 186, 187]
T60.18	Prediction interval approach	[188, 189, 190, 191, 192]
T60.19	Estimation tools	[193, 194, 195, 196, 197]
T60.20	Use case-based estimation	[198, 199, 200, 201, 202]
T60.21	Grey relation analysis	[203, 204, 205, 206, 207]
T60.22	Literature reviews	[208, 33, 209, 27, 28]
T60.23	Change impact analysis	[210, 211, 212, 213, 214]
T60.24	Software evolution	[106, 215, 216, 217, 218]
T60.25	Fuzzy analogy	[89, 30, 219, 220, 221]
T60.26	Object-oriented metrics	[222, 223, 224, 225, 226]
T60.27	Maintenance effort	[227, 228, 229, 230, 231]
T60.28	Country specific surveys	[232, 233, 234, 235, 236]
T60.29	Work breakdown structures	[237, 238, 239, 240, 241]
T60.30	Requirement elicitation impact	[242, 243, 244, 245, 246]
T60.31	Neural networks	[108, 247, 248, 249, 23]
T60.32	Reliability modelling	[250, 251, 252, 253, 254]
T60.33	Size estimation	[255, 256, 257, 87, 258]
T60.34	Estimation in cloud computing	[259, 260, 59, 261, 262]
T60.35	Case based reasoning	[263, 264, 265, 266, 267]
T60.36	System engineering	[268, 69, 269, 270, 271]
T60.37	Estimation for web applications	[272, 73, 273, 274, 275]
T60.38	Nature inspired algorithms	[276, 277, 278, 279, 280]
T60.39	Estimation for reusable components	[281, 282, 283, 284, 285]
T60.40	Parametric models	[286, 287, 288, 289, 290]
T60.41	Estimation in agile projects	[83, 291, 292, 293, 76]
T60.42	Test effort estimation	[294, 295, 296, 74, 297]
T60.43	Simulation techniques	[298, 299, 300, 301, 302]
T60.44	Data specific estimation	[50, 54, 303, 52, 304]
T60.45	Fuzzy logic	[305, 306, 307, 109, 308]
T60.46	Small datasets	[101, 309, 310, 311, 312]
T60.47	Evidence based judgement	[313, 314, 315, 316, 317]
T60.48	Factors influencing expert judgement	[64, 318, 65, 319, 320]
T60.49	Similarity measurement methods	[91, 321, 322, 323, 324]
T60.50	Empirical studies	[325, 326, 327, 328, 329]
T60.51	Strategy selection	[330, 331, 332, 333, 334]
T60.52	Global software development	[335, 62, 34, 336, 337]
T60.53	Software process improvement	[338, 339, 340, 341, 342]
T60.54	Regression techniques	[343, 344, 345, 346, 347]
T60.55	Support vector regression	[348, 349, 350, 96, 97]
T60.56	Evaluation criteria and metrics	[51, 53, 351, 352, 353]
T60.57	Function point analysis	[84, 354, 355, 356, 357]
T60.58	Ensemble models	[358, 359, 114, 360, 361]
T60.59	Impact of CMM levels	[362, 75, 363, 364, 365]
T60.60	Windowing approach	[81, 79, 80, 366, 367]

Table 7: Semantic mapping between twelve topic and sixty topic solution

Topic id	12 topic labels	Topic id	60 topic labels
T12.1	Validation of estimation models	T60.56	Evaluation criteria and metrics
		T60.40	Parametric models
		T60.44	Data specific estimation
		T60.39	Estimation for reusable components
		T60.54	Regression techniques
		T60.45	Fuzzy logic
T12.2	Reviews and mapping studies	T60.15	Surveys
		T60.22	Literature reviews
		T60.39	Estimation for reusable components
		T60.58	Ensemble models
T12.3	Application specific estimation	T60.34	Estimation in cloud computing
		T60.22	Literature reviews
		T60.47	Evidence based judgement
		T60.36	System engineering
T12.4	Expert judgement	T60.48	Factors influencing expert judgement
		T60.45	Fuzzy logic
		T60.60	Windowing approach
		T60.51	Strategy selection
		T60.47	Evidence based judgement
T12.5	Estimation for web applications	T60.37	Estimation for web applications
		T60.19	Estimation tools
		T60.36	System engineering
T12.6	Factors affecting estimation	T60.10	Missing data effects
		T60.59	Impact of CMM levels
		T60.54	Regression techniques
		T60.42	Test effort estimation
T12.7	Project data selection	T60.60	Windowing approach
		T60.44	Data specific estimation
		T60.41	Estimation in agile projects
		T60.4	Estimation by analogy
T12.8	Size metrics	T60.57	Function point analysis
		T60.33	Size estimation
T12.9	Estimation by analogy	T60.25	Fuzzy analogy
		T60.2	Dynamic estimation
		T60.10	Missing data effects
		T60.49	Similarity measurement methods
T12.10	Machine learning techniques	T60.12	Morphological approach
		T60.38	Nature inspired algorithms
		T60.31	Neural networks
		T60.35	Case based reasoning
		T60.17	Feature selection in problem domain
		T60.55	Support vector regression
		T60.45	Fuzzy logic
T12.11	Ensemble models	T60.58	Ensemble models
		T60.42	Test effort estimation
		T60.46	Small datasets
		T60.16	Risk assessment
T12.12	Dynamic effort estimation	T60.11	Cost estimation models
		T60.24	Software evolution
		T60.26	Object-oriented metrics
		T60.13	Factors affecting estimation
		T60.5	Productivity measurement
		T60.7	Project scheduling
		T60.27	Maintenance effort

emerged to depict handling and assessing of missing data [157, 158, 160, 161, 392]. "Impact of CMM levels" (T60.59) trend focuses on the effect of process maturity on SEE [75, 362, 364].

"Estimation by analogy" (T12.9) generates an effort estimate for software project based upon the data of similar past projects. There has been tremendous research in this area and it has uncovered "fuzzy analogy" (T60.25) trend that focuses on combining analogy and fuzzy logic [89, 219, 221]. The trend "dynamic estimation" (T60.2) emerged from this area reports on SEE models in dynamic environment [120, 123]. Various models have been developed by combining "estimation by analogy" (T60.4) with other techniques [201, 219, 220, 221, 310, 312, 359, 393, 394]. Various techniques have been suggested to improve the estimates by fuzzy analogy-based estimation including linguistic variables, learning adaptation, and k-modes algorithm [91, 221, 395]. The success and performance of all these techniques depends on availability of environment specific historic data. The research trend called "missing data effects" (T60.10) depicts the techniques for handling missing data in estimation by analogy [359, 396]. The "similarity measurement methods" (T60.49) provides leads on techniques to identify the similarity in different projects by way of using analogy [91, 321, 397].

In the field "application specific estimation" (T12.3), various trends have emerged after the year 2013. One such trend is called "estimation in cloud computing" (T60.34) which provides the model for estimation of cost in cloud environment [59, 60, 259, 260]. The other trends include "evidence based judgement" (T60.47) [314] and "system engineering" (T60.36) [268, 269, 270]. The "evidence based judgement" (T60.47) trend provides the model to estimate effort in web service composition-based projects estimation [314], while "system engineering" trend offers models to estimate system engineering cost [268, 269, 270] and heuristics for system engineering [398].

In "dynamic effort estimation" (T12.12), the trends identified are "cost estimation models" (T60.11), "software evolution" (T60.24), "object-oriented metrics" (T60.26) [222, 223], and "maintenance effort" (T60.27). The trend called "cost estimation models" (T60.11) helps in finding the cost of various components in SEE [103, 104, 163, 164]; the "software evolution" (T60.24) focuses on certain trends [106, 215, 399], while the "maintenance effort" (T60.27) trends provides the models for effort estimates in maintenance phase [227, 228, 229, 230].

The research carried out in the field of SEE, has proved that no single method performs consistently in all environments. So, it is advisable to generate estimates from ensembles of estimation methods. Multi-objective "ensemble models" (T12.11) have been the area of recent years [114, 361, 400]; and it consistently out-performs other techniques in various scenarios [358]. The core research area "ensemble models" (T12.11) has provided research trend "ensemble models" (T60.58) which focuses on ensemble generation [114, 309, 358]. "Object-oriented metrics" (T60.26) discuss metrics in object-oriented domain [222, 224, 226].

The core research area "validation of estimation models" (T12.1) has provided "evaluation criteria and metrics" (T60.56) which describe the metrics used for assessing the performance of estimation models and their modification [51] and comparative study of MMRE, MSE, Pred [351, 352, 353]. "Parametric models" (T60.40) having a focus on segmented models [286, 287, 289], "data specific estimation" (T60.44) focusing on cross-company, and within-company [50, 52, 31, 401], "estimation for reusable components" (T60.39) reporting on reuse framework [281, 283] have emerged from this research area. Certain others research trends have also been uncovered such as "regression techniques" (T60.54) which focus on calibration of models [344, 347] and "fuzzy logic" (T60.45) reporting on models based on fuzzy logic [26, 308, 402].

6.2. *RQ2 What research methods have been used for SEE?*

On the basis of analysis of high-loaded articles, it has been observed that diverse estimation approaches have been employed in SEE. The methods can be grouped into three groups, namely, formal, expert-based and hybrid. However, a few leading methods have been discovered though this study. Formal methods require large data sets for developing and validating, but the data set is generally sparse, incomplete, and inconsistent. Parametric approaches such as "case-based reasoning" [32, 185, 263, 264, 403, 404] and "support vector regression" [96, 349, 350, 405] assume data to be complete which is quite rare in the software domain. Non-parametric methods such as "neural networks" [108, 375, 248, 249, 378, 379, 406, 407], "genetic algorithms" [196, 277, 382, 408, 409], "fuzzy logic"

[91, 109, 110, 286, 305, 306, 378, 406, 410]. "Windowing approach" uses a window of recent projects as training data for building an effort estimation model [79, 80, 81, 83, 388]. Expert-based estimation is not based upon any project but it has limitation of being biased, time-consuming and dependent on estimator's experience. The methods such as "expert judgement" [28, 64, 313, 320, 411, 412], and "work breakdown structures" [237, 238] use the concept of expert-based estimation. Since no method performs consistently in all the environments, hybrid methods have been the area of concern. "Ensemble models" [102, 114, 201, 358, 359, 413, 414], "SRS based estimation" [148, 151] and "use case-based estimation" [415, 416] have been proposed for the purpose.

6.3. RQ3. Which research areas demand greater attention of researchers?

Although research in the field of SEE is being conducted for the last four decades, yet a complete study on effort estimation remains to be seen. The researchers have been unable to fully understand the requirements of the software industry in developing and validating the generic model to predict effort for all type of projects. The limitations which exist provide several opportunities for further research. In particular, Minku and Yao [361] realised that SEE is a multi-objective problem; and more attention is required to validate different models. It was observed that few longitudinal studies have been reported. To understand all the consequences of different aspects of SEE research, there is need to have more in-depth case studies. We can find the research areas which demand more attention through the interpretation of semantic mapping of twelve and sixty topic solution and loading of articles to topic solutions. The topics discussed below may form the basis for further research on SEE.

"Size metrics" (T12.8). SEE process begins with the prediction of the size of deliverables to be developed in a software. Many claim that the established size metrics are sufficient for measuring the complexities involved in SEE [354]. However, the study conducted by de Freitas Junior et al. [417] is one of the few studies with a longitudinal view emphasising on the need to improve size metrics. Thus, we need to focus on the following:

- Improvements in existing size metrics and their effectiveness in different environments.
- Standardization of conversion between different size metrics.

"Factors affecting estimation" (T12.6). Effort estimation is often influenced by several factors, both intrinsic and extrinsic. Very few studies have identified the factors which affect effort estimation [169, 418]. One of the biggest challenge is data imputation; and research area is available for improvements due to issues related to the application of existing methods [35, 160]. Further, these studies are not validated for sparse and high missing data imputation. This demands more rigorous research on the following:

- Longitudinal studies to identify the social, geographical and temporal factors which affect estimation.
- Developing an effective framework for handling data imputation based on the characteristics of effort data.

"Machine learning techniques" (T12.10). The study conducted by Wen et al. [27] provided an in-depth investigation of empirical evidences on machine learning models used in SEE. Machine learning models have been promising and most widely applied than any other approach in SEE. But the application of these machine learning models in the industry is still limited. Hence, more intensive research is required to identify the barriers in the adoption of machine learning models in the industry. Further, increased usage of performance metrics other than conventional metrics, application of machine learning in SEE projects, and increased collaboration between machine learning researchers, will create trust and promote machine learning usage in industry. Thus, there is a potential for further research on:

- Which of machine learning approach is suitable for specific environment based on characteristics of available data?
- Application of optimization techniques to tune parameters used in various machine learning approaches.
- Design and development of machine learning framework for solving multi-criteria effort estimation problems.

"Expert judgement" (T12.4). Jørgensen [28] advocated that expert judgement is leading estimation method adopted by organisations. To enable the organizations to get benefited from expert judgement, they must identify the human factors affecting the expert judgement [419] and apply practical guidelines for producing better estimates [316]. Jørgensen and Gruschke [65] concluded that it cannot be defined whether expert judgement is better or weaker than formal models. But practitioners need to identify the situations, when to use expert estimation and when to use formal models. Shepperd and Cartwright [420] tried to conceptualise framework of integration of computational approach and expert judgement, but lacked validation and generalization. This area is also open to research as the researchers have yet to focus on enhancing expert judgement in conjunction with computational models. The research community should pay more attention to the questions concerning:

- Longitudinal studies on identifying the motivational factors involved in intentional and unintentional distortions.
- Artificial intelligence based framework for integrating expert judgement with computational models.
- Elaborative studies on identification of steps to reduce the biasing and uncertainty.

"Ensemble models" (T12.11). The weakness of existing estimation models gave rise to ensemble models in SEE. A systematic review of ensemble estimation methods [29] explored the use of machine learning approaches for ensemble model generation and suggested to further investigate existing established approaches. Moreover, ensemble models have not been popular among practitioners in the real world. So research community is encouraged to conduct research on :

- Empirical studies to identify the suitable candidates for ensemble generation
- Design methodology to evaluate the performance of ensemble models based on different performance measures.

"Validation of estimation models" (T12.1). Findings of current study reveal that a large number of proposed estimation models lack validation and generalization of the results. Very few studies have reported on issues pertaining to model validation [50, 347, 421]. As suggested by Kocaguneli and Menzies [179], performance of a model can be assessed by dataset used and model evaluation criterion. Mean magnitude of relative error (MMRE) as evaluation criterion has been empirically studied and criticized by [53, 422], and suffers from rank reversal. Thus elaborative research can be conducted on :

- Comprehensive study of different performance measures to assess the accuracy of estimation models.

Other areas. Besides research topics discussed above, some recent areas have emerged from the study including "morphological approach", "use case-based estimation", "feature selection", "windowing approach", "grey relation analysis" but high loading articles count for these areas is quite low. These areas are potential topics for further exploration. Designing of a formal design methodology and validation of "morphological approach" on large datasets is still an open area in morphological approach. Future work in "windowing approach" should focus on optimum window size and steepness of weighted function. Since these areas have not been widely investigated, research community should focus on exploring these areas to find the challenges ahead.

7. Threats to validity

Threats to the validity of our study and their corresponding mitigation strategies have been described and detailed as follows:

Selection of the search string. This threat refers to the effectiveness of the applied search string to find a sufficiently large number of relevant articles. Limitation of selecting search terms and their synonyms, search string design, and search engines may result in incomplete literature dataset. Therefore, due to our choice of keywords and search string, there is a risk that relevant articles may be omitted. In this study, to ensure the relevancy of collected articles in the literature dataset to SEE, they were reviewed thoroughly by two step review process.

Subjectivity in topic labelling. The labelling of topics is a great concern due to the subjectivity and biasing involved in it. To overcome this limitation, two authors of the paper did topic labelling individually and later on it was combined to generate conclusive label.

8. Conclusion

This research is based on mathematical foundations and discovers the research trends in SEE literature. It uncovers the research trends by analysing 1178 documents published by the researchers. The approach generated n-topic solution, and corresponding term and document loadings. These loadings explain the proximity to a given topic. Only highly-loaded terms and documents above the threshold were considered relevant to the topic.

Researchers can understand not only the trends prevailing in SEE research, but the potential research areas can also be identified. Moreover, researchers can analyse any one core research area out of twelve research areas identified in the current study for further exploration. Further, references have been provided to a large number of success stories which not only educate practitioners, but also make them feel more confident about adopting SEE. Although some limitations have been identified during research on SEE in organisations, yet there is enough scope for future research. The results of current study can enable the researchers to face new research challenges and align their work with contemporary research. They may also use other topic modelling techniques to identify the hidden patterns and trends from a large bibliographic dataset.

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