Latent Dirichlet Allocation modeling for CPS patent topic discovery

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Abstract – **Industry 4.0 is an organized framework to infuse the latest technology in the manufacturing sector. The inclusion of next-generation technologies such as Cyber-Physical Systems (CPS), cloud computing, big data and artificial intelligence approaches increases productivity and manufacturing output in today's dynamic industrial environments. This research is a Latent Dirichlet Allocation (LDA) topic modeling extension from a prior research on technology standards and patent portfolios for industrial CPS [1]. Topic modeling is a statistical approach for discovering topics that occur in a document corpus [2]. Latent Dirichlet Allocation (LDA) is an unsupervised technical approach in topic modeling for efficient and insightful data analysis. A collection of 1868 CPS patents from the US patent database has been used as input to group patents in several relevant topics for industrial CPS using LDA model in this research. Topic modeled patent groups allowed for the identification of relationships between terms and topics, enabling better visualizations of underlying intellectual property dynamics. Top assignees for each group are computed based on LDA results, these insights were unknown in prior investigations. Further, a graphical representation of the topic trend across groups present a direction of promising patents towards industrial application. The correlations presented enhances patent utilization and promotes cross-licensing commercialization.**

Keywords- Topic Modeling, patent analysis, industrial Cyber-Physical Systems (CPS).

I. INTRODUCTION

Industry 4.0 is the fourth wave of the industrial evolution by the inclusion of technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Big data analytics in manufacturing to achieve advancements. Manufacturing remains a critical force in economies and Industry 4.0 mission is to include innovations concerning information systems and technologies in manufacturing [3]. Germany is leading the Industry 4.0 transformation based on CPS inclusion [4].

CPS is an umbrella term that includes sensors, actuators, architectures, tools, databases, applications, and methodologies [1]. Prior publications in CPS for Industry 4.0 has extensively covered a wide array of theoretical and practical aspects [4-10]. CPS enables manufacturing and service innovation using integration of software-based embedded intelligence. Self-learning machines thus derived engage automatically in performance improvement and maintenance [4]. Intelligent assembly line operators now need data visualization and decision-making skills as the earlier redundant tasks are now handled by automation [5]. CPS currently is transforming the interaction of engineered systems. Emerging CPS is expected to be coordinated, distributed, connected, robust and responsive [6]. While the current and future role of CPS is further emphasized in publications [7-10]. The cost of investment combined with lack of clarity on intellectual property dynamics discourages industries from CPS automation.

Understand business objectives and to formulate core strategies of a company to emerge as market leader understanding the patent dynamics is imperative. While prior research standards and patent portfolios for industrial CPS is a key step in this direction [1]. Latent Dirichlet Allocation (LDA) as an unsupervised topic modeling technique can further achieve a host of patent analytics grouping functions. Topic modeling based grouping is used extensively in many industries, the adoption in the patent information space has however been sporadic. The key challenge in LDA adoption for patent modeling has been in the lack of overview, simplification and case demonstrations [16].

This research addresses gap by presenting a simplified background for LDA, followed by an application extension of an online LDA variation [18] on prior validated CPS research patent dataset. The topic modeling based patent groping presented for CPS data set is from 2006 to 2016 with the scope of The United States Patent and Trademark Office

(USPTO). The ontology used to query the USPTO database is extended and improvements from validated ontology industrial CPS [1]. This research allows the identification of current industry trends and interesting future applications, thus highlighting opportunities for further research. The paper is organized as follows, Section 2 is an overview of CPS and patent query based on prior research for background building. Section 3 presents topic modeling algorithm LDA overview and application. Followed by results and discussed in Section 4 and conclusions are summarized in Section 5.

II. BACKGROUND

A. CPS Outline

CPS in the prior research for Technology Standards and Patent Portfolios has been outlined as the merger of electric, electronic and software systems to real-world physical objects [1]. Out of the many architectures reviewed an architecture proposed by Lee, et al. [13] was chosen as the base for building systematic review, ontology, and outlining and mapping standards and patents because of its comprehensive association Industry 4.0 objectives. A Five-layer model called 5C cyber-physical architecture proposed by Lee, et al. is shown in Fig 1.

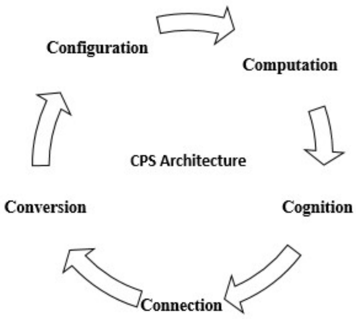

Fig 1. 5C architecture for CPS [26].

The 5C's model represents connection as the primary building block as it deals with the first level connectivity both internal and external. Circuits, controllers, sensors, actuators, and protocols are parts of this layer. Conversion is the block where data collected from seamless connectivity is merged and unified in a format for higher layers. Sensor data, point of sale terminal data are data sources that are converted for higher level constructs such as cloud computing and big data analytics. Computation block uses mathematical transformations in the form of algorithms to analyze trends and predict future trends. Cognition block represents the data collected by prior blocks for informed decisions. Configuration block helps to convert derived cyber intelligence to real-world physical changes thereby completing the cyber-physical systems cycle.

B. Patent Search Query

A patent is the legal right of ownership for an invention. patents give exclusive rights to the owner and prevent copying, selling and manufacturing inventions without permission for a pre-determined period. Patenting prevents theft of the invention, increases profit margins by preventing unauthorized usage, reduces competition by increasing risks of infringement, expand market share and encourage collaboration using strategies such as licensing. The prior research systematically evolved a comprehensive ontology from the literature review. This research extends the ontology and regenerates a search query with optimization towards USPTO with a search scope of ten years starting 2006 [1].

TABLE 1. SEARCH QUERY TABLE.

Manufacturing terms
((CTB=("cyber* physical*" or "manufactur*" or "factor*" or "plant" or "produc*" or "machine")
CPS main topic terms
AND CTB=(("remote*" or "real-time" or "cloud*")
CPS ontology terms
NEAR5 ("sensor*" or "actuator*" or "controller*" or "circuit*" or "sensor* network*" or "protocol*" or "wireless* network*" or "data*" or "network* control*" or "power* consumption*" or "simulat*" or "secur*" or "prognos*" or "predict*" or "diagnos*" or "monitor* " or "interconnect" or "information display" or "comput*" or "decision"))
Search Timespan (years)
2006-2016

Table 1 is a breakdown of the USPTO optimized search query used for the current research. The search query consists of manufacturing terms dealing with industrial engineering and manufacturing, combined with CPS main ontology and domain terms extended from prior research ontology [1].

The search query results in a total of 1868 US granted patents. The top assignees of the patent results in US industrial CPS area are IBM, Intel, Microsoft, Rockwell, SAP, Dell EMC, General Electric and Siemens in that order. The patent count from 2006 to 2016 can be seen as an incremental 82, 82, 84, 106, 140, 132, 144, 172, 277, 323, and 326 patents each year in that order. This result is consistent with the results of the prior publication validating the current search query generation and dataset extraction process. Further, the prior research analyzed the data set in the context of quality and quantity by comparisons such as top assignee versus patent families where patents covering more technology family were presented as patents with greater importance, CPS patent pool versus top IPC category comparison, top IPCs versus assignees analysis, Sub-technologies analysis with respect to IPC, followed by the construction of a patent technology-function matrix from an analytical perspective

[1]. The current paper is a text mining driven CPS patent data topic modeling. The following sections systematically apply and group the extracted 1868 patent using LDA topic modeling.

III. LDA MODELLING

A. LDA Modeling

Latent Dirichlet Allocation (LDA) [2] is a generic model for representing semantic word structures to topics from a patent data corpus D by assuming Dirichlet prior for per topic word distribution and per patent topic distribution. Let the corpus D have M patents and each patent be composed of $N_{d=1,\ldots,M}$ words from vocabulary V. In vocabulary V, there are $|V|$ semantic words. Denote $N = \sum_{d=1}^{M} N_d$. Set K topics as the model output. Order and Index words in V as $\{1, \ldots, |V|\}$ and latent topics as $\{1, \ldots, K\}$. Based on these two latent Dirichlet distributed assumptions and at most K the output topics in corpus D, the structures of words and topics can be shown as probability matrices evaluated from the joint probability $P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\Theta}, \boldsymbol{B};\ \boldsymbol{\alpha}, \boldsymbol{\eta})$, where $\boldsymbol{Z} \in \{1, \ldots, K\}^N$ and $\boldsymbol{W} \in \{1, \ldots, |V|\}^N$ are both N-dimension topic-indexing and word-indexing vectors respectively. Let $\mathbb{R}_+$ be nonnegative real number. Here, $\boldsymbol{\Theta} \in \mathbb{R}_+^{M\times K}$ is a probability matrix made up of row vectors $\boldsymbol{\theta}_{d=1,\ldots,M}$,where $\boldsymbol{\theta}_d \sim$ Dirichlet($\boldsymbol{\alpha}$) and $\boldsymbol{\alpha} \in \mathbb{R}_+^K$. Similary, $\boldsymbol{B} \in \mathbb{R}_+^{K\times V}$ is a matrix with row vectors $\boldsymbol{\beta}_{k=1,\ldots,K}$ where $\boldsymbol{\beta}_k \sim$Dirichlet($\boldsymbol{\eta}$) and $\boldsymbol{\eta} \in \mathbb{R}_+^V$. Fig 2 shows a graphical representation of LDA.

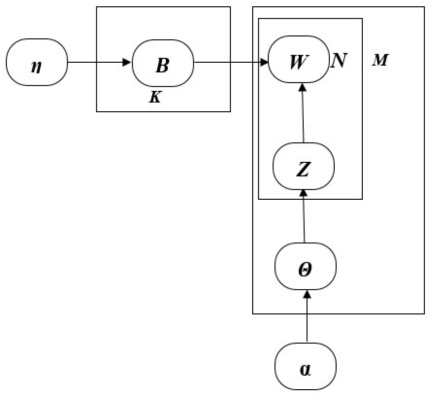

Fig 2. LDA model [2].

LDA applies hierarchical Bayesian models to encode K abstract, latent topics via vocabulary V which gives its state-of-the-art specialty to identify multiple topics in one document. However, for the Bayesian models, the posterior distribution of model parameters and latent variables is always hard to compute. In classical LDA [2], the variational inference is used to approximate the hidden variables $\boldsymbol{\alpha}$ and $\boldsymbol{\eta}$ in the posterior distribution with variational parameter matrices, $\boldsymbol{\Gamma}$, $\boldsymbol{\Lambda}$, respectively. By minimizing the KL divergence between the variational distribution $q(\boldsymbol{\Theta}, \boldsymbol{Z}, \boldsymbol{B})$ and the true posterior $P(\boldsymbol{\Theta}, \boldsymbol{Z}, \boldsymbol{B}|\boldsymbol{W}, \boldsymbol{\alpha}, \boldsymbol{\eta})$, $\boldsymbol{\Gamma}$ and $\boldsymbol{\Lambda}$ can be optimized to train $\boldsymbol{\alpha}, \boldsymbol{\eta}$.

In this research, we utilize module Gensim [14][17] implementing on-line LDA [18] with a fully factorized distribution q,

$q(z_{di} = k) = \varphi_{dw_{di}k}$; $q(\boldsymbol{\theta}_d)$ = Dirichlet$(\boldsymbol{\theta}_d;\ \gamma_d)$;
$q(\boldsymbol{\beta}_k)$ = Dirichlet$(\boldsymbol{\beta}_k;\lambda_k)$,

where d stands for the d-th patent, $\varphi_{dw_{di}k}$ is the probability for the i-th words in d-th patent as topic k in d-th patent and $\boldsymbol{\theta}_d \in \boldsymbol{\Theta}$, $\gamma_d \in \boldsymbol{\Gamma}$, $\lambda_k \in \boldsymbol{\Lambda}$, $\boldsymbol{\beta}_k \in \boldsymbol{B}$. In d-th patent, equation (1) and (2)

$$\varphi_{dwk} \propto \exp\{\mathbb{E}_q[\log \theta_{dk}] + \mathbb{E}_q[\log \beta_{kw}]\}, \tag{1}$$

$$\gamma_{dk} = \alpha_k + \textstyle\sum_w \varphi_{dwk} n_{dw}, \quad k = 1, \ldots, K \tag{2}$$

are updated repeatedly until $\gamma_{dk} \in \gamma_d$ is converged. In equation (1) and (2), w stands for a word in vocabulary V and n_{dw} is its cardinality in d-th patent. With converged φ_{dwk}, $\boldsymbol{\lambda_k}$ is updated which was initialized randomly. Then, by using the optimized $\boldsymbol{\gamma}_d$ and λ_k, the parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\eta}$ are renewed by on-line method [18] in this d-th iteration. Therefore, after M iterations, we have the trained $\boldsymbol{\alpha}, \boldsymbol{\eta}$ for the joint distribution in equation (3).

$$P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\Theta}, \boldsymbol{B};\ \boldsymbol{\alpha}, \boldsymbol{\eta}) = \prod_{k=1}^{K} \text{Dirichelt}(\boldsymbol{\beta}_k;\ \boldsymbol{\eta}) \prod_{d=1}^{M} \text{Dirichelt}(\boldsymbol{\theta}_d;\ \boldsymbol{\alpha}) \prod_{j=1}^{N_d} P(z_{dj}\,|\boldsymbol{\theta}_d) P\left(w_{dj}\,\middle|\boldsymbol{\beta}_{z_{dj}}\right). \tag{3}$$

Further, integrating $\boldsymbol{\Theta}$ and $\boldsymbol{B}$ out, a patent S with N_s indexed words $\boldsymbol{w}$ can be matched to a topic via the indicator function in equation (4)

$$I_{z=k}(\boldsymbol{w}) = \begin{cases} 1, & \sum_{n=1}^{N_s} P(\,w_n, z_n = k;\ \boldsymbol{\alpha}, \boldsymbol{\eta}) > \varepsilon \\ 0, & \text{otherwise} \end{cases}. \tag{4}$$

LDA in patent analytics was used prior to forecast vacant technologies by using the technology clusters obtained by the patent documents and perform topic modeling by using taxonomy and to enhance interpretability [11][12]. However, on-line LDA model and the Gensim based application have not been covered in the scope of prior work.

B. LDA Industrial CPS Application

A topic model captures intuition in a mathematical framework, which allows topic discovery [2]. The flowchart given in Fig 3 gives a systematic overview of the various steps involved in the LDA application for the industrial CPS patent dataset derived from search query customization shown in Table 1. The obtained dataset is filtered by cleaning, preprocessing and normalization of the patent data corpus. Online LDA model is applied using genism library [14][17]. The algorithm generates corpus using the patent documents which is the compilation of patent metadata field’s title, abstract, summary, and claims section.

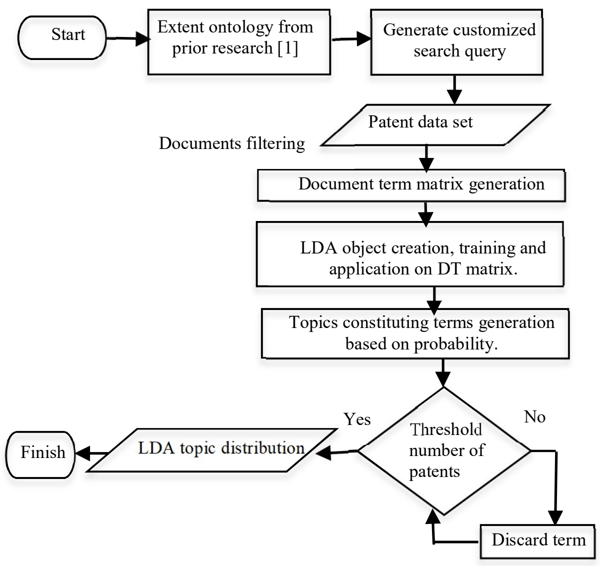

Fig 3. The flowchart for LDA application.

A document term matrix is then generated on which LDA object is trained and applied and the resulting topics are simplified, grouped, and analyzed. If the terms surpass a minimum number of patents, they are then further extracted and LDA topic distribution is carried out on those selected topics. Since LDA is probabilistic one patent can be a part of more than one topic thereby resulting in better patent value utilization in cross-licensing scenarios.

IV. RESULTS AND KEY FINDINGS

Online LDA application results in 309 topics with an average of 23 patents per topic. The result shows that while topics with higher patent frequencies represent broader technological domain, topics with lower patent frequencies represent very specific technology. Since the objective of this analysis is to identify broader topics composition of CPS patents, their trends and evolution only topics with patent representation frequencies greater than 9 are considered. The cut-off value of 9 is decided with the help of subject matter expert (SME) empirical review of topics modeled and its underlying patent encapsulation. This approach reduces topics to be considered further to 160, increases average by 39 patents per topic and retains broader CPS domain focus. Further, based on subject matter expertise the 160 topics obtained by LDA having similar semantic sense were reduced to a common term. This SME driven manual term reduction results in a dictionary shown in Table 2 and reduces effort in the analysis in further sections.

TABLE 2. CPS TERM DICTIONARY.

Reduced terms	Similar LDA topics from the same domain
Data	Frame, data, file, packet, document, database, backup, transfer, storage, memory, content
System	System, server, client, service, interface, host, local, query, resource, process, object Parameter
Device	Device, sensor, configuration, hardware, controller, control, cache, processor, processing
Industrial	Machine, power, energy, engine, equipment, appliance, tool, physical, apparatus, industrial
Mobile	Mobile, remote, access, target, location, address
Network	Time, connection, transmission, channel, digital, network, comunication, node, signal, protocol, terminal, proxy, queue, source, wireless, medium, environment, message, request, session
State	State, virtual, real, platform, realtime
Compute	Output, logical, computing, computer, module, monitoring, operation, web, search, metadata, instruction, link, input, command, code, operating, program, software, site
Graphics	Image, graphic, video, monitor, stream, display
Security	Encryption, key, security
Distribution	cluster,pattern,segment,distributed,portion,level,entity,layer,field,item,instance,point,center, block

The frequency counts of reduced terms represented in CPS term dictionary in Table 2, is further represented in Table 3. Topics covering technological domains such as data (consisting of LDA derived topics frame, file, packet, document, backup, storage), system and device form the maximum frequencies. gives an idea about the relevant term frequencies of the reduced term obtained from Table 2. The modeled result is further used in the upcoming sections in order to reduce the results in 5C layer model.

TABLE 3. REDUCED TERM FREQUENCY COUNT

No	Term	Frequency count
1.	Data	1115
2.	System	975
3.	Device	527
4.	Industrial	349
5.	Mobile	259
6.	State	195
7.	Network	703
8.	Compute	548
9.	Graphics	149
10.	Security	57
11.	Distribution	205

The reduced terms are further categorized into the 5C layer according to their broader definitions which are shown in Table 4. The extracted terms are thus finally classified into different layers of the 5C layer model and thus can be studied to get further insights from the dataset.

TABLE 4. 5C MODEL TERM ASSIGNMENT.

Layer	Reduced term
Connection	Network, Mobile, Device
Conversion	Data, Distribution
Computation	Compute, System, Security, State
Cognition	Graphics
Configuration	Industrial

The top assignees using reduced term combination for connection, conversion, computation and cognition layer is computed as IBM followed by Intel which is consistent with generic prior findings. The additional findings are that in the connection layer assignee AT&T Intellectual Property has a good volume of patents and licenses in networking, mobility, and device-related patents for third-party distribution to partners who build new features and services that are not formal products or services from AT&T. Similarly, in the conversion and computation layer QST Holdings, has market share in data system and compute related topics. Positron Telecommunication Systems has patent grants in the cognition layer. Positron Inc. the parent company has several operating subsidiaries in the telecom domain and has key patents in topics related to monitoring, streaming and displaying information. In the configuration layer Rockwell Automation, Mayfield Heights, and General Electric, Schenectady, are top assignees. The companies have industrial CPS patents in the areas of industrial sensors, networks, controls and execution systems. Further evolutionary trends of topics over a period of 10 years' period are calculated and presented in appendix1. Fig 4 shows a graphical outline of the patenting topic trend across the 5C topic spectrum.

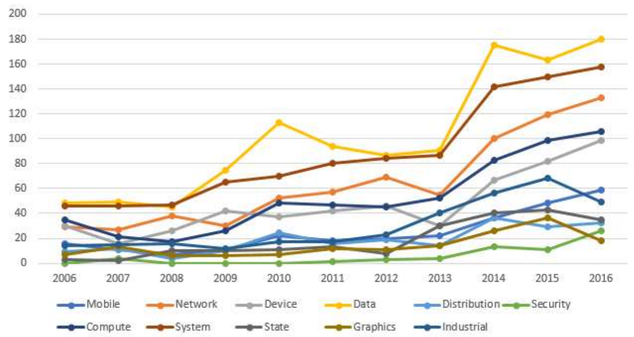

Fig 4: Evolutionary trends in CPS topics.

The evolution graph shows that patents related to data, system, and networking technologies have the most progressive trends in the past 10-year frame. The topic evolution graph presented identifies the direction of promising patents for frequent transfer transactions for future industrial use. Technology transfer and licensing are mechanisms for industrial collaboration. This helps secure innovative and advances technological outlook in high-tech industries.

V. CONCLUSION

CPS enabled manufacturer is the key aspect of future manufacturing. A systematic derivation of the topics that constitute the CPS patent framework using unsupervised LDA is presented and consolidates in the 5C layer model to achieve in-depth patent analytics functions. Further, since it is now desirable to have algorithms that assign a patent as belonging more than one group probabilistic LDA, the generative model is used. Patent groups created on top of LDA semantics help in preventing revenue leaks and increase cost efficient for in-licensing and cross-licensing scenarios. This research extends prior industrial CPS patent portfolio dynamics to identify technological opportunity, conduct in-depth competitor portfolio analysis, IP Infringement Analysis, Competitor Trend Analysis, locate areas of risk, opportunity within a given technology area for industry managers. Further, the paper solves key challenges of simplified industrial application of LDA algorithms in the area of industrial IP analytics and ensures transparency for IP professionals and industry practitioners who usually find it hard to accept results of black-box engines [15].

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APPENDIX 1. YEAR WISE TOPIC PROGRESSION

Layer	Reduced Term	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Connection	Mobile	16	11	7	11	22	18	20	22	36	48	59
	Network	29	27	38	30	52	57	69	55	100	119	133
	Device	30	16	26	42	37	42	46	30	67	82	99
Conversion	Data	48	49	45	75	113	94	87	91	175	163	180
	Distribution	9	12	4	10	24	16	19	14	36	29	32
Computation	Security	0	4	0	0	0	1	3	4	13	11	26
	Compute	35	21	17	26	48	47	45	52	83	99	106
	System	46	46	47	65	70	80	84	87	142	150	158
	State	3	2	10	10	11	13	8	30	40	43	35
Cognition	Graphics	7	13	6	6	7	12	11	14	26	36	18
Configuration	Industrial	14	15	16	12	17	17	23	40	56	68	49