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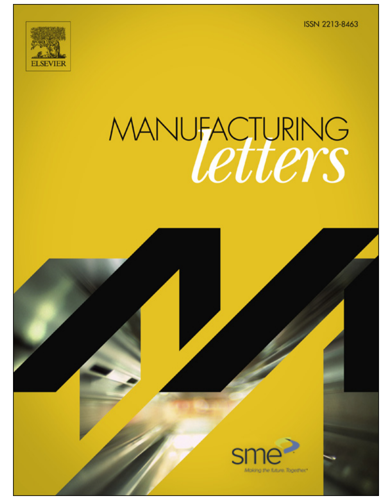

A knowledge-based social networking app for collaborative problem-solving in manufacturing

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A knowledge-based social networking app for collaborative problem-solving in manufacturing

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Abstract

Employees within companies act as "social machines" that process data and information, and produce valuable, yet tacit knowledge. This paper considers a smart factory framework inspired from social networking, in which employees collaborate to tackle problems related to product and production. A knowledge-based mobile app, based on the Root Cause Analysis process, formalises problem-solving instructions and expert opinions described in natural language via the Vector Space Model method. The utilised cloud infrastructure facilitates knowledge sharing and provides a business-oriented social network for employees. Both method and developed app are validated in a case study obtained from the automotive die-construction domain.

Keywords: Manufacturing system, Knowledge management, Social Manufacturing

1. Introduction and State of the Art

Modern enterprises function on the basis of collaboration among stakeholders across the product/service value-adding chain [1][2]. Current collaboration practices, however need modernisation [3]. Meanwhile, employees are perceived as "social machines" [4], which process data/information, and produce valuable, yet implicit knowledge. Constituting this knowledge reusable, entails major advantages for problem-solving [5] among other domains [6][7]. The adoption of social media in manufacturing can empower corporate collaboration and provides a knowledge capturing mechanism [4].

Furthermore, Root Cause Analysis (RCA), a formal problem-solving method widely used in industrial practice [8] can be facilitated by Cloud Manufacturing. Moreover, mobile devices, which are acknowledged as IT megatrends [9][10] can act as information brokers and enable interactivity and constant awareness on core enterprise functions [11].

2. Method

Towards improving problem-solving, this work proposes a method mimicking social networking in which employees collaborate to deal with problems emerging during an engineering project's lifecycle. Within the social manufacturing eco-system, the RCA method is used to support formal problem-solving, identification of causes, and formulation of effective solution steps (Figure 1).

A key step in problem identification is problem statement [12], yet, current practice treats it from a heuristics approach. In this study this step is enhanced by exploiting previous knowledge. During the submission of a new problem to the social platform, natural language descriptions are used by engineers, which are processed by the Vector Space Model (VSM) method, to extract from the knowledge base similar problems with reported solutions. If a problem has been encountered previously, its solution is retrieved from the repository and is adapted to the new situation. If not, the problem description is posted to the business social network, in search for a solution. Problems already resolved are marked with a "green" traffic light. Problems still pending but with known solutions are marked with "orange". Serious problems that do not have a known solution or could cause major disruptions to a project are marked with "red".

Problem descriptions are restricted to 150 characters long for the sake of conciseness and avoidance of story-telling. Keywords, which characterise a problem, are signified using the '#' symbol and are automatically assigned with a higher similarity weight factor [13]. The recipient individual or group is signified using the '@' symbol. Engineers belonging to the same team are automatically subscribed to notifications. For instance, when a "red" problem arises, the project manager and team members are notified through the developed mobile app to submit possible solutions and causes. Each participant can vote submitted solutions/causes either positively (thumbs up) or negatively (thumbs down) to promote best practices. Finally, the problem, root causes, and solutions are queued up for approval by an administrator and are afterwards stored and indexed into the knowledge base, to become reusable in future cases.

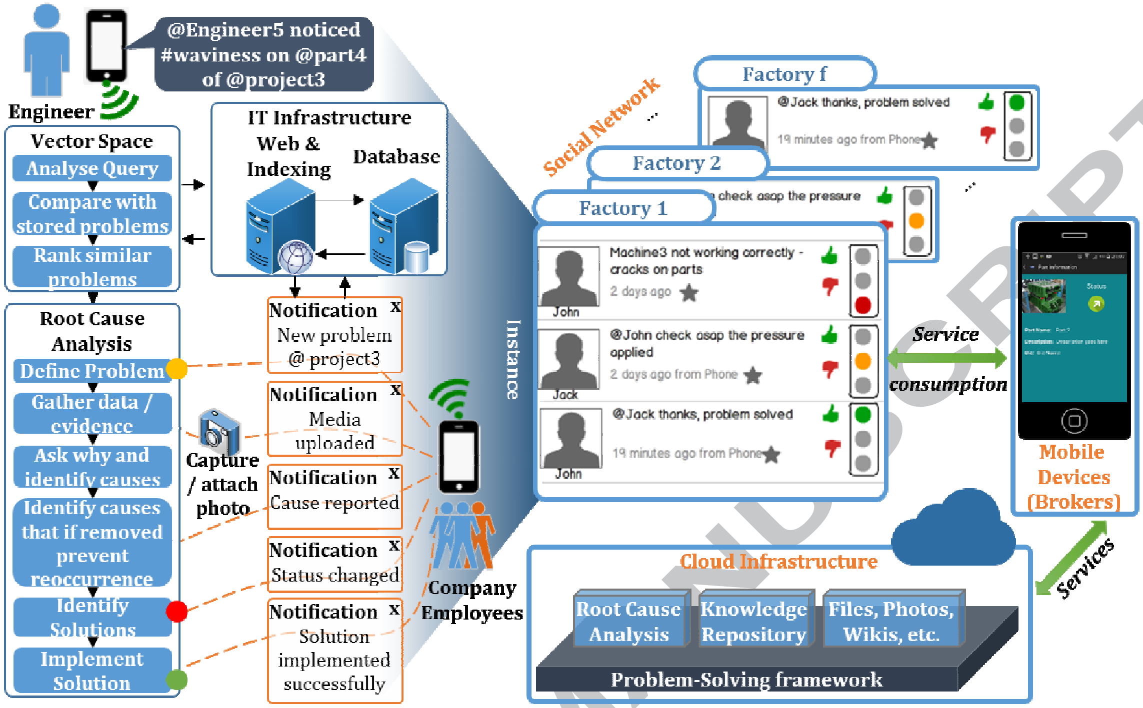

Figure 1. Framework components and the problem submission process

Stored problems, in the context of Natural Language Processing (NLP) referred to as documents, represent formalised explicit problem-solving knowledge. An indexing method parses these documents to tokenise words and associate them with a unique document identifier [14]. After all documents are parsed, the inverted file is sorted out by terms.

A new problem description submitted by an engineer comprises essentially a query for this accumulated knowledge (Figure 2). Considering that word-by-word comparisons are required for such short queries, VSM is selected as the most suitable NLP method [14] and implemented by the Elasticsearch engine [15]. In VSM, sets of documents and queries are represented as vectors with dimensionality equal to the number of dictionary terms. The bag-of-words assumption is considered, since the order of words in short descriptions does not affect the retrieval accuracy. Let us assume a query q, an already stored document d in a database of D documents, and t a term from the vocabulary T. Vectors d and q are formed to represent the total weights for each term in documents and queries respectively. The weighting method applied is an enhanced version of *tf-idf* (term frequency-inverted document frequency), which uses custom weights to distinguish keywords from less important terms. The *tf* method gives extra weight to terms used repeatedly in a document and the *idf* method attenuates the effect of common terms that occur in multiple documents, by counting the number of documents that contain a term t (df_t). The result is a composite weight comprised of individual weights for terms dt, $t \in [1,\ldots T]$, calculated by (1). In case a term is hash-tagged, i.e. is a keyword, then its weight is multiplied with the factor 1.5 for improving its relative significance. The cosine similarity between the query vector q and the document vectors d_i is calculated by (2) and takes values in range [0, 1], with 0 denoting absolute dissimilarity and 1 denoting total similarity between query and document vectors.

$$d_t = tf_{t,d} \cdot idf_{t,d} = (1 + log tf_{t,d}) log \frac{D}{df_t} \qquad (1)$$

$$cosSim(\vec{q}, \vec{d_i}) = \frac{\vec{q} \cdot \vec{d_i}}{|\vec{q}||\vec{d_i}|} = \frac{\sum_{t=1}^{T} q_t \times d_{it}}{\sqrt{\sum_{t=1}^{T} q_t^2 \times \sum_{t=1}^{T} d_{it}^2}} \qquad (2)$$

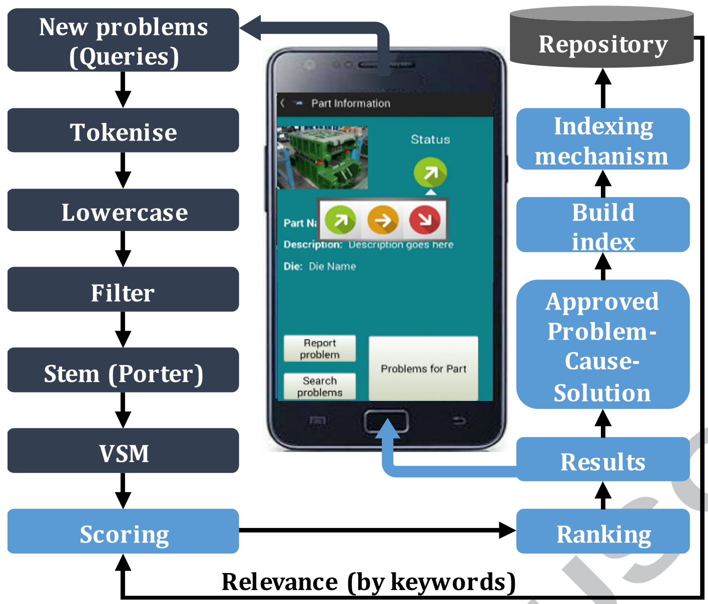

Figure 2. NLP algorithm workflow

The method is developed into a native Android app to provide: mobility to the entire process, capturing and attaching photos of defective parts to problems, and exploiting geotagging information to capture the location (i.e. factory) of the problem. The framework can be hosted on an enterprise-owned private Cloud to ensure accessibility to functionalities and data security [16], while facilitating information sharing and synchronisation of project elements across the enterprise.

3. Case Study

A case study related to the launch of a new car model is used to validate the proposed method. In the automotive industry, launching new models is critical factor for sustainability. The release cycle is a complex, time-consuming, and experience-based procedure. Moreover, it requires great management capacity and synergistic efforts among engineers of different backgrounds [17]. Stamped car parts are produced using a number of die-sets, each including 4-6 dies, each die being an assembly of numerous sub-components. The die-set construction phase initiates 54 months prior to zero-part stamping and involves several steps (Figure 3).

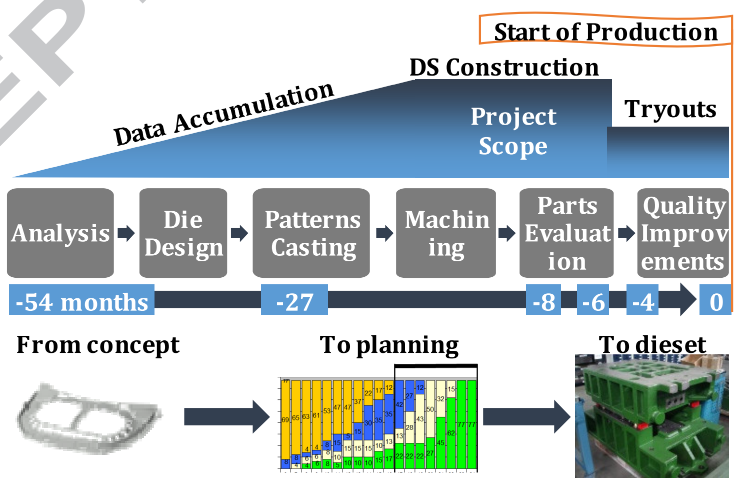

Figure 3. Product release cycle

Evidently, teams of engineers responsible for the execution of such projects must effectively tackle any emerging problem. A typical problem dealt with in most projects, is a waviness effect noticed on stamped parts. An experienced planner can immediately identify possible causes for this problem (e.g.

wrong material properties, blank properties, stamping method). Yet, an inexperienced employee, once presented with this problem, has to use the method developed into the mobile app to identify solutions borrowed from similar past problems.

The social networking aspects and the performance of the NLP mechanism are tested on a scenario, where different employees report the same problem using quite different descriptions. For instance, the aforementioned “waviness” problem can be reported in the following analogous forms (queries): (Q1) “I noticed a slight waviness on part 5”, (Q2) “#waviness @part5”, and (Q3) “the stamping of part 5 is defective and the produced surface presents #waviness”. Once these queries are applied to the underlying repository of stored problems, the similarity results and their ranking are calculated (Table 1). The method correctly identifies the most relevant stored problem (No. 2) in all three cases. Even so, the inexperienced planner sets the status of the part to “red”, since it has a serious problem without reported solutions. The experienced planner and other notified employees, who may be dispersed worldwide, provide possible causes and solutions (e.g. fine-tune press force, geometry of blank-holder, blank/part geometry). The triplet problem-causes-solutions is stored into the database for future reuse. In a future die-set construction project, if the same problem reappears, the engineers will search the database, retrieve the stored problem, and reuse the accumulated solutions steps.

Table 1. Ranking and similarity results

Doc No.	Stored Problem Description	Query 1		Query 2		Query 3	
		Rank	Sim.	Rank	Sim.	Rank	Sim.
1	Lack of available storage for part	2	0.011	2	0.007	4	0.005
2	Waviness or low thickness on parts	1	0.589	1	0.590	1	0.430
3	Stamping failure produces cracked components	5	0	5	0	2	0.403
4	Slightly defective material on parts	3	0.011	3	0.007	3	0.284
5	Heat checks on the part (thermal fatigue cracks)	4	0.006	4	0.004	5	0.003

4. Conclusions and Future Work

This research work proposed a social network-based collaborative problem-solving method utilising RCA that is accessed through mobile devices. This business-oriented social network adds a layer of engineering expertise to the enterprise’s competences, helps enterprises to establish and continuously upgrade a repository of best practices for engineering problems, reduce the training curve of new employees, diminish recurrent problems, and maintain team dynamics in a context of continuous improvement, or kaizen [18].

The limitations to be considered for the employees include: (i) overcoming their hesitation to share knowledge, (ii) assure their commitment to report new problems, and (iii) avoid distracting them with the use of mobile devices on the shop-floor.

Future work will focus on enhancing the method in order to cope with the ever-increasing number of stored information and address to corporate data and business intelligence protection issues.

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