Static and Semantic Social Networks Analysis: Towards a Multidimensional Convergent Model.

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***Abstract*—Social networks of the Web 2.0 have become global (*e.g.*, FaceBook, etc). In 1977, FREEMAN published generic metrics for Social Networks Analysis (SNA), mainly based on graph-mining models. The objective of our work is to extend these static analysis models by taking the conceptual aspects of enterprises and institutions social graph into account. These conceptual aspects are embedded in trades-oriented ontologies extracted from the endogenous information, connate to the studied social networks. The originality of our multidisciplinary work is to define new multidimensional measures in SNA for new decision-making functions in Human Resource Management (HRM). This paper introduces three new contributions: (1) a metric of *tension* of a social network, (2), an extension of the FREEMAN's betweenness measure named *semantic betweenness* and (3) a notion of *reactance* of a social network used for the evaluation of the individual *stress*.**

***Keywords*-social, networks, analysis, ontologies, semantic, betweenness.**

I. INTRODUCTION

Current trends and needs of communication permanently require new functions and applications of social networking, as demonstrated by the constant eruption of new socialisation modes (*e.g.*, Twitter, Facebook Diigo). In comparison with the real spaces of exchange, these virtual spaces facilitate the static analysis and the emergence of metrics and methods dedicated to Social Networks Analysis (SNA). The measures of *centrality* introduced by FREEMAN are the basic foundation in SNA [1]. Naturally, SNA is gradually extended to enterprises, in order to provide new management tools dedicated to work organisation, workforce and human resource management tools. The culture of collaborative work is more and more paired to "Web 2.0" tools, characterising a form of enterprise "2.0", aware of human and social capital management. A social network can be formalised with a (not) directed, labelled and weighted graph. From such a structure, two kinds of SNA can be differentiated: *static SNA* and *semantic SNA*.

Static SNA studies the state S of social graphs at a time t. It is grounded on models and measures dedicated to structures - such as defined in [1], [2], [3] -, or flow-based models [4], [5]. The graphs can be random graphs [6], pseudo-random graphs [7], scale-free graphs [8] or hybrid graphs. *Static SNA* enables the classification of individuals groups or communities and the discovery of implicit relationships between individuals involved into the social graph, by computing *degrees*, *connectivities*, *distances* and *flows*. Basically, the count of edges connected to a vertex v is the *degree* of v. The count of other vertices accessible from v is the *connectivity* of v. The *distance* between two vertices is the minimal count of edges between them. An elemental *flow* is characterised by a count of units circulating between two vertices - *cf.*, electrical or hydraulic networks, road networks.

Semantic SNA studies the conceptual aspects of social graphs. It is based on the principles underlying conceptual graphs theory and semantic networks theory [9]. Semantic SNA refers to the Semantic Web standards (*i.e.*, W3C languages and micro-formats, such as RDF, OWL or FOAF), Ontology Engineering [10] and logical inferences, in correlation with cognitive sciences [11], [12]. With the exponential growth of social networks and information flows, semantic SNA becomes crucial for knowledge discovery and knowledge management, from the enterprise content to the large communities of the Web. Semantic SNA can notably bring real advantages in the areas related to social and human capital management or optimisation of work-groups and working methods, within professional organisations (societies, institutions).

Currently, not many works try to integrate the differentiated forms of analysis. The purpose of our work consists in filling this gap by defining a new convergent system based on both static and semantic analysis of Enterprises and Institutions Social Networks (EISN). Our approach is multidisciplinary, since it is based on physics and cognitive sciences. It leads to the definition of a multidimensional model enabling the development of new decisional tools for the optimisation of work and well-fare at work and for the social and human capital management. In its current version, this model includes three new contributions: (1) a metric of *tension* of a social network, (2) an extension of the L.C. FREEMAN's betweenness measure, named *semantic betweenness*, and (3) a notion of *reactance* used for the evaluation of the individual *stress* within a professional social networks.

Our work is funded by the French State Secretariat for prospective and development of the digital economy, in the context of the SOCIOPRISE project [13]. It is developed in collaboration with a French IT service and software engineering company which provides industry-leading software and implementation services dedicated to human capital management.

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The rest of this paper is structured as follows. Section 1 introduces, in a synthetic way, the principles and methods respectively used for static SNA and semantic SNA. Section 2 presents in details the approach we advocate to integrate static and semantic SNA. Our contributions are based on (1) a bridge-building between knowledge engineering and the measures of static analysis and (2) a bridge-building between the semantic SNA introduced in (1) and electric principles. Our work is dedicated to Enterprises and Institutions Social Networks Analysis - EISNA.

II. UNIDIMENSIONAL APPROACHES

A. Static Analysis

Static SNA studies the state *S* of a social graph at a time *t*, *S* being defined by the structures and/or the flows of the studied graphs. The first notions of SNA were focused on the leadership in communities [14]. These notions have been enriched with measures of centrality and betweenness [1], which characterise properties of social networks in terms of *power*, *prestige*, *proximity* and *confidence*.

The centrality measures are based on the comparison of a vertex degree or flows, to those of the graphs, neighbours or distant ones. A vertex connected to a large count of vertices in the graph (directly or not) holds an important *centrality of power* ratio. A vertex connected with the vertices of the social graphs bearing the strongest degrees holds an important *centrality of prestige* ratio. A vertex connected with a large count of close or neighbour vertices owns a high *centrality of proximity*. By induction, an important centrality of prestige and proximity can reveal a significant *trust* coefficient.

A measure of betweenness defines how an individual is important to interconnect his neighbourhood. According to [1] and [15], we formalise it as follows:

$$\forall i \neq u \neq j, \sigma(i,u,j) > 0, Iu = \sum_{(i,j)} \frac{\sigma(i,u,j)}{\sigma(i,j)} \qquad (1)$$

where $\sigma(i,j)$ is the count of shortest chains between *i* and *j*, $\sigma(i,u,j)$ is the count of shortest chains between the vertices *i* and *j* crossing *u*. The ratio $\sigma(i,u,j)$ by $\sigma(i,j)$ is cumulated for the (i,j) where $\sigma(i,u,j) > 0$. The sum can be restricted to the couples *(i, j)* for which $\sigma(i,u,j) > 0$, in order to define an approximative measure adapted to large social graphs analysis.

1) Structural Analysis: Classification (*graph-clustering*) and characterisation of graphs are the basic foundations of static SNA. Structural properties are defined for the main types of social graphs and they provide some elements of static SNA. In the context of random graphs [6], the degree of the n vertices of the graph is determined by a probability $p(n)$ with $p \mapsto [0;1]$. With pseudo-random graphs, the degree of n vertices is distributed according to an uniform distribution law (*e.g.*, law of Laplace-Gauss) where $G(V,E)$ owns a probability $p = \mid E \mid \div (\frac{|V|}{2})$, with V a set of vertices and E a set of edges. With scale-free graphs [8], the most connected nodes increase their connection degree following a power law (*"richers get richer"*). By defining specific behaviours for each type of networks and sub-graphs, these structural static properties also provide elements for dynamic analysis of social graphs.

2) Flows Analysis: Several works of graph theory (*e.g.*, the maximal flow problem) are applicable to static analysis of flows within social networks. It is particularly the case of the *small world* study in which V. LATORA et M. MARCHIORI have introduced the notion of *efficiency*, defined as a measure of communication weighted inversely proportional to the shortest path between two vertices *i* and *j* [4]. The work of J. LESKOVEC and E. HORVITZ about large social graphs (MSN - 179 millions of vertices), updates the "six degrees of separation" hypothesis, a *small world* characteristic. In [16], the MILGRAM hypothesis, advocating the ability to reach 100% of the vertices of a graph in 6 hops [17], is dropped down to only 48% of vertices reached. Following a *long-tail* curve, the distribution reaches 78% of vertices within 7 hops and for 90% of vertices, the measured mean is 7,8 hops, with a maximal shortest path of 19 hops between two vertices (measured on a sample set of 1000 vertices).

Some physics models are also treated with help of graphs for the understanding and discovery of theoretical principles. In the electricity area, the KIRCHHOFF's *law of nodes* and *law of meshes* are the most well-known illustration of this trend. The work of [5] about resistance and currents of finite networks, demonstrating the unity and continuity of flows within large graphs, brings a new hypothesis to be validated in SNA.

To sum up, static SNA provides a large set of mathematical, sociological and even physics models. These models are mainly based on the graph theory and and they can be used to discover explicit or implicit knowledge within social graphs. Some of these models are also extended to dynamic SNA [18], an aspect out of scope for this paper.

B. Semantic SNA

Semantic SNA studies the conceptual aspects of social graphs. It is founded on conceptual graphs and ontologies coupled with SNA principles [12]. Currently, to our knowledge, no significant work has been published in the domain, but the attractiveness of the subject is visible.

We define an ontology as *a formal and explicit specification of a shared conceptualisation* [10]. J. JUNG AND J. EUZENAT comment the description of a three-dimensional view of semantic SNA, putting together social graphs, annotations and ontologies *ERgraphs* - Entities/Relationships graphs, [19]. Their proposal overlays and makes the three dimensions coincide in order to build "consensual" ontologies, where annotations are linked to the social graph. ALEMAN-MEZA AND AL. introduce a semantic application for interest conflicts detection within social networks of scientific publications [20]. Based on the research of syntactico-semantic patterns, the application measures the semantic similarity between authors corpus, in order to detect possible redundancies or concurrencies within subjects shared or divided across teams. The work of [21] about semantic SNA paves the way of semantic and statistic analysis. It makes the outline of SNA operational, by integrating it to the models and languages of the Semantic Web (*i.e.*, OWL, RIF, FOAF, SIOC, MOAT, POWDER).

Rules and inferences systems, in correlation with cognitive sciences, bring a main line of SNA developments towards a semantic dimension. These developments are submitted to vertices and edges annotations, by automatic means such as statistic learning and natural language processing, or human treatments such as *social tagging*. *Reciprocal evaluation* between members of a social network shows how human interaction produces a valuation on which a reliable *degree of confidence* can be computed. We talk of *favours network* when the graph structure depends on peer-to-peer evaluations. Eventually, the integration of cognitive sciences such as linguistics, psychology or neurosciences, produces interesting results as demonstrated by ontology personalisation [11]. The hypothesis of derived methods specifically adapted to semantic SNA can be considered.

T. GRUBER cheers on initiatives which tend to integrate semantic web principles and languages, to social networks for the development of *Collective Intelligence* and *Collective Knowledge Systems* [12]. From the large Web communities to the enterprises social networks, semantic SNA can bring real progresses in different domains, such as global marketing linked to globalisation, social and human capital management or work-groups and work-methods optimisation within professional organisations, the domain in which we are interested.

III. MULTIDIMENSIONAL SYNERGIES IN EISNA

The main objective of our work is to exhibit multidimensional synergies between the static and semantic aspects in Enterprises and Institutions Social Networks Analysis - EISNA. The specificities of EISNA are: (1) social graphs composed of up to 100 000 nodes, (2) endogenous data restricted to a few specific and connate domains and (3) intensive collaborative work with trade-oriented information sharing.

The methodology we have adopted respects the segmentation of the problematics:

- Static SNA is integrated without any change. Our contribution mainly consists in providing relevant bridge-building of known methods and identified models, originally from physics or cognitive sciences. The results we provide concern new flows metrics of social graphs. Devoted to EISNA for the prevention of social risk, they consist in the definition of 2 metrics. The first metric is dedicated to evaluate a new notion named *tension of a social network* (*cf.* section III-A1). The second metric extends the L.C. FREEMAN's measure of *betweenness* (*cf.* section III-A2) which becomes semantic - *semantic betweenness*.
- Semantic SNA is developed by integrating social graphs, conceptual graph, ontologies and inferences rules. The contributions we provide can only be applied to EISNA and they are specially devoted to work organisation and social/human capital management. Currently, our third contribution consists in defining a new notion of *reactance*, which aims at the evaluation of individual stress (*cf.* section III-B).

The results we provide are jointly afforded to converge in a multidimensional model, leading to the development of decision-making tools for enterprises and institutions social networks.

A. Static EISNA, Physical Models and Cognition

Our model adopts FREEMAN's centrality and betweenness measures, starting with non-directed graphs. For instance with directed graphs, *Page-Rank* provides a score easily assimilated to a measure of *prestige* [22], and an extrapolation integrating an *authority coefficient* (author reputation), *Trust-Rank*, gives a *confidence/trust score*, also adaptable to non-directed graphs as a complement of other measures [23].

1) Static EISNA, Flows and Physical Models: To introduce some new flows measures, we test assimilation of the graph edges to conductors transporting electrical flows. Our method consists in quantifying and qualifying flows embedded in social networks with semantic ratios. These ratios are defined according to percentages of read, written or shared in common documents (*e.g.*, office, mails, instantaneous messages), exchanged data packets (ToIp, VoIp) and other numerical marks able to characterise conceptual links between individuals. Some electrical principles are adapted to static analysis of flows around a vertex, among which the KIRCHHOFF's *laws of nodes and meshes*. Figure 1 illustrates the *Law of nodes*, with *I* intensity of electrical charges for an output quantity *Q* by time unit *t*.

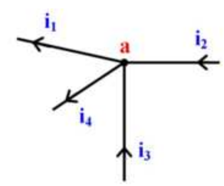

Fig. 1. Law of nodes, $\sum I_{input} = \sum I_{output}$, i2 + i3 = i1 + i4

The originality of our work consists in introducing the concept of *tension* in a social network related to the notions of *crossing flow intensity* and vertex *resistance*. A vertex *s* directly connected with two other vertices *r* and *t* can be likened to a dipole which resistance is noted *R*. We use OHM's laws:
$Urt = Rs.Irt$ and $Ps = Rs.Irt.Irt^2 = Urt.Irt^2/Rs = Urt.Irt$,
where Urt represents the electrical tension depending on Rs and Irt, and Ps represents the delivered power by a vertex of which maximal admissible power is noted $Pmax$, with $Umax = \sqrt{R.Pmax}$ and $Imax = \sqrt{Pmax/R}$.

By applying OHM's law upon a social graph, it is possible to compute a *charge-capacity* ratio of the enterprise social network, by analogy with $Ps, Pmax$. The purpose is to introduce a *stress* measure of individuals and communities. This measure uses the *Joule effect* to estimate the enterprise social network components *warm-up* and to prevent risks of performances degradation, instability or breakdown (socio-psychological trouble). The warm-up *T* depends on dissipated energy and material resistivity ρ. Since the value of ρ varies according to diversity of molecular structures, its computation gets out of the scope of this paper. So, it must be considered that the *social material* is *a priori* abstracted as a constant by initialising algorithms with ρ = 1, let $T.\rho = W = R.I^2.\Delta t$. Next, ρ should be refined by $\rho \mapsto [0;1]$, according to a defined determinant used to induce recursive interaction between *T* and *R* encountered in physics, where ρ is varying according to *T*.

2) Static EISNA and cognition: Manual resources tagging requires cognitive processes. In the context of EISNA, this method can lead to psychological rejects mainly caused by political and ethical aspects. To be more ethically acceptable, manual tagging should be limited to non-human resources (documents, textual corpus, databases). The characterisation of individuals and groups must be based on criterias respecting persons and privacy.

By associating terms used to annotate trades-oriented resources with of concepts of an ontology, the semantisation of annotation process facilitates the discovery of *communities of practice* by the means of implicit relationships between annotated resources. According to this standpoint, we use trades-oriented ontologies to qualify numerical analysis of social graphs. Technically, this is done by correlating statistic results obtained on flows and structures to ontological conceptual graphs.

From the equation (1), we define a new measure of *semantic betweenness* weighted by endogenous resources (*i.e.*, mainly annotated documents with help of terms) where (1) each annotation is associated to at least one individual of the considered social network and where (2) the sum of annotation occurrences calibrates favourably the measure for the individuals who share resources associated to the majority annotations.

This new measure is defined in the following context. Explicit relationships between the set of human resources *Rh*, the set of resources *Rsi* extracted from the information system and the set of content annotations *Esi* are used to enrich EISNA and discover some implicit relationships.

We introduce the sets Rh, Rsi, Esi and the relationships R, R' and avoid to compute wastefulness reflexive relationships (*e.g.*, relationships in $RsiXRsi, EsiXEsi$).
We define a relationship $R(D, D')$ where:
$D = Rh$ or $D = Rsi$, $D' = Rh$ or $D' = Rsi$ or $D' = Esi$.
We define a new set of measures by introducing a weighting ratio C_p, based on the cardinality of R. When the SNA metric to which we apply our semantic extension method gives a result superior to 0, for a vertex u within a social graph, we modify the metric by integrating the C_p factor. The factor increases the value of the SNA measure for the vertices sharing the same knowledge. C_p uses the cardinality of the relationship R, relationship between the graph represented by pD, and the endogenous content or its indexation, represented by pD'. pD and pD' are respectively restricted by the arguments eD, eD', where eD represents an element of pD (*e.g.*, u) and eD' represents one or several elements of the content or the index, given by pD' (*e.g.*, some keywords). C_p is formalised as follows:

$$\textit{SNA metric} > 0 \wedge C_p = |R(pD, pD', eD, eD')| \quad (2)$$

We have simulated the behaviour of a betweenness centrality incorporating the C_p factor. The simulation is combining some one-decimal values ranged from $0,1$ to 1.0 for the centrality, and some values from 1 to 10 for the C_p factor. It aims at the estimation of three alternatives of the use of C_p. These alternatives are formalised as follows, with V the vertices of $G(V, E)$, $semindex$ a semantic index of the endogenous content, u a vertex in V and $knowledge$, a knowledge set related to seized keywords:

$$B_{Cp}(u) = \sum_{ij} \frac{\sigma(i,u,j)}{\sigma(i,j)} \times |R(V, semindex, u, knowledge)| \quad (3)$$

$$B_{Cp}(u) = \left(\sum_{ij} \frac{\sigma(i,u,j)}{\sigma(i,j)} \right)^2 \times |R(V, semindex, u, knowledge)| \quad (4)$$

$$B_{Cp}(u) = \sum_{ij} \frac{\sigma(i,u,j)}{\sigma(i,j)} \times \sqrt{|R(V, semindex, u, knowledge)|} \quad (5)$$

The figure 2 illustrates the behaviour of the equation (3) in green, of the equation (4) in blue and of the equation (5) in red (*i.e.*, the lowest curve). The output values are presented vertically and the samples used for the simulation are numbered horizontally.

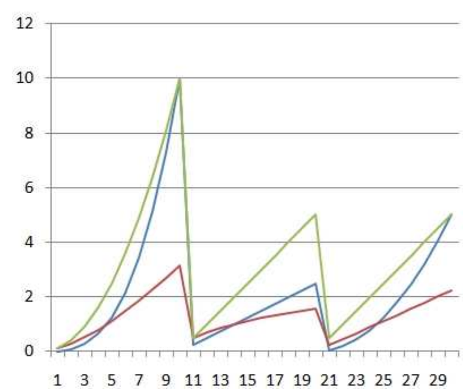

Fig. 2. Simulation of the C_p integration with the betweennes centrality.

C_p can reach a value superior to 1000 in the context of the *Socioprise* project. Therefore, we choose to weak its influence, using equation (5). When $C_p > 0$, the equation (1) is modified as follows:

$$B_{Cp}(u) = \sum_{ij} \frac{\sigma(i,u,j)}{\sigma(i,j)} \times \sqrt{|R(V, semindex, u, knowledge)|} \quad (6)$$

Equation (6) introduces a new measure of *semantic betweenness*, based on [1]. This measure takes a qualitative dimension into account by integrating endogenous information contained in Rsi and Esi, to the calculus of betweenness centrality. C_p is quantified and qualified by eD, eD' through ontologies enabling semantic association of elements in Rsi and Esi. The discovered knowledge in these conceptual associations is the strong point of this new "smart" measure.

B. A use case of semantic EISNA

Sections III-A1 and III-A2 have introduced an analogy between flows and structures analysis within social networks, and some principles close to radio-electricity which seem to be relevant. We have put forward notions of *resistance, charge, capacity, warm-up* and *powers*. This context is used to characterise implicit or explicit relationships $R_s(i,j)$ between the vertices of a social graph. Our goal is to cross these relationships with semantic properties (object or data properties) represented by one or more domain ontologies to conceptualise interactions within the social graph.

The notion of *reactance* already exists in electrodynamic and social psychology. In electrodynamic, the reactance (in Ohms) describes the energy opposed to an alternative current. WANG uses reactance as a parameter of a neuron network, to control the defects of an electrical network, depending on the kind of element crossed [24]. In psychology, the reactance characterises "*a state of negative motivation following a menace (supposed to be real) of individual freedom restriction that is translated into a influence resistance*" [25].

In our work, we propose to use the *reactance* Ψ as a notion of individual stress. From the metric of *tension* defined in section III-A, we draw up the following assertions :

Let a graph $G(V,E)$ where vertices of V are connected by the edges of E, respecting the following properties:

- Each element v of V intrinsically holds coefficients resulting from classical measures of social networks (*cf.* Freeman) or possible refinements.
- $\forall(u,v) \in V$ connected by $e \in E$, u, v intrinsically holds analogical values of *resistance, charge, capacity, warm-up, powers* depending on V, E.
- $\forall e \in E$ assimilated to an uncharacterised flow ϖ, owning a quantifiable value $\varphi_\varpi \neq 0$, e is intrinsically described by values of *resistance, charge, capacity, warm-up* and *powers*. For e, $\vec{\varpi}$ or φ_ϖ are measured as a pseudo-tension T_e or pseudo-intensity I_e.

From these assertions and the results of experiments managed in the context of the SOCIOPRISE project (*i.e.*, a project dedicated to human and social capital management) within trade-oriented organisations, we offer a first set of knowledge dedicated to the identification of individual stress. This set of knowledge can be represented by the following rules and axioms:

* **rule 1**:
  If $CC_u = \frac{charge_u}{capacity_u}$ increases and $CC_u < 80\%$,
  then Ψ_u increases.
  By analogy with electronic power networks, we integrate the notions of minimal charge threshold under which the performance collapses.
* **rule 2**:
  if $P_u = \frac{resistance_u.intensity_u^2}{Pmax_u}$ increases and $P_u \leqslant 1$,
  then Ψ_u and $warm{-}up_u$ increases (P_u represents a used power).
* rule 2 *bis* (inference learning on rule 2):
  if $warm - up_u$ increases,
  then Ψ_u increases.
* **rule 3**:
  if P_u increases and $P_u > 1$,
  then Ψ_u decreases, $Pmax_u$ decreases and $warm - up_u$ quickly increases (P_u has exceeded $Pmax_u$).
* **rule 3 *bis*** (*inference learning on rule 3 and experts supervision*):
  if Ψ_u decreases and $warm - up_u$ increases,
  then quick decreasing of $Pmax_u$ and destruction risk.
* **axiom 1** (*inference supervised learning on rule 1*):
  if $CC_u \leqslant 0.8$,
  then risk to lose socio-professional performances.
* **axiom 2** (*inference learning on rule 3 and 3 bis*):
  if $P_u > 1$,
  then risk of socio-professional troubles.
* **axiom 3** (*inference supervised learning on axioms 1 + 2 and their premisses*):
  performance optimisation is equivalent to $CC_u > 0.8$ and $P_u \leqslant 1$.
* **axiom 4** (*learning from symmetry on axiom 3 and his premisses*):
  risk of socio-professional troubles is equivalent to risk of loss of socio-professional performances.

From the equations system underlying these rules and axioms, we are currently formalising an innovative scalar metric of *reactance* Ψ_u. From the multidisciplinary model we define, we plan to get an innovative tools-set for decisional applications dedicated to social capital management. These tools combining SNA metrics, knowledge engineering, ontologies and sociology, applied to enterprise content and to enterprise or institutions social networks (*e.g.*, LDAP Directories or other structures), will enable an innovative approach of human capital management and human risk management.

IV. CONCLUSION

The purpose of our work is to define a model of enterprises and institutions social networks analysis (EISNA). The main originality of this model is to integrate the static and the semantic dimension of EISNA. Our current proposal is based on 3 contributions, defined in the context of a multidisciplinary approach. These new contribution are respectively dedicated to the evaluation of *tension*, *semantic betweenness* and *reactance*, for professional social networks analysis.

Our introduction of semantics in the FREEMAN's measures enables to qualify some collaborative and quantified exchanges, while establishing new centrality degrees for a semantic identification of knowledge communities within enterprises and institutions social networks. The possible new measures extended by our approach correlate statistic and conceptual dimensions through endogenous resources and scientific multidisciplinarity.

This work is a baseline for the development of new decision-making functions and tools applied in social and human capital management of enterprises and institutions. Compared to some usual methods of sociometry such as internal surveys, our model ought to significantly reduce the bias, while answering to the problems of socio-professional troubles risk prevention, performances loss risk prevention and social risk prevention.

From an applicative standpoint, our proposal is currently evaluated in the context of an experiment related to the SOCIOPRISE project. From a theoretical standpoint, this work is currently in progress towards the integration of dynamic aspects of EISNA. We plan to use AMPERE's laws and MAXWELL's laws of electrodynamic, in order to advocate a predictive analysis of social networks structural evolution.

The main applicative perspective of this approach is to assist the optimisation of work-groups and performance in an enlarged context, such as a pool of enterprises and institutions. The main theoretical perspective is to formalise *a complex and multidimensional model (static, dynamic and semantic) dedicated to professional social network analysis*.

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