USN: Multi-Objective User-centric Social Networks with Decision Making

Panayiotis Andreou*, Panagiotis Germanakos†, Andreas Konstantides‡,
Dimosthenis Georgiadis*, Marios Belk* and George Samaras*
*Department of Computer Science
University of Cyprus, P.O. Box 20537, 1678 Nicosia, Cyprus
Email: {panic,cspggd,belk,cssamara}@cs.ucy.ac.cy
†Department of Management and MIS
School of Business, University of Nicosia, Cyprus
Email: pgerman@cs.ucy.ac.cy
‡Department of Computer Science
Frederick University, 1036 Nicosia, Cyprus
Email: com.ca@fit.ac.cy

***Abstract*—Social network portals, such as Facebook and Twitter, often discover and deliver relevant social data to a user's query, considering only system-oriented conflicting objectives (e.g., time, energy, recall) and frequently ignoring the satisfaction of the individual "needs" of the query user w.r.t. its perceptual preference characteristics (e.g., data comprehensibility, working memory). In this paper, we introduce *User-centric Social Network (USN)*, a novel framework that deals with the conflicting system-oriented objectives of the social network in the context of Multi-Objective Optimization and utilizes user-oriented objectives in the query dissemination/acquisition process to facilitate decision making. We present the initial design of the USN framework and its major components as well as a preliminary evaluation of our framework. Our trace-driven experimentation with real datasets show that USN enhances the usability and satisfaction of the user while in parallel provides optimal system-choices for the performance of the network.**

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I. Introduction

The evolution of smartphone devices (e.g., Android, iPhone) along with the ascend of social networks (e.g., Facebook, Twitter) has enabled the invention of myriad of applications that allow users to continuously interact and share social data (i.e., images, videos, documents, etc.) [1]. This is more evident in the case of mobile smartphone users, where new data is generated arbitrary at runtime within the context of a social event (e.g., taking pictures of sights, participation at social events). This data is typically accessed using a portal provided by the social network provider, which often includes utilities for searching and retrieving social data based on keywords that describe their content [2]. Additionally, since this data are socially related with real events, they are often augmented by time and location properties that enable mobile users to search/query data based on spatio-temporal parameters. The results of the query are often ranked by their social relevance to the query user. Social factors (e.g., common friends, similar interests) are fed into the ranking process in order to present to the user what is perceived to be the "most relevant" content for his/her query. Even though these social factors can efficiently determine the *what* social content is more relevant, they do not take into consideration the *how* this social content is presented to the query user.

It is a fact that the environment of most social network portals is not user-centric (i.e., social content is presented using a global representation scheme applicable to all users based on predetermined categorization). For example, searching for images of the Parthenon in Athens will always return a list of relevant images in a predefined manner (e.g., thumbnail, description). However, this global representation scheme is not always optimized based on specific user intrinsic characteristics (e.g., cognitive learning ability, working memory span) that could significantly enhance its understanding and satisfaction. Hence, a number of researchers studied adaptivity and personalization [3], [4], [5], [6], [7] to address the comprehension and orientation difficulties presented in such systems; to alleviate navigational difficulties and satisfy the heterogeneous needs of the users.

Content adaptation techniques require the existence of a user profile, which is constructed based on a number of user-centric parameters. A subset of these parameters quantify the users' intellectuality, mental capabilities, socio-psychological factors, emotional states and attention grabbing strategies. These are further augmented by the traditional user characteristics (i.e., name, age, education, etc.) in order to constitute a more comprehensive user profile that typically classifies users to various cognitive typologies (e.g., imager/verbalizer[1]). The process of content adaptation takes into account the parameters included in the user profile and returns the best adaptive environment that meets the individual preferences and demands of each user. The majority of social network portals do not take into consideration this process thus decreasing the usability of the results, which may also have a negative effect on the

[1]Users that belong in the imager class can proportionally process image content more efficiently than text, whereas users that belong in the verbalizer class the opposite.

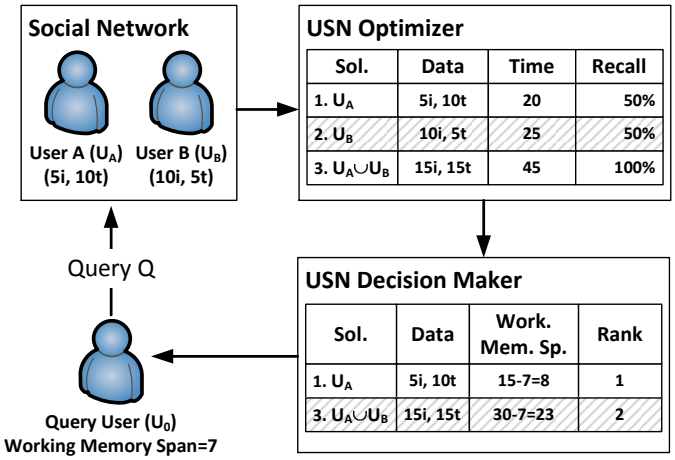

Fig. 1. Example of query dissemination and data acquisition in the USN framework.

performance of the network; omitting a subset of the results because of low usability metrics will require less time/energy for transmitting them over the network. An example that demonstrates this argument is a verbalizer user requesting recent newsfeeds on his/her friends. The results may include undesirable content (i.e., images) that can significantly hamper the user's comprehension capability and additionally require more resources (i.e., energy, time) in order to be transmitted. One way to cope with the aforementioned problem is to introduce a ranking process at the social network portal that dynamically adapts/filters the results in order to meet the individual requirements of the user.

Enabling dynamic adaptation of the environment while in parallel aiming to optimize the runtime performance requirements of the network is not a trivial task as it requires tackling a number of conflicting parameters (e.g., energy, time, usability). This process becomes even more complicated if we additionally take into account the recourse limitations of smartphone devices (e.g., battery, screen size) and the security/privacy[2] requirements of the user. Because so many different parameters are involved, the respective problem is a proper object for *Multi-objective Optimization (MOO)*. In MOO, there is no single solution that optimizes all objectives simultaneously but instead a set of non-dominated solutions commonly known as the Pareto Front (PF). Our framework opts for a subset of these solutions that increase the usability of the social network taking into account the individual preferences of each user, facilitating in this way decision making.

In particular, in this paper we present User-centric Social Network (USN), a novel framework that combines system-oriented with user-oriented objectives in order to increase both the network performance as well as the query user's satisfaction. To the best of our knowledge, no previous work has combined the disciplines of multi-objective optimization and decision making with content adaptation and personalization in order to increase both the performance of the network and usability of the users' tasks and experiences.

To facilitate our description consider a simple scenario, as the one depicted in Figure 1, which demonstrates how a query $\mathcal{Q}$ is processed by the USN framework. Assume that the Query User (U_0) posts $\mathcal{Q}$ to the Social Network Portal, which contains two users (User A (U_A) and User B (U_B)) that maintain social data relevant to $\mathcal{Q}$. The *optimization phase* of the USN framework starts by producing a set of *solutions* (i.e., different combinations of the social data of users A and B) and then evaluates them using the system-oriented objectives. In our example, three solutions are produced: 1. U_A (data from U_A); 2. U_B (data from U_B); and 3. $U_A \cup U_B$ (data from U_A and U_B). These solutions are then evaluated using the Time overhead and Recall system-oriented objectives. We observe that solution 2 has been eliminated as it is dominated by solution 1 (i.e., Time(Solution 1)$<$Time(Solution 2) and Recall(Solution 1)=Recall(Solution 2)). In the *decision making phase* of the USN framework, both solutions generated by the optimization phase are used as input in the decision maker in order to be evaluated using the user-oriented objectives. In our example, we have utilized the user-oriented objective Working Memory Span, which indicates the amount of information that can be efficiently processed by a user in a restricted period of time. Note, that the Working Memory Span value is directly drawn by the User Profile of the Query User. In our example we have set the Working Memory Span of U_0 to 7, which means that U_0 can only process 7 elements efficiently. Solution 1 ranks 1st as it produces 15 objects (5 images and 10 text fields), 8 more than U_0's Working Memory Span preference whereas Solution 2 produces 23 objects more. In the final step, the social data objects from U_A are returned to U_0.

In our example, we have demonstrated the usage of two system-oriented objectives (i.e., Time and Recall) and one user-oriented objective (i.e., Working Memory Span). However, the USN framework's architecture is open to support a number of system-oriented objectives as well as various user-oriented objectives. In Section IV, we demonstrate how three representative system-oriented objectives and two representative user-oriented objectives can be utilized in USN. The decision on which of these objectives should be utilized and their importance rests upon the administrator of the social network portal according to the organization's quality metrics. For example, an administrator may assign different weights to the objectives according to the requirements of the application (e.g., Time is 70% important, Recall is 20% important and Recall is 10% important).

USN extends our previous work in [8] by introducing three new features. Firstly, in addition to system-oriented objectives, in this work we introduce user-oriented objectives that are based on cognitive factors (i.e., cognitive styles and working memory) and represent the internal psychological traits of users. These traits tend to enrich decision making mechanisms for increasing usability and satisfaction during interaction. Secondly, we present an open architecture design, which can accommodate a different number of system-oriented

[2]In this paper, we do not consider security/privacy requirements but we plan to address them in a future work.

and user-oriented objectives. These objectives can be expanded according to the needs and requirements of the organization. Finally, we introduce a decision maker that opts for the most efficient solution automatically by utilizing the user-oriented objectives extracted from the user profile.

Our main contributions are summarized as follows:

- We propose a novel framework, coined USN, that combines system-oriented with user-oriented objectives into the query execution process increasing in this way the network performance as well as the query user's satisfaction.
- We present the architecture of the USN framework including detailed descriptions of its major components.
- We present a preliminary evaluation of the proposed framework using real datasets with user profiles and mobility patterns derived from the GeoLife project [9].

The remainder of the paper is organized as follows: Section II discusses the related work. In Section III and Section IV we present our system model and a formal definition of the proposed problem. The architecture of the proposed USN framework is introduced in Section V, providing details for each component. The experimental methodology, setup and results are shown in Section VI and Section VII. Finally, Section VIII concludes the paper.

II. BACKGROUND AND RELATED WORK

The USN framework is primarily composed of two phases: i) the optimization phase, which incorporates system-oriented objectives in order to produce a set of non-dominated solutions (i.e., collections of data from different users); and ii) the decision making phase, which takes as input the solutions of the optimization phase and the user-oriented objectives derived from the query user's profile in order to rank the solutions and select the most suited one. In this section we provide related research work on multi-objective optimization and cognitive user profiles both of which lie at the foundation of the aforementioned phases.

A. Multi-Objective Optimization (MOO) & Decision Making

MOO is a new area in smartphone networks and relatively new area in mobile/wireless networks, in general. As a result, existing linear/single objective methods cannot be used to directly tackle a Multi-objective Optimization Problem (MOP), such as the one presented in this paper. On the other hand, *Multi-Objective Evolutionary Algorithms (MOEAs)*, have been shown effective in obtaining a set of non-dominated solutions in a single run. In the literature, several MOPs were proposed within the context of Wireless Sensor Networks and Mobile Networks [10], tackled in most cases by Pareto-dominance based MOEAs, such as the state-of-the-art Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) [11], the Strength-Pareto Genetic Algorithm II (SPGAII) [12], etc. The particular class of decompositional MOEAs (MOEA/D) [13] utilized in this work, have been shown to be efficient and effective with combinatorial real life MOPs [14], [15] by incorporating scalar knowledge and techniques. MOEA/D has been applied to the Deployment and Power Assignment Problem (DPAP) of Sensor Networks [14] as well as the Mobile Agent-based Routing problem [15].

In general, a MOP solution obtained by MOEA refers to a feasible set of pareto-optimal solutions without committing any information about what represents a suitable compromise solution. This is due to the fact that all solutions are equally important. Therefore, in most cases a decision making phase [16], [17] is required after the optimization phase to address this problem (i.e., select the most suitable compromise solution from the pareto-optimal set). A decision maker [18] is usually a human expert about the problem and is utilized for deciding which is the most appropriate solution. In our setting, the decision making is accomplished using the user-oriented objectives derived from the query user's cognitive profile.

B. Cognitive User Profiles

Effective personalization of content involves two important challenges: i) accurately identifying users comprehensive profiles, and ii) adapting any content and processes in such a way that enables efficient and effective navigation and presentation to the user. User Perceptual Preference Characteristics (UPPC) [6], [7], serve as the primal personalization filtering element that, apart from the "traditional" (predetermined characteristics), emphasizes on a different set of characteristics, which influence the visual, mental and emotional processes that mediate or manipulate new information that is received and built upon prior knowledge, respectively different for each user or user group. These characteristics (see Figure 2), which have been primarily discussed in our previous works [6], [7], have a major impact on visual attention, cognitive and emotional processing that takes place throughout the whole process of accepting an object of perception (stimulus), until the comprehensive response to it. Figure 2 also shows the possible content transformations/enhancements during the adaptation process based on the influence of the human factors and the theory of individual differences. The information processing parameters that we have used and evaluated in the case of an eLearning and eServices [7] environment comprise a comprehensive user model that includes the following three dimensions: i) Riding's and Cheema's Cognitive Style Analysis [19], ii) Cognitive Processing Speed Efficiency, and iii) Emotional Processing. The role of cognitive abilities and information processing within mobile environments constitutes a core research direction considering the constraints and characteristics of such environments.

In our context-based mobile social network setting, we have opted for two representative cognitive factors (i.e., user-oriented objectives), the Cognitive Style and Working Memory Span that are considered of high significance in such environments [20], [6], [7], [21], [22]. Mainly, our approach has been driven by the difference in cognitive information processing capabilities [23] of the user. The efficient delivery of data in terms of presentation and capacity can balance the users' cognitive load (maintaining this way the same efficiency levels during a task's execution), while at the same

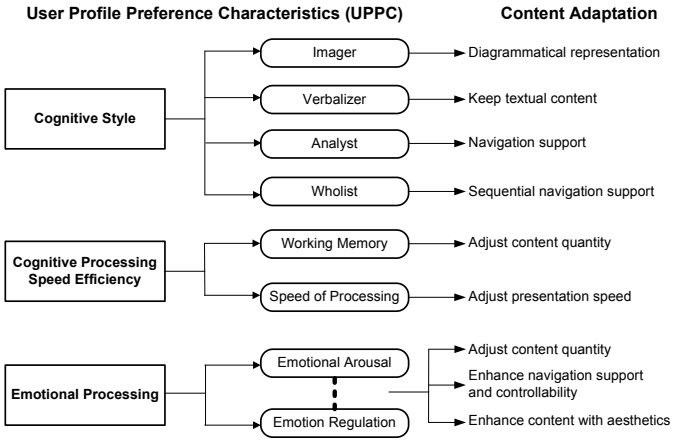

Fig. 2. Cognitive Styles Classification [6]

time keeping mobile systems at an optimized level of functionality and performance. Many reviews have suggested that hypertext and hypermedia reading induces higher cognitive load to users [20], [21], [22] and that proper structuring the content and reducing the number of objects presented are both beneficial for users with lower cognitive abilities.

III. SYSTEM MODEL

In this section, we formalize our system model and the basic terminology upon which we describe our framework. The main symbols and their respective definitions are summarized in Table I. Let SNP denote a social network portal that maintains a set of users $\mathcal{U} = \{u_1, u_2, ..., u_N\}$ along with their respective profiles $\mathcal{P} = \{p_1, p_2, ..., p_N\}$. The profile p_i of a user u_i contains its UPPC attributes, including its cognitive style p_i^{cs}, and its working memory p_i^{wm}. Additionally, we augment each user u_i with a set of social data (e.g., text, images, documents). In our setting, we assume that a subset of this data is stored in $\mathcal{S}$ and is publicly available to other users[3]. At an arbitrary moment, a user U_0 disseminates a query $\mathcal{Q}$ to the network requesting social data from other users. Users in close proximity to u_i may be queried using short range wireless connectivity (e.g., Bluetooth). This process can be repeated recursively in order to reach users that are located more than 1-hop away from U_0. Finally, other users can be queried through the social network portal $\mathcal{S}$, which creates a network with users that are currently online and in social or location proximity to the query user. In this paper, we adopt the notion of a *social network graph*, $\mathcal{G}$ ($\mathcal{G} \subseteq \mathcal{U}, \mathcal{G} \neq \emptyset$), for all the users that receive Q from u_i (i.e., in close proximity, or through the network portal). A solution $X = \{X_i : X_i \subseteq \mathcal{U}, X_i \neq \emptyset\}$ generated by the optimizer contains a set of users that can produce results for query $\mathcal{Q}$. Each X_i is then evaluated using a set of system-oriented objectives $f_1, f_2, ..., f_i$ and a set of non-dominated solutions X' is produced. In the next step, the ranking of each

[3]In this work, we do not consider security/privacy requirements but we plan to address them in a future work.

TABLE I
TABLE OF SYMBOLS

Symbol	Description
$\mathcal{S}$	Social Network Portal
$\mathcal{U}$	Users of $\mathcal{S}$ ($\{u_1, u_2, ..., u_N\}$)
$\mathcal{P}$	User Profiles of $\mathcal{S}$ ($\{p_1, p_2, ..., p_N\}$)
p_i^{wm}	Working Memory value stored in u_i'profile
p_i^{cs}	Cognitive Style value stored in u_i'profile
U_0	Query User
$\mathcal{Q}$	Query for social data
$\mathcal{G}$	Social Network Graph
PF	Pareto-front: set of non-dominated solutions
$\mathcal{X}$	a solution ($\mathcal{X} \in PF$)

$X'_i \in S'$ is evaluated using a set of user-oriented objectives $g_1, g_2, ..., g_j$ and the k-highest ranked solutions are returned to the query user U_0. In the cases where k=1 then only the solution with the highest rank is returned to the query user U_0.

IV. PROBLEM FORMULATION

In order to formulate our problem as a Multi-objective Optimization Problem (MOP) with Decision Making (DM), we need to explicitly define the MOP objectives as well as the objectives for posteriori DM. Recall that these objectives are classified into two categories: i) system-oriented objectives; and ii) user-oriented objectives, respectively. In this work, we start by formulating our MOP problem using three representative system-oriented objectives S1:Energy Consumption, S2:Time Overhead and S3:Recall.

Objective S1: *Minimize the total* Energy *consumption of* $\mathcal{G}$

$$Energy(\mathcal{G}) = MIN(\sum_{u_i \in \mathcal{G}} e(u_i, \mathcal{Q})). \tag{1}$$

where, $e(u_i, Q)$ denotes the energy consumption for transmitting all data objects of u_i that satisfy the filters of Q over the respective edge (WiFi, Bluetooth and 3G).

Objective S2: *Minimize the* Time *overhead of* $\mathcal{G}$

$$Time(\mathcal{G}) = MIN(\sum_{u_i \in \mathcal{G}} t(u_i, Q)). \tag{2}$$

where, $t(u_i, Q)$ denotes the time overhead for transmitting all data objects of u_i that satisfy the filters of Q over the respective edge.

Objective S3: *Maximize the* Recall *rate of* $\mathcal{G}$

$$Recall(\mathcal{G}, \mathcal{Q}) = MAX(\frac{Relevant(\mathcal{G}, \mathcal{Q}) \cap Retrieved(\mathcal{G}, \mathcal{Q})}{Relevant(\mathcal{G}, \mathcal{Q})}) \tag{3}$$

Our framework utilizes the aforementioned system objectives in order to obtain the pareto-front PF. In order to facilitate DM and opt for the most user-efficient solutions, the Pareto-optimal solutions $\mathcal{X} \in PF$ obtained are then evaluated using U1:Comprehension Ability and U2:Cognitive Overload

user-oriented objectives. Note that the values for U1 and U2 are extracted from the profile p_i of the user u_i:

Objective U1: *Maximize Comprehension Ability*

$$CA(\mathcal{X}, p_i) = MAXcs(r(\mathcal{X}), p_i). \quad (4)$$

where, $cs(r, p_i)$ denotes the evaluation of the comprehension ability of user u_i over the results $r(\mathcal{X})$ based on its *cognitive style*.

Objective U2: *Minimize Cognitive Overload:*

$$CO(\mathcal{X}, p_i) = MIN(wm(r(\mathcal{X}), p_i)). \quad (5)$$

where, $wm(r, p_i)$ denotes the evaluation of the cognitive overload of user u_i over the results $r(\mathcal{X})$ based on its *working memory*.

Decision Making/Support Fitness Error:
In order to rank each PF solution, we define the *fitness error* as the *distance* of a solution $\mathcal{X}$ from the optimal solution (i.e., the difference between the obtained user-oriented objective values and the actual/exact values provided from the user profile).

$$FitnessError = |CA(\mathcal{X}, p_i) - p_i^{cs}| + |CO(\mathcal{X}, p_i) - p_i^{wm}|. \quad (6)$$

In the final step, USN ranks the solutions based on the fitness error and returns either the first one (i.e., automated decision making) or the k-most important ones (i.e., decision support).

V. USN FRAMEWORK

In this section, we provide the architecture of the USN framework including descriptions of its major components. Figure 3 illustrates the components of the USN framework and their interactions.

In the USN framework, each smartphone device stores its data (e.g., images, documents) in the device's local storage. This data can be augmented with location and time attributes to enable spatio-temporal queries. The current location can be retrieved either by using absolute means (e.g., GPS) or relative means (e.g., WiFi RSSI).

When a user u_0 decides to search for social data, then the device's interface generates a query $\mathcal{Q}$ and disseminates it to the social network. The social network portal recursively forwards $\mathcal{Q}$ to users not in close location or social proximity to u_0, similar to [24]. In the end, a set of candidate users that can participate in $\mathcal{Q}$ are discovered. Candidate users can be in close social proximity (i.e., the query is received by the portal) or in actual proximity (i.e., the query is received by another smartphone device, which then forwards the query to near-by users).

As soon as candidate users are selected then they are forwarded to the *Optimizer* which generates solutions (i.e., sets of users, their social data and the connectivity among them).

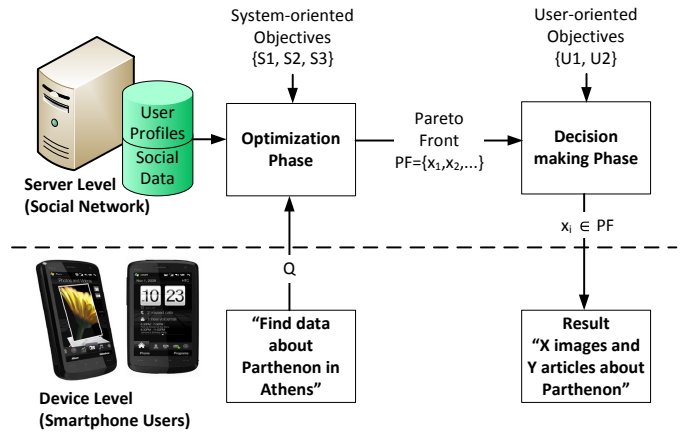

Fig. 3. USN Framework Architecture

Then, these combinations are evaluated using the system-oriented objectives until the set of non-dominated solutions (PF) is generated. The PF is then fed to the *Decision Maker*, which takes as input the query user's profile and extracts the user-oriented objectives. Each solution in the PF is then ranked using the fitness error (calculated by user-oriented objectives and the values in the query user's profile). The data of the most efficient solution are returned to the query user's smartphone.

The sections below we provide more detailed information on the major components of the USN framework.

A. User Profiles

The User Profiles comprises of all the information related to the user (traditional characteristics, cognitive characteristics, and characteristics that change over time (i.e., users current location, navigation experience, etc.). It consists of two phases:

1) *User Profile Construction*: The user profile construction process takes place on a workstation with adequate resources (e.g., large screen size) because the online realtime psychometric tests each user has to undertake require realtime performance. Users provide their traditional characteristics (i.e., name, age, education, etc.) and perform a number of interactive tests using attention and cognitive processing efficiency grabbing psychometric tools [25], [6], [7] in order to quantify the cognitive characteristics of the user. These characteristics, include: i) Ridings Cognitive Style Analysis (CSA) [19] for the Cognitive Styles dimension, and ii) a series of real-time measurements for Working Memory Span [26], similar to tests developed on the ePrime platform [25].
2) *User Profile Maintenance*: The user profile maintenance process is responsible for maintaining up-to-date profiles with regards to the dynamic characteristics of the user (i.e., time and location, navigation experience, device/channel characteristics, etc.). This is achieved by continuously profiling the user's navigation experience on the personalized content (e.g., with the use of click streams or explicit feedback of the user).

B. Optimizer

The USN optimizer utilizes the MOEA/D approach for generating the Pareto-optimal set of solutions (i.e., Pareto-Front), since it has been shown promising in dealing with real life MOPs as discussed in Section II. In order to accomplish this, the MOP is firstly decomposed into m subproblems by adopting any technique for aggregating functions [13] (e.g., the Tchebycheff approach used here). The ith subproblem is in the form

$$maximize \quad g^i(\mathcal{G}|w_j^i, z^*) = max\{w_j^i|f_j(\mathcal{G}) - z_j^*|\} \qquad (7)$$

where f_j, ($j = S1, S2, S3$), are the system-oriented objectives of our MOP formulated earlier in Section IV, $z^* = (z_1^*, z_2^*, z_3^*)$ is the reference point, i.e. the maximum objective value $z_j^* = max\{f_j(\mathcal{G}) \in \Omega\}$ of each objective f_j and Ω is the decision space. For each Pareto-optimal solution $\mathcal{G}^*$ there exists a weight vector w such that $\mathcal{G}^*$ is the optimal solution of (7) and each solution is a Pareto-optimal solution of the MOP in Section IV.

In MOEA/D, the Internal Population (IP), which is the set with the best solutions found for each subproblem i during the search, is randomly initialized. At each generation (i.e., iteration) a new solution O is generated using the genetic operators [13] (tournament selection, 2x crossover, random mutation). Next (during update), the IP, the neighborhood of i (i.e., the solutions of the T closest subproblems of i in terms of their weight coefficients $\{w_1$,..., $w_m\}$) and the external population (i.e., the PF which stores all the non-dominated solutions found so far during the search) are updated with O. The search stops after a predefined number of generations. More details on MOEA/D are presented in [13]. In the final step, the generated PF solutions are fed into the Decision Maker for ranking.

C. Decision Maker

The Decision Maker calculates the fitness error of each solution $\mathcal{X} \in PF$ based on Equation 6. Next, it ranks the solutions based on the calculated fitness error and opts for the most efficient one w.r.t. the user preferences.

The Decision Maker also supports a k-ranking process that and opts for the k most efficient solutions instead for a single one [18]. The intuition behind utilizing a ranking mechanism instead of opting for a single solution $\mathcal{X}$ w.r.t. the fitness error is that in some cases, a solution $\mathcal{X}$ with the lowest fitness error may be less preferable (by the network administrator) than a solution $\mathcal{Y}$ w.r.t. its system-oriented objective values (e.g., $\mathcal{Y}$ requires less energy than $\mathcal{X}$).

As soon as the final set of solution(s) is produced, the Decision Maker returns the results to the query processing mechanism, which in turn forwards the results to the query user.

VI. EXPERIMENTAL METHODOLOGY

In this section, we describe our trace-driven experimental methodology in order to assess the effectiveness of our framework.

Datasets and Queries: For our problem setting, we have used the following three datasets:

i) *UPPC*: This is a real dataset, obtained by the AdaptiveWeb project[4] which includes user profiles of a number of students of the University of Cyprus and University of Athens. It contains profiles of 327 students; 40% male, and 60% female, with ages varying from 19 to 23. Each profile contains information regarding the students cognitive characteristics including its Cognitive Style (objective U1) and Working Memory Span (objective U2). These profiles were derived after running a number of psychometric experiments provided by the AdaptiveWeb Project.

ii) *SocialData*: Each user profile from the UPPC dataset was augmented with the user's social data content of Facebook. Using the Facebook's Developer API [5], we retrieved the photo albums (i.e., photo album description and number of photos [6]), posts from the UPPC users's Facebook accounts and friend list. The text contained in the album descriptions and posts where used for keyword-based queries. The friend list was utilized for building the social network graph for our experiments. In the cases where users did not provide consent album descriptions and posts, we retrieved only their friend list.

iii) *GeoLife* [9]: In order to introduce mobility in our experiments, we have utilized a publicly available real dataset by Microsoft Research Asia, which includes 1,100 trajectories of a human moving in the city of Beijing over a life span of two years (2007-2009). The average length of each trajectory is $190,110 \pm 126,590$ points, while the maximum trajectory length is 699,600 points. In order to link datasets (i+ii) and (iii) we randomly selected 327 users of the GeoLife dataset and mapped them with users of the UPPC dataset. At each timestamp, we select a user u_i as the query user and execute the following query (in SQL-syntax:
$\mathcal{Q}$= `''SELECT * FROM Users WHERE keyword LIKE filter''`, where *filter* is a keyword (e.g., dancing).

Experimental Setup: Our simulation experiments were performed on a Lenovo Thinkpad T61p PC with an Intel Core 2 Duo CPU running at 2.4GHz and 4.0 GB of RAM. In order to collect realistic results for a long period of time, we collect statistics for 100 timestamps in each experiment. To increase the fidelity of our measurements we have repeated each experiment 5 times and present the average performance for each type of plot.

VII. EXPERIMENTAL RESULTS

In this section we present the results of our evaluation.

Experimental Series 1: Comparison of USN solutions
In the first experimental series we study the Pareto-Front (PF) solutions provided by the USN framework. More specifically, we compare the best solution and the top-k solutions w.r.t.

[4]The AdaptiveWeb Project, http://adaptiveweb.cs.ucy.ac.cy/
[5]http://developers.facebook.com/
[6]We assume a fixed size of 3MBs for each photo

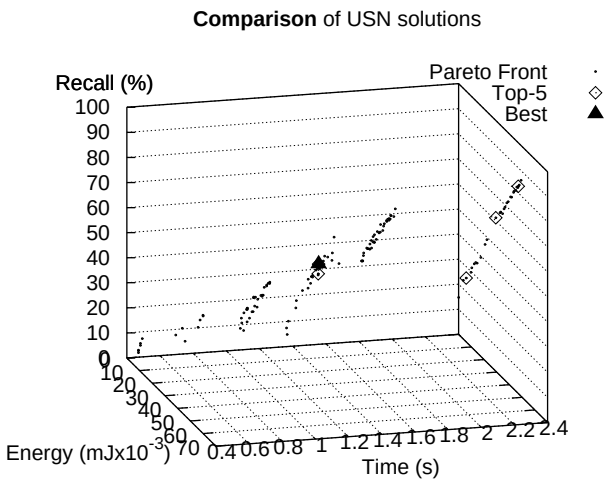

Fig. 4. Optimal and Top-k solutions compared to the Pareto-Front (PF) solutions provided by the USN framework.

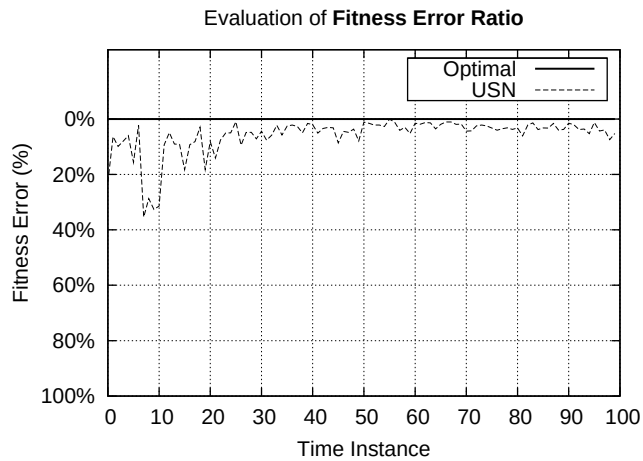

Fig. 5. Comparison of the fitness error of the best solution provided by the USN framework with the actual/exact values of the query user's cognitive style.

the fitness error. In Figure 4, we demonstrate the results for a single timestamp (τ=19) for all solutions in the system-oriented objective space with the Energy,Time and Recall metrics. The PF solutions are represented by solid circles. The Top-k (k=5) solutions and the best solution are represented by diamonds and a solid triangle, respectively.

We observe that the Top-k solutions w.r.t. the fitness error provided by the USN framework almost spread across the whole system-oriented objective space. This is important as it enables the network decision maker to efficiently tune the system according to specific network requirements (e.g., low energy is more important than low time and high recall objectives) providing at the same time near-optimal user-oriented fitness. Additionally, the execution time required for generating the solutions is ≈32562±3409ms which is not applicable for systems requiring realtime performance. However, parallel processing can greatly reduce the processing speed by evaluating each solution in each generation independently. Since network operators employ typically server farms that feature thousands of processing cores running in parallel, the execution time can be reduced by several orders of magnitude thus offering realtime performance.

Experimental Series 2: Evaluating the fitness error of the USN framework

In the second experimental series, we evaluate the fitness error of the USN framework by using 100 consecutive timestamps from the GeoLife dataset. At each timestamp τ, we show the ratio of the best solution generated by the USN framework compared to the actual/exact values of cognitive style p_0^{cs} and working memory p_0^{wm} stored in the profile p_0 of the query user u_0.

Figure5 illustrates the results of our experiment. We observe that in most timestamps, the fitness error of the USN framework is very close to the (5±6%) optimal case. This means that the distribution of data provided to the query user closely matches the cognitive style attributes stored in its profile. However, in τ=5-10 we observe that the fitness error ratio drops to 24±12%. This is because the number of users rapidly decreases $\approx 21\pm6\%$ during these timestamps. This had a significant effect on the overall number of images and text of the network thus decreasing the near-optimal combinations and therefore solutions in the objective space. Overall, the USN framework minimizes the fitness error, which translates to a high satisfaction level with respect to the query user's profile demands.

Experimental Series 3: Leveraging System Performance Metrics

In the final experimental series we assess the optimal solution provided by the USN framework in comparison with the system oriented objectives. Once more, we utilize 100 consecutive timestamps from the GeoLife dataset and record the values for all system performance metrics and fitness error. In order to demonstrate the distribution of values for each objective we have chosen the box plot graph. We plot each objective as a separate box plot and compare the best solution using a dotted line.

Figure 6 shows the results of our analysis. We observe that in order to maintain a minimal fitness error (i.e., satisfy the user objectives) the best solution uses low energy (1st Quartile), average time (1st Quartile) and high recall (3rd Quartile). In conclusion, the best solution provided by the USN framework minimizes the fitness error while in parallel leveraging the performance of the system.

VIII. CONCLUSIONS

In this paper, we introduced *User-centric Social Network (USN)*, a novel framework that incorporates user-oriented objectives in the search process. We presented the initial design of the USN framework as well as a preliminary evaluation of our framework, which demonstrates that USN enhances

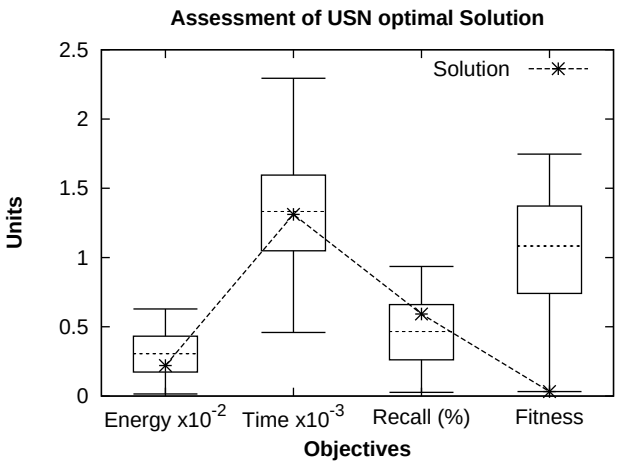

Fig. 6. Assessment of USN optimal solution w.r.t. fitness error in comparison with the system oriented metrics.

usability and satisfaction while in parallel optimizing the performance of the network w.r.t. energy, time and recall. We showed that USN features an open design, which can accommodate a different number of system-oriented and user-oriented objectives. These objectives can be expanded according to the needs and requirements of the organization.

In the future, we plan to implement our framework on real smartphone devices and perform a more comprehensive evaluation utilizing a number of different settings (e.g., real datasets, different query sets, network failures). Additionally, we plan to investigate how emotional factors can be incorporated and measured by the framework. Finally, we plan to study the effect of security/privacy requirements and investigate collaboration aspects amongst users.

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