Leveraging Social IoT to Improve Orchestration of Digital Twin Networks

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***Abstract*—The increasing complexity of telecommunication infrastructures demands advanced mechanisms to support service management. In this context, Digital Twin Networks (DTNs) have emerged as a paradigm to provide virtual replicas of network elements, enabling operators to simulate scenarios and optimize operations without affecting the physical network. However, orchestrating services across large networks of DTs remains a challenging task due to the high number of nodes involved. This paper presents a strategy to reduce orchestration complexity by introducing social mechanisms inspired by the Social Internet of Things (SIoT). By establishing social relationships between Digital Twins, social communities can be established. These communities allow the orchestrator to restrict the analysis to relevant subgraphs rather than the entire topology. A simulation setup over a network of 15,000 nodes demonstrates that the proposed approach effectively reduces the number of elements and the connections the orchestrator needs to process.**

***Index Terms*—Digital Twin Network, Social Communities, Digital Twin Relationships, Network Services Orchestration**

I. Introduction

The advent of fifth (5G) and sixth (6G) generation networks has transformed how network applications are conceived and developed. These technologies have enabled new domains—such as augmented and virtual reality (AR/VR), real-time communications, and telesurgery—that impose strict requirements on latency, flexibility, and reconfigurability. These challenges place increasing pressure on network operators to adopt innovative solutions amid growing service demands and application diversity [1].

To address this complexity, the Digital Twin Network (DTN) paradigm has emerged as a solution for advanced network management. DTNs create virtual replicas of physical components, enabling real-time synchronization, analytics, and safe simulation of new scenarios [2]. This empowers providers to anticipate disruptions, test configurations, and manage services proactively without affecting the physical infrastructure [3].

Recent DTN research has increasingly focused on service orchestration algorithms that use DT data to guide decision-making [4]. These algorithms address requirements via traditional Key Performance Indicators (KPIs) and emerging Key Value Indicators (KVIs), covering aspects like cost, sustainability, and security [5]. Orchestrators rely on this information to allocate resources using optimization or AI-based methods.

Despite these developments, little attention has been paid to the computational burden on orchestrators. As DT populations scale, potentially to tens of thousands, the orchestrator must process large search spaces and make real-time decisions [6]. This can result in scalability issues, degrading the responsiveness and overall efficiency of service delivery, especially in large and dynamic environments.

To tackle this, we propose a strategy inspired by the Social Internet of Things (SIoT) paradigm [7] to reduce orchestration complexity and provide existing orchestrators with a mechanism to identify and manage only the most relevant nodes. We introduce the Social Digital Twin Network (SDTN), where DTs form autonomous social ties based on shared traits like proximity or requirements. These relationships serve as the foundation for building communities of DTs, allowing orchestrators to operate within smaller, relevant subgraphs of the full DTN topology. This paper presents the design, implementation, and evaluation of this social orchestration approach. The main contributions are as follows:

- We propose a model for embedding social relationships into DTNs, using multiple criteria to define affinity between DTs.
- We introduce the concept of social communities, defined as subnetworks of DTs with strong social ties, which serve as localised scopes for orchestration.
- We evaluate our approach through simulations on a large DTN composed of up to 15,000 DTs, showing how the use of social communities enables reductions in orchestration overhead while preserving service quality.

The rest of the paper is organised as follows. Section II reviews relevant literature on DTN orchestration and social networking paradigms. Section III presents the scenario and defines the modelling elements. Section IV details the construction of social communities and their application. Section V presents our experimental evaluation and, finally, Section VI concludes the paper and outlines future research directions.

II. State of Art

A. The Digital Twin Network

Historically, networks were considered static infrastructures, with configurations tailored to specific applications, limiting adaptability and autonomous reconfiguration. The advent of Software Defined Networks (SDN) marked a shift, introducing programmable devices without service interruption [8]. Recent efforts have focused on incorporating AI into network environments, mainly in SDN controllers or orchestrators. Yet, these attempts often face high complexity or data limitations.

The emergence of DTs in networking introduced the DTN concept, helpful in easing operator tasks and enabling innovative approaches to design and management. DTNs empower network operators to optimize, troubleshoot, conduct what-if analyses, and plan upgrades considering projected user growth [9]. Numerous studies have explored DTNs, leading to new architectures and capabilities. A notable example is a four-layer DTN model: physical network, data lake, DT, and application layers [10]. The data lake collects and processes data to support knowledge extraction and DT modeling.

Research has also explored monitoring and service integration. For instance, [11] introduces real-time monitoring and intelligent service invocation via a DTN orchestrator, with visualization tools to aid engineers. Increasingly, DTNs are being paired with AI. Some approaches propose AI-enhanced DTs that emulate network behavior or represent network entities. Others envision virtual parallel networks where DTs of users and devices interact [12]. In next-gen networks, DTs are gaining traction among telecom leaders like Ericsson and Huawei [13], initially to assess performance, environmental impact, and 5G optimization.

As technology advances, DTs are used for simulation too. In [14], a 5G DT architecture is proposed with physical and virtual layers and real-time synchronization. It decouples functions like mobility and edge caching from hardware, implementing them via software. In this context, SDN and Network Function Virtualization (NFV) are key: SDN separates control and data planes, while NFV enables cost-effective function deployment using virtual machines. The resulting network environment will align seamlessly with the slicing capabilities envisioned for 6G. DT-based 6G systems will combine slicing with technologies like data decoupling, advanced interfaces, blockchain, and proactive optimization for intelligent control [15].

B. The Progress of Social Digital Twins

In parallel, the Social Internet of Things (SIoT) paradigm has been introduced to extend traditional IoT architectures by embedding social networking principles. In SIoT, each physical object is associated with a virtual counterpart, i.e. a Social DT, capable of forming social relationships with other entities, like humans do in social networks [16]. These links are built based on criteria such as co-location, i.e. devices that operate in the same location, common ownership, common tasks, or even relationships among respective users. As a result, the SIoT networks evolve into dynamic social graphs, where the structure of communication is guided by social ties. The integration of social principles into the IoT has shown significant benefits in terms of service discovery, network scalability, and trust management [17].

As illustrated in the previous section, the concepts of DTs and SIoT can be extended in the same way to telecommunication infrastructures, where DTs represent not users or sensors, but network elements themselves (e.g., routers, switches, access points) [18]. In such a vision, with the association of SIoT, DTs associated with network devices can interact, collaborate, and establish relationships to form a social network of networked entities [5]. This approach enables the creation of logical links, supported by the physical ones, that reflect shared deployment contexts, vendor origins or operational roles.

Building on this social vision, the work presented in [19] proposes an interpretation of SIoT adopted in communication networks. In this approach, authors introduce social DT communities, i.e. groups of DTs clustered according to one or multiple shared social dimensions. These communities are not static or manually defined but emerge from network mechanisms, where DTs that meet specific relational criteria are logically connected via dedicated IP subnets within a Virtual Application Network (VAN). Each DT, upon joining a community, is able to navigate and exchange information within its scope, avoiding global discovery procedures.

In this paper, we build upon these two foundational ideas, i.e. the concept of social relationships from SIoT and the notion of social communities, to propose an SDTN approach, where social DT represents network components. Specifically, we leverage the relationships defined in SIoT as the basis for establishing relations between DTs in the telco environment. From these links, we dynamically construct social communities, each grouping together DTs that share specific relations. The key insight is that these communities can serve as search domains for the orchestrator: instead of querying or analyzing the entire DT network, the orchestrator can restrict its scope to a relevant subset of networks that are more likely to provide the requested services. This targeted exploration enables the orchestrator to fulfill SLAs and KPIs while reducing complexity.

III. Scenario

This paper introduces a framework for network orchestration that leverages the dynamics of social relationships among network elements. The considered scenario involves a large-scale network topology, potentially spanning a national network infrastructure, where K different network operators $\mathcal{O} = \{o_1, ..., o_k, ..., o_K\}$ own both the network elements (such as routers, radio-base stations, etc.) and the connections between them. Users within the network may issue queries, characterized by the following parameters:

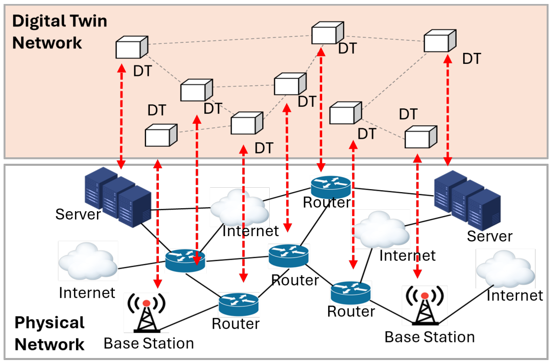

Fig. 1. An example of how real-world network elements are virtualized within Digital Twins.

- **Key Performance Indicators** (KPI): these specify predetermined measurable performance targets, such as latency or throughput;

- **Key Value Indicators** (KVI): these reflect the user's preference for meeting certain criteria, such as sustainability.

To manage network operations and traffic, network elements are virtualized within a respective DT as shown in Figure 1. Just like a group of interconnected network devices creates a network, DTs together create a Digital Twin Network (DTN). Each DT, representing a network element, is defined by a profile, directly linked to the real-world object [20].

Let $\mathcal{N} = \{n_1, ..., n_i, ..., n_I\}$ be the set of I network elements virtualized into DTs, where each generic $n_i \in \mathcal{N}$ can be described by its profile. Among all the important information, the parameters useful for the considered scenario, used to create social relationships, are depicted below:

- C_i represents the network element geographical location, given in terms of longitude and latitude coordinates;

- O_i denotes the owner of the network element n_i and is an element of the set $\mathcal{O}$ of operators;

- $P_i^{(max)}$ represents the maximum processing capability of the network element, measured in [cycles/s] [21];

- $G_i^{(\%)}$ represents the percentage of green energy used in relation to the total energy consumed by the network element;

- $S_i^{(\%)}$ symbolizes the likelihood of attacks against the security of the network element. It represents the probability that a threat will exploit a vulnerability, causing damage [21];

- $\vec{B}_i^{(min)}$ is a vector containing the minimum guaranteed values of the available bandwidth from the directly connected network elements, measured in [Mbps]. Therefore $B_{ij}^{(min)}$ is the minimum guaranteed bandwidth;

- $\vec{L}_i^{(max)}$ is a vector containing the maximum expected values of latency from the n_i network element to reach the set of directly connected network elements, measured in [s]. Therefore $L_{ij}^{(max)}$ is the maximum expected latency.

We are considering bandwidth and latency parameters that are strictly related to the communication links' physical properties. Therefore, in this model, it is assumed that these parameters are symmettric, i.e. $B_{ij}^{(min)} = B_{ji}^{(min)}$.

All of these parameters are selected according to what service requests may demand in terms of KPIs and KVIs, enabling efficient orchestration.

IV. Social Networks among DTs: How to Create Relations

Building on Section II, this paper envisions a scenario where DTs of network elements form an SDTN by establishing social connections. These relationships enable dynamic network management, supporting tasks like path discovery, service orchestration, and provider selection [22], while incorporating broader goals such as sustainability and security [23]. The decentralized structure of DT connections also lessens dependence on centralized control.

Social links are formed between DTs physically adjacent in the network, i.e. that are directly connected in the physical network topology. These are established at deployment, based on profile-based condition checks. Each link is assigned a weight (0–1), reflecting potential performance and derived from relationship parameters. The specific collaborative conditions for establishing these links are detailed below (where the prefix "Co-" stands for "Collaborative"):

Co-Location relationship is established between two DTs if their physical distance is below a predefined threshold. The distance between two generic DTs n_i and n_j is calculated using the Haversine formula, which provides an estimation of the distance between two points on a sphere based on their latitude and longitude, accounting for the Earth's curvature [24]. Then, the distance is computed as:

$$d_{ij} = R \cdot c_{ij} \tag{1}$$

where R represents the mean radius of the Earth. The parameter c_{ij} is calculated using the following formula:

$$c_{ij} = 2 \cdot \operatorname{atan2}\left(\sqrt{a_{ij}}, \sqrt{1 - a_{ij}}\right) \tag{2}$$

where a_{ij} is an auxiliary quantity defined as:

$$a_{ij} = \sin^2\left(\frac{\Delta\phi_{ij}}{2}\right) + \cos\left(\phi_i\right) \cdot \cos\left(\phi_j\right) \cdot \sin^2\left(\frac{\Delta\lambda_{ij}}{2}\right) \tag{3}$$

Here, ϕ_i and ϕ_j represent the latitudes of DTs n_i and n_j, respectively, while λ_i and λ_j represent their longitudes. The terms $\Delta\phi_{ij} = \phi_j - \phi_i$ and $\Delta\lambda_{ij} = \lambda_j - \lambda_i$ denote the differences in latitude and longitude. The condition required to establish the relationship is defined as $d_{ij} \leq d_{th}$. The corresponding weight is computed as:

$$W_D = (d_{th} - d_{ij})/d_{th} \tag{4}$$

where the weight decreases linearly with the distance between two DTs, reaching its maximum value when $d_{ij} = 0$ and zero when $d_{ij} = d_{th}$.

Co-Ownership represents the social relationship between DTs owned by the same operator. Given two DTs n_i and n_j, a Co-Ownership relationship exists if they belong to the same owner, i.e. if $O_i = O_j$. The associated weight is set to 1. As an extension, agreements between different operators could be modeled by assigning a lower weight to cross-operator interactions, reflecting partial trust or collaboration.

Co-Bandwidth is the social relationship established between two DTs that can guarantee a sufficient minimum bandwidth when communicating with each other. For this relationship to be established, the bandwidth parameters of the two DTs must satisfy the following condition: $B_{ij}^{(min)} = B_{ji}^{(min)} \geq B_{th}$. Since the available bandwidth can theoretically grow without bound (i.e., it ranges from B_{th} to $+\infty$), the weight is modeled using an exponential function. This ensures that the weight increases with available bandwidth, while the rate of increase gradually decreases as the bandwidth grows. To guarantee that a useful relationship is established even at the threshold bandwidth, a minimum weight value $W_B^{(min)}$ is introduced, representing the minimum utility level of the relationship. The weight is computed as:

$$W_B = W_B^{(min)} + (1 - W_B^{(min)}) \left(1 - e^{\frac{B_{th} - B_{ij}^{(min)}}{k}}\right) \quad (5)$$

where $W_B^{(min)}$ represents the minimum relationship weight guaranteed when the available bandwidth is exactly equal to the threshold B_{th}, ensuring a non-zero weight for the relationship.

Co-Latency relationship, similarly to Co-Bandwidth, is established between two DTs that can guarantee a lower latency compared to a certain threshold. Therefore, to be created, the DTs' latency parameters must satisfy the following condition: $L_{ij}^{(max)} = L_{ji}^{(max)} \leq L_{th}$ For latencies, a linear function can be used to calculate the weight. To ensure the existence of a useful relationship even at the latency threshold, a minimum weight value $W_L^{(min)}$ is introduced, ensuring that the relationship remains meaningful even when the latency is exactly at the threshold. The weight is then computed as:

$$W_L = W_L^{(min)} + (1 - W_L^{(min)}) \left(\frac{L_{th} - L_{ij}^{(max)}}{L_{th}}\right) \quad (6)$$

Co-Green relationship is established between two DTs referring to network elements with a low environmental impact. Given two generic DTs, this relationship is created only if the following conditions are satisfied: $G_i^{(\%)} \geq G_{\text{th}}^{(\%)}$ and $G_j^{(\%)} \geq G_{\text{th}}^{(\%)}$, where $G_{\text{th}}^{(\%)}$ represents the threshold percentage of green energy usage.

Additional parameters related to total energy consumption or energy efficiency might also be considered to include DTs with low energy usage, even if not entirely based on renewable sources. The weight is calculated using a linear function based on the average green level of the two DTs. The relationship weight is then computed as:

$$W_G = W_G^{(min)} + (1 - W_G^{(min)}) \left(\frac{\frac{G_i^{(\%)} + G_j^{(\%)}}{2} - G_{\text{th}}^{(\%)}}{100 - G_{\text{th}}^{(\%)}}\right) \quad (7)$$

where $W_G^{(min)}$ represents the minimum guaranteed weight.

Co-Security is a social relationship established between two DTs when the communication between them satisfies specific conditions that classify it as secure. Similarly to Co-Green, this relationship is created only if both DTs satisfy the following conditions: $S_i^{(\%)} \geq S_{\text{th}}^{(\%)}$ and $S_j^{(\%)} \geq S_{\text{th}}^{(\%)}$, where $S_{\text{th}}^{(\%)}$ is the security threshold. The weight is then computed using a linear function based on the average security level of the two DTs. To ensure a minimum weight even at the threshold level, a parameter $W_S^{(min)}$ is introduced. The weight is computed as:

$$W_S = W_S^{(min)} + (1 - W_S^{(min)}) \left(\frac{\frac{S_i^{(\%)} + S_j^{(\%)}}{2} - S_{\text{th}}^{(\%)}}{100 - S_{\text{th}}^{(\%)}}\right) \quad (8)$$

It is important to note that social relationships within the SDTN serve as a reference for the orchestrator. When making decisions, the orchestrator will retrieve the real-time performance to accurately evaluate the current state of the network and select the most appropriate links to exploit.

A. Social Communities

Each DT autonomously records its social links, used to identify suitable service providers and make preliminary decisions within its neighborhood. In contrast, social communities are groups of DTs connected by common relationships and are globally managed by the orchestrator. By tracking these communities, the orchestrator can select optimal paths and service groups, leveraging overlapping communities to enhance search efficiency. For example, a low-latency community, based on Co-Latency links, is ideal for services with stringent latency KPIs. Community definitions may also include additional DT profile parameters, such as geographical location, to group nearby network elements.

Social communities can be defined as groups of DTs that meet the following criteria:

1) **Internal Connectivity**: all DTs within the community must be able to communicate without leaving the community, requiring a physical topology among them;
2) **Shared Social Relationship**: at least one social relationship must exist between DTs, defining the community's characteristics. For example, if all DTs share a Co-Bandwidth relationship, the community can be classified as a "high-bandwidth community".

Additional details can further refine the definition of social communities. For instance, a *maximum distance* between DTs within the same community could be considered, particularly relevant for Co-Latency relationships, as latency accumulates with each traversed DT network element. Other factors such as the relationship weight or the history of past interactions between DTs may also be taken into account to restrict community membership.

An illustrative example is shown in Figure 2. The figure depicts a DTN where social relationships based on Co-Location, Co-Ownership, and Co-Bandwidth have been estab-

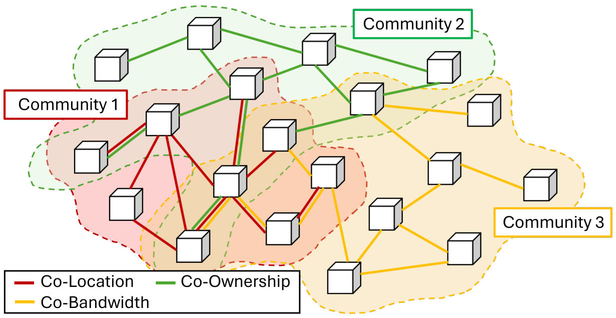

Fig. 2. Example of DTN, which becomes an SDTN with established social relationships among the DTs, and creation of social communities.

TABLE I
THRESHOLD LEVELS

	B_{th} [Mbps]	L_{th} [ms]	G_{th} [%]	S_{th}
Low	500	20	40	2
Medium	750	10	60	3
High	1200	1	80	4

lished among the DTs, leading to the formation of distinct social communities based on shared Relationships.

Communities can be created either on *start-up* or *on-the-go*. In the first case, a DT joins all eligible communities immediately after its social links are established, enabling rapid orchestration and allowing immediate use of social communities. In the second, communities form only after successful interactions among socially connected DTs. Though slower, this ensures only effective communities emerge. In both approaches, communities evolve over time based on interactions, a DT may leave a group as performance changes.

Effective social community management enables orchestration at a higher abstraction level. Instead of assessing each DT individually, communities group DTs by shared traits, simplifying decisions and reducing interactions. This aggregation improves scalability and supports lighter, more efficient orchestration.

V. Experimental Evaluation

A. Simulation Setup

The simulation setup comprises a large network consisting of 15,000 nodes interconnected by 400,000 links, generated according to [21]. Specifically, we used the following parameters: minimum link bandwidths up to 1500 Mbps, maximum link latencies up to 30 milliseconds, green energy utilization expressed as a percentage, and a security level ranging from 1 to 5. To evaluate the performance of the social approach, three threshold levels (low, medium, and high) have been defined; these are summarized in Table I.

These thresholds are applied to construct four types of social graphs based on different relations: Co-Bandwidth, Co-Latency, Co-Green, and Co-Security. To illustrate how the graphs formed by social relationships can significantly reduce network complexity, Table II compares the original physical network topology with the derived social graphs (constructed using the medium threshold level). While this table provides a preliminary comparison, the next section will present a more detailed analysis of how the proposed approach can substantially reduce the complexity of an orchestrator.

TABLE II
PHYSICAL TOPOLOGY AND SOCIAL GRAPHS COMPARISON

	Physical	Bandwith	Latency	Green	Security
# Link/Relations	400000	119834	240247	133372	144632
Avg. degree	53.3	15.98	32.03	17.78	19.28
Giant component	100%	100%	100%	58%	60%
Avg. path length	2.81	3.75	3.04	2.93	2.92
Diameter	4	6	4	4	4

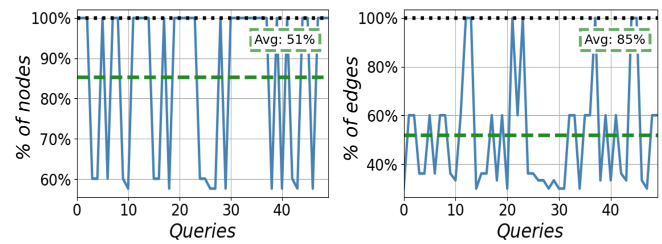

Fig. 3. Percentage of nodes and edges provided to the orchestrator across 50 queries.

B. Performance Evaluations

The performance of the proposed setup is evaluated based on the number of nodes and links provided to the network orchestrator upon the arrival of queries. By filtering and consequently reducing the size of the candidate subgraph, the computational load on the orchestrator is reduced. Figure 3 illustrates the percentage of nodes and links involved in each query when social relationships are considered with medium threshold values. Queries have been simulated by randomly selecting a node as the requester and designating 10% as the possible providers. If a social community is capable of satisfying the request, only the community is passed to the orchestrator, rather than the entire network topology. As shown in the figures, the proposed approach does not always reduce the number of nodes or links passed to the orchestrator. In some queries, the entire network must still be considered to locate a suitable provider, resulting in no reduction. However, on average, the approach significantly decreases complexity, reducing the number of nodes passed to the orchestrator to approximately 85% and the number of links by nearly 51%. This leads to a substantial reduction in the amount of data the orchestrator needs to process to solve queries.

Figure 4 shows how results vary with different threshold levels (Table I), considering an increasing number of requirements for forming social communities. Unlike earlier tests, based on a single requirement (e.g., Co-Bandwidth or Co-Latency), these experiments combine multiple requirements. Communities now form only when 2 or 3 social relationships are simultaneously satisfied, resulting in more numerous, smaller,

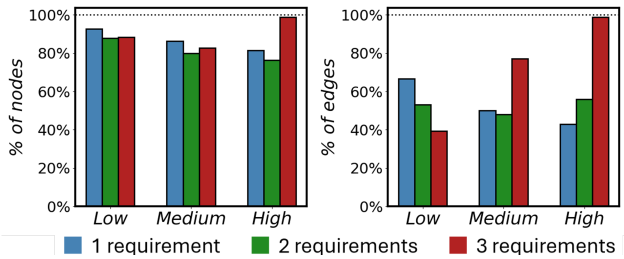

Fig. 4. Average percentage of nodes and edges over 10,000 queries, grouped by threshold levels and for different communities' requirements.

and fragmented communities. As shown in the left graph, for queries with one or two requirements, higher thresholds lead to fewer nodes due to larger communities. Conversely, with three requirements, thresholds cause excessive fragmentation, making it impossible to resolve queries within a single community and forcing orchestration across the entire topology. A similar pattern emerges in the link percentage graph: for 1 or 2 requirements, higher thresholds reduce social links, complicating discovery. Still, for simple queries with 1 requirement, link reduction doesn't significantly affect discovery efficiency.

These results underscore the importance of selecting relationship thresholds not only based on profile similarity, but also on the complexity of target queries.

VI. Conclusions

This paper presented a novel approach to reduce orchestration complexity in large DTNs by leveraging social mechanisms inspired by the SIoT paradigm. By embedding social relationships among DTs and organizing them into social communities, the proposal demonstrates how orchestrators can operate within smaller subnetworks, thus reducing computational overhead without compromising service quality. Specifically, the evaluation on a DTN of up to 15,000 DTs showed that the proposed social orchestration approach can decrease the number of nodes and links involved in service management.

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