MISTA 2017

Home Health Care Delivery Problem

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Abstract We address the Home Health Care Delivery Problem (HHCDP), which is concerned with staff scheduling in the home health care industry. The goal is to schedule health care providers to serve patients at their homes that maximizes the total collected preference scores from visited patients subject to several constraints, such as workload of the health care providers, time budget for each provider and so on. The complexity lies in the possibility of cancellation of patient bookings dynamically, and the generated schedule should attempt to patients' preferred time windows. To cater to these requirements, we model the preference score as a step function which depends on the arrival time of the visit and the resulting problem as the Team Orienteering Problem (TOP) with soft Time Windows and Variable Profits. We propose a fast algorithm, Iterated Local Search (ILS), which has been widely used to solve other variants of the Orienteering Problem (OP). We first solve the modified benchmark Team OP with Time Window instances followed by randomly generated instances. We conclude that ILS is able to provide good solutions within reasonable computational times.

1 Introduction

The demand for home health care (HHC) services has increased substantially due to population aging [20]. HHC provides a wide range of services, including nursing care, medical, paramedical and social services, that can be provided to patients at home [14,16]. Due to aging populations, the demand for HHC is rapidly increasing. For example, in 2011, more than 4 million patients received HHC services in the

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U.S. [6]. Ministry of Health (MOH) Singapore introduces Intermediate and Long-Term Care (ILTC) services for patients who require further care and treatment after being discharged from an acute hospital as well as community-dwelling senior residents who may be frail and need supervision or assistance with their activities of daily living. In 2013, MOH developed a set of home care guidelines.

This study addresses a particular application problem of the staff scheduling in the home health care industry, namely the Home Health Care Delivery Problem (HHCDP), on a daily basis. In the context of the classical scheduling problem, HHCDP is considered as a workforce scheduling and routing problem. Workforce scheduling and routing problem refers to those scenarios involving the mobilization of personnel in order to perform work related activities at different locations [2]. Staffs are mostly required to travel from one location to other locations in order to perform the work since the number of works across different locations is usually larger than the available number of employees. Several real-world requirements, such as time windows, transportation modality, start-end locations, skills and qualifications, increase the complexity of the problem. For more details about workforce scheduling and routing problems, the reader can refer to [2]. The HHCDP is considered as a combination of staff rostering and VRP with time windows in [25].

In our context, instead of considering as a VRP (which is in essence a demand perspective), we view this problem from the supply perspective as well. While we try to satisfy as many patients as possible, the number of requests may exceed the service capacity and some of them may be cancelled after the schedule has been generated. Since we want to maximize the patients' satisfaction, measured in terms of scores, our problem can be modelled as a variant of the Orienteering Problem (OP).

In the standard OP, a set of agents are scheduled to serve a set of customers (e.g. patients). Each agent is limited by the time budget and time windows. Each customer can only be visited at most once. For simplicity, we assume that all agents start and end at the same location (e.g. the hospital). The problem incorporates other real-world requirements related to the health care industry, such as the continuity of care, workload fairness and demand uncertainty (due to request cancellations). We allow the agent to arrive late with a certain penalty value rather than not visiting the patient. In the OP term, the collected score is affected by the penalty value, if any. As some requests from patients may be cancelled due to unforeseen factors after the schedule has been generated, we express such uncertainty as a probability of occurrence which is assumed to be known beforehand.

Hence, this paper considers HHCDP from both provider and patient perspectives - while we maximize the workload utilization rate of providers without violating their time budgets, we also maximize the satisfaction level of patients with respect to the number of patients to be visited by allowing late arrivals. We term our problem as the Team OP with soft Time Windows and Variable Profits (TOPsTWVP). For a comprehensive review of the OP, the reader can refer to the two surveys by Vansteenwegen et al. [23] and Gunawan et al. [10].

We explore the potential of Iterated Local Search (ILS) to solve HHCDP. ILS is a simple but effective metaheuristic [15] and has been applied successfully to solve different variants of the OP, such as works by Vansteenwegen et al. [24] and Gunawan et al. [8, 11]. We adopt a similar algorithm [11] with several modifications, such as tackling variable scores/profits, and soft time window constraints. Here, we name it as Enhanced ILS (EnILS).

The main contributions of this paper are listed below:

– We introduce a new variant of the Team Orienteering Problem with soft Time Windows and Variable Profits (TOPsTWVP). To the best of our knowledge, this is the first study dealing with both soft Time Windows and Variable Profits. In this problem, late service is allowed with an appropriate penalty that affects the score/profit. By relaxing the time windows, the number of visited patients will increase without affecting patients' satisfaction significantly.
– Most of interesting applications of the OP are in logistics, tourism and defense. We extend the application of the OP to solve the Home Health Care Scheduling Problem (HHCSP).
– We adopt and implement a fast Iterated Local Search algorithm that has been used for solving other variants of the OP [11]. Note that some obtained results are also feasible for the original TOPTW problem. They are comparable to the state-of-the-art algorithms.

The remainder of this paper is organized as follows. Section 2 summarizes the relevant literature. The description of the HHCDP problem including the mathematical formulation, is presented in Section 3. The Iterated Local Search is explained in Section 4. Section 5 presents computational experiments. Finally, Section 6 describes the conclusions, limitations and possible future works of our research.

2 Related Work

Since our problem is an extension of the TOPsTWVP model, we start by reviewing the literature on the OP and its related variants briefly, followed by the related research on the HHCDP. The OP has been extensively studied in various applications, such as the mobile crowdsourcing problem, the Tourist Trip Design Problem (TTDP), the logistic problem and others [10].

Erdoğan and Laporte [5] introduced the OP with Variable Profits (OPVP). The score for each node is associated with a parameter that determines the percentage of score collected, either as a discrete or continuous function of the time spent. One example of the OPVP application arises in the fishing sectors. Longer stays at certain locations may increase the amount of fish caught. In their work, a branch-and-cut algorithm is proposed to solve some modified TSP instances. There is still room for improvement since the algorithm requires large computational times and can only solve small instances.

Mota et al. [18] modeled the operating room scheduling problem in terms of choice elective patients, aiming for throughput maximization, as a new variant of the TOPTW, namely the TOP double Time Windows (TOPdTW). Both paths and nodes have a time window to be fulfilled. The number of paths equals to the number of operating rooms times the number of shifts times the number of days while the number of nodes refers to the number of operating rooms. A genetic algorithm is proposed to solve benchmark TOPTW instances and randomly generated TOPdTW instances. The computational results are promising although they are still preliminary.

The Home Health Care problem aims to provide the care and support needed to patients in their own homes [1]. It covers different supports, such as elderly people, people with physical disabilities. Cisse et al. [4] classified the Home Health Care Routing and Scheduling Problem (HHCRSP) process into three different levels: strategic, tactical and operational levels, and mapped the into related OR problems. They extended the earlier review [6] which only covers articles before 2016. The details of relevant features, constraints, objectives and methods in the existing HHCRSP studies are also presented.

Rasmussen et al. [21] looked at the daily home care crew scheduling problem as a generalization of the Vehicle Routing Problem with Time Windows (VRPTW). The problem is formulated as a set partitioning problem and solved by an exact branch-and-price algorithm. Visit clustering schemes are also developed in order to reduce computational times significantly, with the cost of the quality of the solutions. The schemes are able to find solutions of larger instances, which cannot be solved optimally. Akjiratikarl et al. [1] also considered the home care worker scheduling problem as the VRPTW.

Yuan and Fügenschuh [25] presented a case study on the problem of scheduling nurses on a weekly basis with the objective of minimizing the total cost as well as the total working time, without compromising the service quality. The problem is treated as a combination of the staff rostering problem and the VRPTW. The proposed algorithm which is based on local search approaches can produce an estimation of cost reduction up to 10% in solving a real-world instance.

Lin et al. [14] addressed a particular problem of the Home Health Care that provides therapy services, namely the Therapist Assignment Problem (TAP). The problem is described from patient and therapist perspectives and modeled as a mixed-integer programming model. The model is validated by using an instance extracted from a rehabilitation service provide in Hong Kong and some randomly generated instances.

Chen et al. [3] introduced a multi-period Home Health Care Scheduling Problem under stochastic service and travel times. The chance constraints are introduced into the formulation in order to cope with uncertainty in durations. The effectiveness of the proposed approaches is tested on synthetic instances for both deterministic and stochastic scenarios.

Nguyen and Montemanni [19] addressed the nurse home services problem and proposed two mixed integer linear programming models based on Big-M method and arc timing method, respectively. Both models cater soft and hard time windows. Certain penalties would be imposed if the service starts between certain periods. However, hard time windows are also imposed to avoid unnecessary overtime. Experiments are conducted on a set of randomly generated instances.

3 Home Health Care Delivery Problem (HHCDP)

We formulate the HHCDP as an Integer Linear Programming (ILP) model. The HHCDP is defined as the following tuple: $\langle N, T \rangle$. Let N be a set of locations, $N = N_t \cup N_s$, where N_t and N_s represent a set of patients' locations and health care providers' start-end locations, respectively. Here, we assume start and end locations for all providers are at the same location, location 0 ($N_s = \{0\}$). T is a symmetric pairwise travel time matrix and $t_{ij} \in T$ denotes the travel time between two different locations i and j. Let M be a set of health care providers.

Each patient's location $i \in N_t$ has a positive dependent reward u_{im} that would be collected when he/she is visited by provider m. In most cases, patients prefer to be visited by their primary provider. This is reflected by a higher reward in our case. Each visit requires a service time T_i and it should be started within a particular time window $[e_i, l_i]$. e_i and l_i refer to the earliest and latest times allowed for starting the visit at location i. We allow a late arrival with the cost of penalty although this is undesirable. On the other hand, if the provider arrives before e_i, the waiting time occurs.

Since we assume location 0 is the start and end locations, therefore $u_{0m} = T_0 = 0$. Each provider $m \in M$ is constrained within the time limit $[e_0, l_0]$. We have $e_0 = 0$ and $l_0 = T_{max}$, where T^{max} is the time budget or the maximum duration to complete a duty day. The objective is to maximize the expected total collected score from visiting patients by all providers. We include the penalty in the objective function value due to a late visit. The penalty is calculated by multiplying a certain percentage of reduction to a particular score $\{(R_1, R_2, \ldots, R_n) \in [0, 1]\}$. For example, if the arrival at location i is late and less than δ_i, the adjusted score would be $R_1 \times u_{im}$. The details can be referred below:

$$\hat{u}_{im} = \begin{cases} 0, & \text{if } (S_{im} - l_i) \leq 0; \\ R_1 \times u_{im}, & \text{if } 0 < (S_{im} - l_i) \leq \delta_i; \\ R_2 \times u_{im}, & \text{if } \delta_i < (S_{im} - l_i) \leq 2 \times \delta_i; \\ \vdots & \\ R_n \times u_{im}, & \text{if } (n-1) \times \delta_i < (S_{im} - l_i) \leq n \times \delta_i. \end{cases}$$

The following decision variables are used in the mathematical model:

- $X_{ijm} = 1$ if a visit to patient i is followed by a visit to patient j by provider m, 0 otherwise.
- $Y_{im} = 1$ if a visit to patient i by provider m, 0 otherwise.
- $\hat{S}_{im}$ = the start time of service at patient i by provider m.

The HHCDP mathematical formulation is adopted from the work of [11] with several modifications:

$$Maximize \sum_{m \in M} \sum_{i \in N \setminus \{0\}} \pi_i Y_{im} \hat{u}_{im} \tag{1}$$

$$\sum_{j \in N \setminus \{0\}} X_{0jm} = 1 \;, \forall m \in M \tag{2}$$

$$\sum_{i \in N \setminus \{0\}} X_{i0m} = 1 \;, \forall m \in M \tag{3}$$

$$\sum_{i \in N \setminus \{0\}} X_{ikm} = Y_{km} \;, \forall k \in N \setminus \{0\}, m \in M \tag{4}$$

$$\sum_{j \in N \setminus \{0\}} X_{kjm} = Y_{km} \;, \forall k \in N \setminus \{0\}, m \in M \tag{5}$$

$$\sum_{m \in M} Y_{im} \leq 1 \text{ , } \forall i \in N \setminus \{0\} \tag{6}$$

$$\hat{S}_{im} \geq e_i \text{ , } \forall m \in M, i \in N \tag{7}$$

$$\hat{S}_{im} + T_i + t_{ij} - \hat{S}_{jm} \leq \hat{L}(1 - X_{ijm}) \text{ , } \forall i, j \in N, m \in M \tag{8}$$

$$\sum_{i \in N \setminus \{0\}} (T_i Y_{im} + \sum_{j \in N \setminus \{0\}, j \neq i} t_{ij} X_{ijm}) \leq T_{max} \text{ , } \forall m \in M \tag{9}$$

$$\hat{S}_{im} \geq 0 \text{ , } \forall i \in N, m \in M \tag{10}$$

$$X_{ijm}, Y_{im} \in \{0, 1\} \text{ , } \forall i, j \in N, m \in M \tag{11}$$

The objective function 1 is to maximize the expected total collected score from visited patients' locations from all providers. Each location i has a probability of occurrence π_i on a particular day. Each patient has a chance to cancel the appointment. Constraints 2 ensure that each provider starts and ends at location 0. Constraints 4 and 5 determine the connectivity of each provider m. Constraints 6 guarantee that each location i, except location 0, is visited at most once.

Constraints 7 ensure that the start time at location i of provider m is after e_i. Constraints 8 imply that if locations i and j are visited consecutively, then the start time at location j has to be greater than or equal to the start time at location i plus the service time at location i and the travel time from locations i to j. They ensure the timeline of each provider m. Note that $\hat{L}$ is a very large constant value. Constraints 9 limit the time budget for each provider m by T_{max}. Constraints 10 are the non-negativity condition for $\hat{S}_{im}$. Finally, the binary conditions for X_{ijm} and Y_{im} are constrained by equations 11.

4 Solution Approach

In this section, we describe the Iterated Local Search (ILS) algorithm, namely Enhanced ILS (EnILS), which is adopted from the one proposed by Gunawan et al. [11]. ILS has been successfully used to solve various variants of the OP, such as OPTW [8], TDOP [9] and TOPTW [11]. We extend the applicability of the algorithm in solving the HHCDP. EnILS consists of two phases, constructive and improvement phases. We only briefly explain the algorithm especially the parts which are different from the original one. For more details of the original ILS, readers can refer to the work of Gunawan et al. [11].

4.1 Construction Phase

An initial solution is built by a construction heuristic. The idea is to generate a set of all feasible candidate requests F that can be inserted. Each element of F, denoted as $\langle n, p, m \rangle$, represents a feasible insertion of request n in position p of provider m. This set can be very large; therefore, we only consider a subset of possible insertions $F_s \subset F$. Those feasible insertions are ranked according to their $ratio_{n,p,m}$ values. The ratio value for each insertion is calculated based on equation 12. $Diff_{n,p,m}$ represents the difference between the total time spent before and after the insertion of location n in position p of provider m.

$$ratio_{n,p,m} = \left(\frac{\pi_i \times \hat{u}_{nm}^2}{Diff_{n,p,m}} \right) \tag{12}$$

In order to select which insertion to be picked from F_s, we apply the idea of the Roulette-Wheel selection concept [7]. The main idea is that the probability of an element being selected is proportional to its $ratio_{n,p,m}$ value. The element with a higher probability has a higher chance to be selected. F and F_s are updated iteratively. This constructive heuristic is applied until $F = \emptyset$.

4.2 Improvement Phase

In this phase, we implement a metaheuristic based on Iterated Local Search (ILS) in order to further improve the quality of the initial solution S_0 at a particular iteration. We denote S^* as the best found solution so far at a particular iteration, respectively. For the first iteration of this improvement phase, S^* equals to S_0.

The main idea of ILS is to explore the solution space by generating and evaluating the neighbors of S_0. We apply LocalSearch in order to generate the best neighborhood. In LocalSearch, we run six different operators consecutively, as shown in Table 1. The first four operators focus on rearranging the visited locations of providers in order to provide more times to allocate more locations which is done by the last two operators. The first improving neighbor replaces S_0. If a stagnation condition is met, a perturbation strategy on S_0 is then applied. The outline of the ILS algorithm is presented in Algorithm 1.

Table 1: Local Search operations

Operations	Descriptions
SWAP1	Exchange two locations within one provider
SWAP2	Exchange two locations within two providers
2-OPT	Reverse the sequence of certain locations within one provider
MOVE	Move one location from one provider to another provider
INSERT	Insert locations into a provider
REPLACE	Replace one scheduled location with one unscheduled location

The list of operators are identical with the one of [11]. The major difference lies in the checking process when the operator is accepted or not. For example, we may allow swapping two locations (SWAP1 or SWAP2) although the objective function value maybe worse due to late arrivals; however, we may be able to insert more locations in a particular provider later. This arrangement corresponds to

Algorithm 1 ILS (N, M)

```
S_0 ← Construction(N, M)
S_0 ← LocalSearch(S_0, N*, N', M)
S* ← S_0
NoImpr ← 0
while TimeLimit has not been reached do
    S_0 ← Perturbation(S_0, N*, N', M)
    S_0 ← LocalSearch(S_0, N*, N', M)
    if S_0 better than S* then
        S* ← S_0
        NoImpr ← 0
    else
        NoImpr ← NoImpr + 1
    end if
    if (NoImpr+1) Mod Threshold = 0 then
        S_0 ← S*
    end if
end while
return S*
```

the purpose of HHCDP where we allow providers to reach their destinations late although this is undesirable. Some penalties would be imposed due to lateness.

After applying LocalSearch, we implement the perturbation strategy, Perturbation in order to escape from local optima [11]. If the current solution S_0 is better than S^*, we update the best found solution so far S^*. This part is related to the AcceptanceCriterion component of ILS. If S^* is not updated for a certain number of iterations, ((NoImpr+1) Mod Threshold = 0), we restart the search from the best found solution, S^*. Threshold is a parameter that need to be set. Finally, the entire algorithm will be run within the computational budget, TimeLimit.

In Perturbation, we apply two different steps: ExchangePath and Shake. After a certain number of iterations without improvement, we apply ExchangePath; otherwise, Shake is selected. The efficiency of our algorithm depends on both steps. The strategy of selecting two different providers in ExchangePath are based on generating permutations by adjacent transposition method [13]. This step does not change the objective function value directly since we only swap all locations from two different providers. However, in subsequent iterations especially when we apply LocalSearch, more opportunities for operators that have to be applied from the first provider to the last one. The other step, Shake, is based on the one proposed by Vansteenwegen et al. [24]. The focus is to remove certain nodes from each provider, depends on the starting location and subsequent locations need to be removed.

5 Experiments

A comprehensive analysis of the results is reported in this section. We first describe the experiment setup and instances used. We then summarize the performance of the proposed algorithm, EnILS.

5.1 Experiment Setup and Instances

The algorithm is implemented in Java which is executed on a personal computer with Intel(R) Core(TM) i5-6500 with 3.2 GHz CPU, 16 GB RAM. Each instance is run five times for which the average results are presented. We adopt the same parameter values in the earlier work [11]. The parameter tuning is grounded on the Design of Experiment (DOE) methodology.

We use two different groups of instances in our experiments. The first group of instances is taken from the benchmark TOPTW instances [17, 22]. The size of instances varies from 48 to 228 locations with the number of providers up to four providers. All benchmark instances can be downloaded from `http://www.mech.kuleuven.be/en/cib/op`.

Since there are no benchmark TOPsTWVP instances, we modify the TOPTW instances by 1) assuming the probability of occurrence of node i, π_i, is set to one, 2) setting $R_1, R_2, \ldots, R_n$ values for all nodes and providers. The second group of instances is randomly generated with varying the two above-mentioned points.

5.2 Experiment Results

5.2.1 Modified benchmark TOPTW instances

The most recent comparison of the state-of-the-art algorithms for TOPTW is conducted by Gunawan et al. [11]. Their proposed algorithms are able to find 50 best known solution values on the available benchmark instances. The experiments were compared with other algorithms by using the *SuperPi* [12] in order to ensure the fairness. Basically, the computational time is adjusted to the speed of the computers used in other approaches. We could not directly compare our results with two state-of-the-art algorithms: I3CH [12] and SAILS [11] since we allow soft time windows in HHCDP. Comparisons of objective function values would have no significance.

However, we observe that several results of EnILS are also feasible to the original TOPTW problem. In other words, there is no time window constraint violation. This could happen since providers also prefer not to delay the service to patients unless they can visit more patients with the possibility of getting lower objective function values. The feasible results are summarized in Table 2. We compare with the results of I3CH and SAILS, referring to I3CH computational times.

Table 2: Overall Comparison of EnILS to I3CH and SAILS

Instance Set	$Numb$	I3CH			SAILS		
		$<$	$=$	$>$	$<$	$=$	$>$
$m = 1$	76	21	25	1	22	25	0
$m = 2$	76	17	18	1	18	18	0
$m = 3$	76	10	8	2	10	10	0
$m = 4$	76	18	7	2	18	9	0
Total	304	66	58	6	68	62	0

Each instance set consists of 76 instances ($Numb$). We count how many feasible solutions which are smaller (<), equal (=) and greater (>) than those of I3CH and SAILS for each instance set. For example, feasible solutions of EnILS which are better than the ones of I3CH are 6 instances, in total.

With regards to I3CH results, EnILS is able to obtain 42.8% of feasible instances (130 out of 304 instances). There are 6 instances with better objective function values while 58 instances with the same objective function values with the ones of I3CH. For SAILS results, we also obtain the same amount of feasible instances. Sixty two instances have the same objective function values with the ones of SAILS.

We also calculate the number of visited locations. The results show that the number of visited locations is increased since we relax the time window constraints. The number of visited locations is increased between 6% to 20% from the results of the TOPTW. On the other hand, the total profit collected is decreased due to some penalties. From the provider's perspective in the context of the HHCDP, this is acceptable since more patients are visited.

5.2.2 Randomly generated instances

We extend the experiments by adding two randomly generated instances where each has a set of different m values. We set the number of locations up to 100 with m = four providers. We assume that certain locations have lower probability of occurrence values (π_i). Instance 1 has 50 locations with a probability of occurrence = 0.5 while Instance 2 has a probability of 0.25.

Table 3 summarizes the results of different scenarios. We emphasize on identifying how many locations with high probability values would be visited. From both instances, we observe that the proposed algorithm, EnILS, is able to visit locations with higher probability values. The percentage of locations with lower probability values is only up to 20.9%. When the probability of occurrence is much lower (e.g. 0.25), the results show that we should not visit any patients since they may cancel their appointments on that particular day. In other words, they are not the first priority of the visit. From the provider perspective, it is an indication that resources need to be increased in order to satisfy all patients although they are lower priorities.

Table 3: Random Instances Results

Instance	m	Number of locations with		Number of visited locations with		Total
		$\pi_i = 1$	$\pi_i = 0.5$	$\pi_i = 1$	$\pi_i = 0.5$	
Instance 1	1	50	50	9 (81.8%)	2 (18.2%)	11
	2	50	50	19 (86.4%)	3 (13.6%)	22
	3	50	50	29 (85.3%)	5 (14.7%)	34
	4	50	50	34 (79.1%)	9 (20.9%)	43
		$\pi_i = 1$	$\pi_i = 0.25$	$\pi_i = 1$	$\pi_i = 0.25$	Total
Instance 2	1	50	50	11 (100.0%)	0 (0.0%)	11
	2	50	50	22 (100.0%)	0 (0.0%)	22
	3	50	50	34 (97.1%)	1 (2.9%)	35
	4	50	50	39 (88.6%)	5 (11.4%)	44

6 Conclusion

In this paper, we address the Home Health Care Delivery Problem (HHCDP) and model it as a variant of the Orienteering Problem (OP), namely the Team OP with soft Time Windows and Variable Profit (TOPsTWVP). In HHCDP, we allow a late visit to the patients. The problem is solved by a fast algorithm, Iterated Local Search. The ILS algorithm is able to provide good solutions within reasonable computational times for two different sets of instances: modified benchmark TOPTW instances and randomly generated instances.

We summarize some directions in which future work on this problem can be explored. The optimal solutions or best known solutions for modified instances and randomly generated instances are still unknown. Therefore, we consider to develop an exact algorithm in order to provide us with the optimal solutions. In order to test the robustness of the proposed algorithm, we will apply the sampling based approach in order to simulate the probability of occurrence of demands in certain locations and analyze the performance of the proposed algorithm. Certain locations may have higher probabilities and it is expected that the proposed algorithm select those locations with higher probabilities. More randomly generated instances would be generated in order to provide and capture real world scenarios.

Acknowledgements This research is funded by the National Research Foundation Singapore under its Corp Lab @ University scheme and Fujitsu Limited as part of the A*STAR-Fujitsu-SMU Urban Computing and Engineering Centre of Excellence.

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