ISSN 2395-8618

Towards a Computational Intelligence Framework to Smartify the Last-Mile Delivery

Jhonny Pincay, Edy Portmann, and Luis Terán

Abstract—**Last-mile is the component of the supply chains that has the most potential to be optimized and give advantage to retailers and delivery companies. At the same time, it is the hardest to deal with. Factors such as traffic, weather, unexpected events, or the simple fact that a customer is not at home affect directly the efficiency of the overall shipping process. This work-in-progress article proposes a framework for the improvement of the first-try delivery by studying traffic on the streets and past delivery success as a way of approximating customers' presence at home. In contrast to existing solutions, it is proposed to work only with data that does not compromise the customers' privacy and to get insights about traffic features in cities without the need of deploying expensive equipment to obtain data. The main goal is to provide a route plan to the delivery team and route planners, which allows finishing the distribution of the parcels in the least amount of time, while being able to effectively deliver the highest amount of them. This will be translated into less resource consumption and increased customer satisfaction. The research work is conducted following the principles of design science research for information systems. The implementation will use methods of computational intelligence to address the lack of precise information, following a transdisciplinary approach as industrial partners support the development of this study.**

Index Terms—**Smart logistics, last-mile delivery, swarm intelligence, fuzzy logic.**

I. Background and Aim of the Research Work

ELECTRONIC commerce has grown tremendously in the last decades and shows no signs of declining any time soon. Day to day millions of transactions are performed and the same amounts of articles are being sent using postal services.

Currently, standing out from the competition and responding to costumers' expectations of delivery services are the main concerns for online retailers and postal service companies [1]. Besides quality products and good deals, most customers expect the shipment process of their parcels to be fast and efficient while being inexpensive [2], [3]. These aspects mean added complexity to supply chains and increasing costs of inventory management, packing and picking up, transport, customer service, among others.

Manuscript received on June 24, 2020, accepted for publication on July 31, 2020, published on December 30, 2020.

Jhonny Pincay and Luis Terán are with the Human-IST Institute, University of Fribourg, Bouleverad de Pérolles 90, Switzerland (e-mail: {jhonny.pincaynieves, edy.portmann}@unifr.ch).

Luis Terán us with the Human-IST Institute, University of Fribourg, Bouleverad de Pérolles 90, Switzerland, and the Universidad de las Fuerzas Armadas ESPE, Av. General Rumiñahui, s/n, Ecuador (e-mail: luis.teran@unifr.ch, lfteran1@espe.edu.ec).

While most delivery companies have optimized the majority of their distribution channels, there is still a lack of effective models for the optimization of the so-called "last-mile delivery." According to several authors (e.g., [4], [5], [6]), the last mile—the transportation of parcels from a hub to the final destination—is the component of the supply chains, which has the more potential to be optimized and give advantage to retailers and delivery companies. Nevertheless, the last mile is also the most difficult level to deal with, given the dynamic nature of the conditions where it occurs. Aspects such as traffic jams, weather conditions, unexpected events, or even that the customer is not at home when a postal worker rings the bell, affect directly the efficiency and resource consumption of the overall shipping process and the customers' satisfaction.

In the literature, solutions aiming to improve the last-mile delivery can be grouped into four groups [7]:

1) *Change in location:* Leaving a parcel in an alternative location.
2) *Change in time:* Delivering parcels at the times indicated by the customer.
3) *Change in route:* Closely related to changes in time, meaning that the route is adapted according to the time availability of the customers.
4) *Change in behavior:* Triggering customers to choose certain characteristics or delivery time, by offering cheaper fares for example.

While most of the existing solutions claim to have improved the efficiency of the last-mile delivery, most of them are context dependant are very closely related to the characteristics of an area [7], [5]. Moreover, they face challenges when it comes to obtaining the necessary data to develop prediction models since it comes incomplete, and becomes complex as a consequence of business operations (e.g., road and speed restrictions, multiple delivery stops, and waiting on customers). Another issue is the low sample rate as logistic companies might have unique vehicles covering certain routes. Further issues are related to the fact that is hard to accurately predict where a customer is going to be at a certain time [6], [8], given that privacy is a major concern and most of the time, customers are not willing to share their location with companies and some laws need to be accomplished (e.g., General Data Protection Regulation—GDPR) which increase complexity. Moreover, despite the alternatives provided to customers (e.g., pick-up places, ad-hoc carriers, trunk delivery, and parcel lockers), home delivery is the first choice of the

ISSN 2395-8618

vast majority of people. Therefore, efforts should be directed toward addressing the aforementioned issues.

This research work proposes a framework for the improvement of first-try delivery by studying the behavior of traffic on the streets and customers' presence at home. In contrast to existing solutions, it is proposed to work only with data that does not compromise the customers' privacy (i.e., avoiding the use of tracking data) and getting insights about traffic characteristics without the need of deploying a large number of vehicles or expensive sensors to obtain data. The main goal is to provide delivery route plan to the delivery team and route planners, which allows finishing the distribution of the parcels in the least amount of time, while being able to effectively deliver the highest amount of them, which will be translated into fewer resources consumption and increased customer satisfaction.

The aforementioned could be achieved through the use of fuzzy logic and computational intelligence, as a way of dealing with uncertainty and not accurate data [9], and following a transdisciplinary approach [10] to developing a solution that truly adjusts to the needs of the delivery companies and customers. Furthermore, this work will be conducted following the principles of the design science research for information systems methodology [11] and tested in a real-life scenario.

Considering the aspects presented in the previous section, the questions that need to be answered towards reaching the goals of this study are:

– *Which methods of computational intelligence are suitable towards finding ways of implementing a re-routing algorithm?* Given the nature of the problem, computational intelligence methods could be used to implement an improved routing of delivery. However, all these methods and theories should be studied in detail to find a viable one. Through pre-defined criteria, studying the needs of stakeholders, and a review of the state of the art, it will be possible to find an answer to these unknowns.
– *How can we reduce the first-try delivery failure without compromising customer privacy and while reducing resource consumption?* Considering aspects as the customer's presence at home and traffic characteristics, it will be possible to conceptualize and to build a framework, which will provide the means to process information in a human-like way to create a way that will allow to handling imprecision derived from the nature of the problem and the data studied. The framework will be evaluated utilizing a prototype implementation, experiments, and interviews with customers and experts.

II. Methodology

Design science research methodology guidelines will be used to conduct the present work. This research approach was chosen because it allows implementing artifacts systematically to extend existing knowledge while providing solutions to practical issues or organizational problems [11].

The design science research stages are to be executed in the following manner:

1) **Identify problems and motivation:** Through state-of-the-art review and interviews with people working on the logistics sector, it will be possible to define the current problems that afflict the last-mile delivery.
2) **Define Objectives of a solution**: Given the results of stage 1, the targets and requirements that the developed solutions must achieve can be clearly defined.
3) **Design and development:** After stage 2, it is possible to develop artifacts (i.e., a software prototype) that will allow us to conduct experimental tests to define if suitable solutions to the problems are implemented.
4) **Demonstration:** After the implementation of the artifacts, case studies will be executed towards demonstrating that they fulfill the requirements and meets their purpose.
5) **Evaluation:** By means of comparison with other existing solutions, the performance, and quality of the results provided by the artifacts can be evaluated. Moreover, expert interviews and satisfaction surveys can be conducted to evaluate the results from a qualitative perspective. Once this stage is completed, the researcher will decide if it is necessary to move back to stage 3. to improve the results or to move to the last process step which is:
6) **Communication** of the results, which translates into publishing the findings.

III. Theoretical Framework

This section provides details about the components that will conform a framework aimed at improving the first-try ratio delivery. Details about possible evaluation methods are also presented.

A. Building Blocks and Interplay

A theoretical framework aimed at improving the first-try delivery ratio is depicted in Figure 1. It is composed of four (4) main layers: *data*, *knowledge*, *intelligence*, and *visualization* layer.

The *Data layer* contains the different data sources used to the end of this work. Possible data sources that are the history of successful deliveries, the vehicles' log of events during service hours, and current route planning. The databases needed to conduct this research work are already available, given an existing partnership with an industrial partner.

The *Knowledge Layer* takes data from the data layer and processes it trough fuzzy logic methods; the output of this layer is the categorization of customers according to past deliveries success and critical traffic sectors in a city.

The output from the knowledge layer serves as input for the *intelligence layer* and it constitutes the basis to compute and find the most convenient route to complete deliveries in the least amount of time while saving resources consumption

ISSN 2395-8618

(i.e., less time spent on the streets translates into less fuel). A Swarm intelligence algorithm will be used to find the best candidate routes, considering the customer characteristics and if the routes have to pass by critical traffic areas. Options of swarm intelligence that are suitable for the present research work include Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) [12].

Finally, the *visualization layer* allows displaying of the delivery route which requires the least amount of time to be covered. It will allow logistic planners and the delivery team to interact with the recommended route and to make adjustments and changes; customers will be able to get updates about the status of their delivery. Moreover, it will be possible for the users to provide feedback about how useful the recommended route was and this feedback can be used to improve future recommendations.

Further details about a possible implementation of the knowledge and intelligence layer are presented below.

B. Knowledge Layer

Before attempting to find better ways to increase the first-try ratio of deliveries, it is important to understand the customer and traffic behavior, as those are factors directly affecting whether delivery is successful or not. Moreover, it is necessary to identify routes that have a less successful delivery ratio to be considered when re-routing the vehicles and to have a baseline for comparison and evaluation.

Clustering methods are a powerful way to analyze data and have become essential when developing solutions, interpreting information, and data dimensionality reduction. Unlike hard clustering, fuzzy clustering assigns elements to clusters with gradual memberships, meaning that objects can belong to a certain degree to more than one cluster. This provides more detail when building models and can reveal how ambiguous or certain an element belongs to a cluster [13].

In this work, it is pretended to deal with data that describe non-precise information such as the success of past deliveries (e.g., *"always successful* and *"mostly successful"*) and traffic congestion (e.g., *"congested street"* and *"normal traffic"*). Thus, fuzzy clustering constitutes a better fit towards representing in a better way the information and processing more homogeneous groups rather than a large number of single elements.

In the following, the algorithms and methods that can be used towards building the proposed artifact are explained.

1) Past Deliveries Success: The inclusion of customers' presence at home as a way of improving the first-try delivery ratio is a trend that has been exploited lately [14], [6], [8]. Considering that this work proposes an improvement to the first-try delivery without compromising the customers' privacy, tracking data about their location will not be used as unlike solutions found in the literature. Therefore, the authors propose using data from previous deliveries, which is owned by delivery companies, as a way of approximate the customers' home presence.

Through the Fuzzy C-Means algorithm [15], we propose to cluster addresses of customers according to the incidence of successful deliveries. It is possible to obtain clusters that categorize customers' addresses where the deliveries are for example *"successful most of the times"*, *"usually successful"*, *"rarely successful"*, and *"always unsuccessful"* in a similar fashion as proposed in the work of Mangiaracina et al. [6], but as we are dealing with non-precise concepts, the usage of fuzzy clustering will allow to have more expressive partitions and identify customers that might be on the border of a cluster, and therefore, having a more realistic interpretation of the reality.

2) Critical Areas Identification: With the goal of spending less time on the roads, it is necessary to identify zones inside the cities where traffic anomalies occur since they might provoke delays covering the delivering routes.

Most delivery trucks are fitted with global positioning system (GPS) devices which record their position and events happening when the vehicles are in operation. These tracking data can be used to derive information about what is happening in the streets without the need of deploying a large number of vehicles or expensive equipment [16], [17]. The authors of this article have already performed two case studies to identify anomalies on the streets [18] and predict travel time [19] through the geospatial indexing technique Geohash, and aggregation and mathematical operations.

C. Intelligence Layer

The intelligence layer is the component responsible for determining and recommending the best-performing routes to cover the package delivery. Even if there are various shortest path and optimal route algorithms (e.g., Dijkstra, A* search algorithm, and Bellman-Ford algorithm) [20], [21], they are rather static and do not respond to the need of routing problems in dynamic environments where factors such as traffic conditions and weather play crucial roles when finding optimal routes.

Ant colony algorithms have been used as an alternative to address the aforementioned challenges [21], [22]. They are based on the behavior of ants; these simple insects are able to accomplish complex tasks such as finding food, by working as a unit and lying some sort of pheromone which helps them to find the shortest path from their nests to the food sources [21]. Moreover, ant colony-based algorithms have been applied successfully in different domains of routing problems. One example is the work of Durand et al. [23] in which the authors attempted to optimize the solution of air traffic conflicts; Jiajia & Zaien [24] performed a study for traffic signal timing optimization using ant-based algorithms and obtaining promising results. Further examples include the AntNet algorithm described in [25] which addresses the routing problem in packet-switched networks and the work of Jagadeesh et al. [26] that introduced a hierarchical routing algorithm that computes a near-optimal route in a large city road network.

ISSN 2395-8618

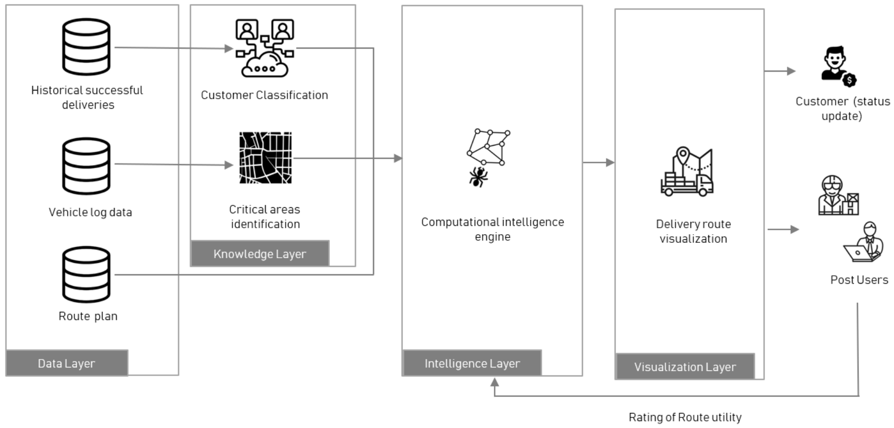

Fig. 1. Building blocks and interplay of the proposed framework.

1) Fuzzy Ant System: The ant colony optimization (ACO) is a metaheuristic that allows solving complex combinatorial optimization problems [22]. It was conceived by Dorigo and Di Caro [27], the researchers applied the ant system to the well-known Traveling Salesman Problem (TCP).

To solve the TSP problem using ACO, artificial ants are the entities in charge of finding a solution in the solution space. At the beginning of the search (time $t = 0$), the ants are located in different towns (nodes) that need to be visited or served by the salesman; then when an ant moves to an unvisited town, it leaves a pheromone (trail intensity) which helps other ants to decide the paths to choose in the future depending on the pheromone intensity [22]. Moreover, the next movement or so-called transition probability $p_{ij}^k(t)$ is defined by the following expression [28], [29]:

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)^{\alpha}\eta_{ij}{}^{\beta}}{\sum_{h\in\Omega_i^k(t)}\tau_{ih}(t)^{\alpha}\eta_{ih}{}^{\beta}}, & if\ j \in \Omega_i^k(t) \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $\Omega_i^k(t)$ corresponds to all the possible nodes to be visited by an ant k; d_{ij} is the Euclidean distance between nodes i and j; $\eta_{ij} = 1/d_{ij}$ is the *visibility* and α, β are parameters that represent the importance given to the trail intensity and visibility.

One important concept from the previous explanation is one of visibility. It refers to the desirability of choosing a city j while currently being in town i [30], meaning that visibility is based on local information. In the case of trail intensity, the more important it is given, the more desirable the link becomes since many ants have already passed that way [22]. Moreover, every ant will complete a traveling salesman tour after n iterations; m iterations of the algorithm are called a cycle and after each cycle, the trail intensity needs to be updated, following the natural behavior of evaporation of pheromones. There are different methods to update the trail intensity (see [30], [27], [22]), and this is made with the goal of discovering a good solution through cooperation.

Teodorović and Lučić [28], [29] go one step further and propose the fuzzy ant system (FAS), which resulted from the combination of ACO with concepts of fuzzy logic. The principles are the same, differing on the way how the utility is calculated to visit the next node. The authors assumed that the ants can perceive the distance between nodes as *small*, *medium* and *big*, whereas the trail intensity can be anticipated as *weak*, *medium* or *strong*. Furthermore, an approximate reasoning algorithm to compute the utility when choosing the next link is composed of fuzzy rules similar to the following:

If d_{ij} is SMALL and τ_{ij} is STRONG
Then u_{ij} is VERY HIGH

where d_{ij} is the distance between node i and node j, τ_{ij} represents the pheromone along the link (i, j), and u_{ij} corresponds to the ant's utility when choosing the node j, considering that the ant is located in the node i.

With fuzzy logic acting as a separate module within an ACO implementation is possible to handle the uncertainty present in complex combinatorial problems [22]. Applying fuzzy rules reduces complexity and allows us to represent nature and reality with higher fidelity, leading to the generation of good implementations that can find solutions in a reasonable computational time [28].

D. Basis of the Proposed Solution

The fuzzy ant system proposes the usage of linguistic variables to approximate the distance between nodes when deciding which place to visit. Taking that approach further and landing it to the last-mile delivery, the authors of this research work propose an practical implementation on boundary of the principles of FAS, by adding further variables that come into play when performing the delivery of packages to households.

As illustrated in Figure 1, the intelligence layer of the proposed framework uses a customer classification according to the success of past deliveries and information related to critical traffic areas. Such concepts are uncertain and imprecise; thus, their representation as fuzzy variables is

ISSN 2395-8618

coherent. Traffic status can be represented in terms of linguistic variables as *"no traffic"*, *"normal traffic"*, *"heavy traffic"*, *"extremely heavy traffic"* for example; whereas the delivery success of parcels in the household could be defined as *"always unsuccessful"*, *"rarely successful"*, *"usually successful"*, *"most of the times successful"*, and *"always successful"*. Possible membership functions of these fuzzy sets are shown in Figures 2 and 3.

When an ant has to decide about the utility of the next link, meaning in this context the next address to visit to deliver a package, it can act in accordance with fuzzy rules composed in the following manner for example:

If d_{ij} is SMALL and τ_{ij} is STRONG and
ϕ_j is ALWAYS SUCCESSFUL and θ_{ij} is NO TRAFFIC
Then u_{ij} is VERY HIGH

where d_{ij} is the distance between node i and node j, τ_{ij} represents the pheromone along the link (i, j), in the same manner as the FAS proposed by Teodorović and Lučić [28]. ϕ_j represents the delivery success of the customer located in node j, and θ_{ij} is the traffic status when transiting from node i to j; u_{ij} corresponds to the ant's utility when choosing the node j, considering that the ant is located in the node i.

The usage of fuzzy rules of this type will allow to address the issues that partially known input brings along.

Furthermore, adapting the FAS [28], [29] algorithm to the conditions of the problem addressed in this work, the delivery routes can be created in the following way:

- **Step 1**: Describe the past delivery success of the households to be visited, in linguistic terms (see 2). Set the counter of the cycles to zero ($c = 0$)
- **Step 2**: Define the number the numbers of cycles C that the algorithm is going to be executed. If the number of cycles is reached, proceed to Step 4, otherwise proceed to Step 3.
- **Step 3:** Set the counter of ants to one ($k = 1$). All m ants are to be located at the starting point. Generate m sets of routes by m ants. Each ant generates a route. When all nodes are visited, ant k will finish with the route design. Increase the ant counter by one after creating one set of the routes. If the ant counter is equal to $m + 1$, increase the cycle counter by one and go to step 2. Otherwise, the next ant creates the set of routes within the considered cycle.
- **Step 4:** Take the routes that perform better in terms of time and that provide allow a higher delivery hit-ratio.
- **Step 5:** Recommend the top-performing routes to the delivery team.

For Step 5, it is possible to rank the top-performing routes found by the artificial ants in terms of the utility perceived by the delivery team. Thus, it is coherent to ask them if the computed routes improve the delivery ratio when delivering parcels. People from the delivery team could make use of natural language expressions to express their satisfaction with the suggested route (i.e., *"not useful"*, *"somewhat useful"*, and *"useful"*) in this way, routes that might not represent any improvements can be identified and adjusts can be made.

E. Evaluation

Controlled experiments, simulations and case studies can be performed to evaluate the quality of the results obtained from the implementation of the artifact. Moreover, given that it is proposed to execute this research work following a transdisciplinary approach, the practice partners are also to be involved in the evaluation of the solution, and thus, qualitative analysis in conjunction with interviews and expert opinions and are also to be performed to measure the performance of the framework.

IV. Outlook and Conclusions

In this article a framework that enables the improvement of the first-try delivery by studying the behavior of traffic on the streets and customers' presence at home. In contrast to existing solutions, it is proposed working only with data that does not compromise the customers' privacy as (i.e., avoiding the use of tracking data) and getting insights about traffic characteristics without the need of deploying a large number of vehicles or expensive sensors. The main goal is to provide a delivery route plan to delivery teams and route planners, which allows finishing the distribution of the parcels in the least amount of time while being able to effectively deliver the highest amount of them. This will be translated into less resource consumption and possible increased customer satisfaction.

The work to be conducted to implement the framework is practice-oriented and aimed at identifying and solving problems that affect societies, industries, and cities, while also expanding knowledge from it. Having the support of practice partners (transdisciplinarity) eases the fact of testing the developed solutions in real-life scenarios, and with that, it is possible to refine them towards finding an optimal solution to the problems addressed.

Moreover, with the execution of this research work, it is expected to contribute to developments in the field of smart logistics, in the assessment of how approximative methods (i.e., fuzzy logic, and computational intelligence) can be leveraged towards building working solutions that do not need large amounts of precise information (i.e., machine learning solutions), and additionally, the results to be obtained can be used as a basis to develop further solutions in the field of green logistics and urban planning. In the practical terms, this project will provide to our practice partners a tool to perform better delivery route plans which translate into less failed delivery, less resource consumption, and therefore, a possible nation-wide more sustainable delivery service.

Acknowledgment

The authors would like to thank the members of the Human-IST Institute at the University of Fribourg for contributing with valuable thoughts and comments. We especially thank

ISSN 2395-8618

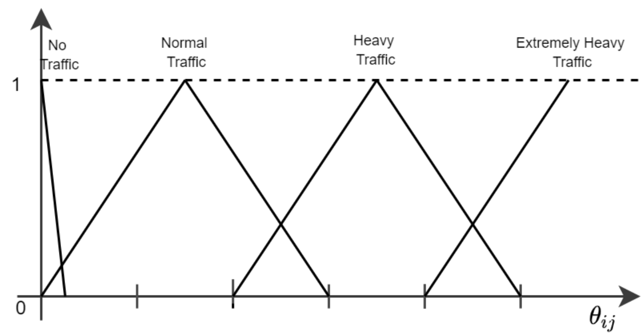

Fig. 2. Membership functions of the fuzzy sets depicting traffic condition between nodes.

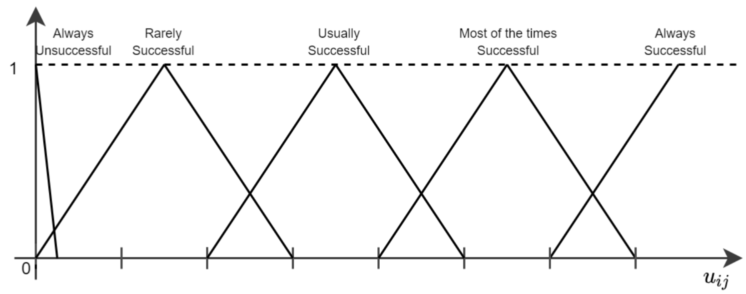

Fig. 3. Membership functions of the fuzzy sets depicting delivery success of parcels in the household.

the Secretariat of High Education, Science, Technology, and Innovation (SENESCYT) of Ecuador and the *Swiss Post* for their support to conduct this research.

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