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RESEARCH ARTICLE

A Scalable and Efficient Backpressure-Based Scheduling Framework for Supply Chain Networks

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ABSTRACT Supply chain networks have proven to be rather important and delicate to seemingly small perturbations of their operations. Although scheduling has been extensively studied in logistics systems, there are several remaining open challenges regarding scalability, stability, and other quality indices. In this work, we present a novel framework denoted as BackPressure-style Packet transfer algorithm for Logistics Systems (BPLS) for making jointly optimal routing and scheduling decisions in freight networks. The proposed approach is based on the backpressure algorithm and maximum weight matching, which have been extensively applied for optimal routing and scheduling of data packet transmissions in communications networks. Our goal is to develop a broader optimal transfer process for freight networks consisting of multiple entities, such as last-mile companies, freight subcontractors, etc., addressing all the previously mentioned challenges and in addition, allow for setting different optimization goals regarding the offered quality of service. Special features of freight networks such as the limited capacities of both storage places and transportation means along with the time-varying availability of the latter are considered by means of integrating pressure functions in the original backpressure approach. We provide extensive simulations with evaluation and comparison results on the performance of the approach, demonstrating its potential to improve up to more than 100× on the traditional BP algorithm. In addition, we have incorporated an implementation in an operational information system to assess the potentials of BPLS with multiple interested stakeholders. Through simulations and the actual evaluation, we were able to show how the framework can be used to provide long and short term decisions for optimizing holistically freight networks.

INDEX TERMS Backpressure scheduling, pressure functions, logistics, information systems, packet priorities, performance evaluation, stability analysis.

I. INTRODUCTION

Recent cases of freight network dysfunctions, such as those experienced during the demand surge in the COVID-19 period in 2020 and the 2021 Suez Canal obstruction [1], have demonstrated evidently the importance of a globalized supply chain network, as well as the gravitational impact that small changes may have in the global and local economies. Blockages of high-frequency channels, spiking demands, and economical paradigm shifts, e.g., e-commerce uptake, pose significant challenges to freight distribution systems, leading potentially to immense recovery costs, waste of resources and retail price surge. Such cases have been observed to have longer-term effects, at least more than anticipated, leading to longer market recovery times, e.g., spanning years instead of the predicted months or weeks. It is therefore necessary to

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optimize holistically such networks and ensure their stable operation, while keeping operational costs restricted and improving the quality of service offered to the end customer, such as shorter delivery times, lower-cost priority handling, etc.

The logistics ecosystem consists of multiple independent carriers, each of different capacity, range and specialization, subcontractors, warehouses, last-mile delivery, etc. A single transfer of a package from a source to a destination location can be typically split in multiple subcontracts, with different carriers implementing different components of the end-to-end transfer. These parties typically behave rationally and attempt to optimize their own operations within the overall ecosystem/competition. Their objectives can be potentially conflicting in the overall ecosystem, and a cumulative optimal decision-making requires considering system state information, e.g., backlogs, deadlines, etc., from the whole distribution network.

The two fundamental problems emerging for each carrier are first where to send loads next so that they move closer to their destination (routing problem) and then when to send them (scheduling problem). Of course, there are other problems, such as where to store and for how long the unprocessed/excessive loads, but these problems are directly related to the decisions made by routing and scheduling (loads not scheduled for transfer will need to be at least temporarily stored, etc.). Typically, scheduling regards the assignment of (often constrained) resources to the execution of tasks. For logistics, these resources constitute loading space (e.g., of a truck), packet volume/weight, etc., and the tasks regard the delivery of packages, storage management, etc. Routing is the process of selecting a path for traffic in a network or across multiple networks, where in logistics the network corresponds to the existing transfer channels (highways, railways, seaways and airways) and traffic describes the loads of packets to be transferred. To date, the above problems have been addressed partially, or only from the perspective of a single entity, e.g., finding optimal solution for the delivery times of one carrier, and not from a holistic perspective, i.e., one that would produce the overall optimal solutions for all stakeholders.

In this work, we address the aforementioned gap and propose a novel framework for making optimal, stable and scalable decisions for the routing and scheduling of packet transfers in freight networks. The framework, entitled Backpressure-style Packet transfer algorithm for Logistics Systems (BPLS), considers the overall logistics network, i.e., the complete network where multiple operators and subcontractors are active, and follows the design principles promoted in [2], while capitalizing on the mathematical basis of [3]. In particular, the backpressure (BP)-based approach for joint scheduling-routing of [3] is adopted and significantly expanded. Specifically, our previous work [2], [3] promoted a simple backpressure algorithm for a case typically including either a very large freight management company, or an ecosystem of smaller-larger companies and individual contractors, which desire to send packets from sources to destinations accounting for the time-varying availability of the transport means as well as their limited capacities. This logistics problem was mapped to a BP scheduling problem and the approach of [3] suggested optimal decisions in the form of a regulation authority. We employ the same perspective as in [3] but expand the BP framework for the case including limited capacity storage places in addition to limited capacity transport means by a more intelligent approach, founded on integrating the concept of pressure functions in the original BP algorithm. Additionally, we consider different traffic priorities as well as delay minimization. Towards the latter direction that is clearly of outermost importance for logistics, it is ensured that in one time-step the complete set of transportation resources between a node pair are utilized, i.e., that no intermediate transportation means remaining under-utilized - corresponding for instance to a truck not sent out for delivery partially empty. We present evaluation results on the behavior and performance of the proposed algorithms demonstrating the feasibility of the overall framework and its potential for optimizing logistics systems management. Furthermore, we present an actual implementation of the algorithm in an operational information system developed from scratch, which can provide real-time decisions to the members of the ecosystem, e.g., small-medium enterprises or independent contractors.

The novelty of this work is in the new backpressure algorithm, which is re-designed in such a way that it could be used by a regulation authority or a coalition of stakeholders in a logistics ecosystem to optimize routing and transfer decisions, while accommodating all the different features of a freight network, not covered by the original backpressure algorithm proposed for data networks. The developed mathematical framework and its evaluation, help in order to gain insights of its potential performance benefits and demonstrate the type of decisions that can be obtained and used in practical scenarios, while the implementation of the framework in an operational information system is very important to assess its potentials with multiple interested stakeholders. Thus, via a combination of simulations and actual evaluation, we were able to show how the framework can be used to provide long-term and short term decisions for optimizing freight networks at small or large-scale.

The rest of this paper is organized as follows. Section II presents relevant works and distinguishes our contribution from them. Section III formulates the problem to be solved and sketches the proposed solution. In particular, Section III-A sketches the changes required on the traditional backpressure algorithm for freight companies, Section III-B defines the employed system model and Section III-C presents the proposed BP-based algorithm for logistics applications (BPLS). Section IV provides indicative results on the performance and behavior of the proposed approach via simulations, and Section V presents an implementation of proposed algorithm in an operational information system.

Finally, Section VI concludes the paper and highlights directions for future work.

For the rest of this paper, we will use the terms package, mainly employed in logistics, and packet, mainly used in data networks interchangeably without loss of generality or accuracy. We will point out the differences and focus on the features relevant to the logistics networks.

II. BACKGROUND AND RELATED WORK

First, we review existing optimization approaches of logistics systems and explain their limitations in terms of providing holistic solutions (i.e., not tailored to specific cases) for the joint scheduling and routing problem, which is a contribution of this work by employing the BP algorithm. Second, we review existing BP-based approaches that mainly lie in the field of communications networks and go through BP's limitations for being directly applied to logistics systems, therefore cumulatively highlighting an evident gap in the corresponding field, addressed by this work. Finally, we point out our contributions by developing BPLS in the domain of logistics transfers towards optimal, stable, traffic-type-specific and delay-aware decisions under limited capacity and time-varying resources availability in a broader freight transfer system.

A. OPTIMIZATION OF LOGISTICS SYSTEMS

The optimization of logistics [4] became an evident necessity already from the late 1800s and early 1900s, and even more pressingly during World War II, where it became apparent that efficient and timely deliveries can be critical [5]. Such effort led to the systematic research and technology development within Operations Research already from the 1960s [6], and notable effort has been devoted to the analysis of scheduling towards joint criteria optimization, e.g., transfer cost reduction and failure minimization. Next, we briefly discuss earlier and latest existing works that are mostly related to our setting. Earlier approaches are mostly based on optimization, typically for a single entity such as a subcontractor, whereas latest approaches employ modern machine learning-based techniques and consider emerging cyber-physical features in the logistics ecosystem.

In regards to earlier approaches, the work in [7] solves a problem where a manufacturer receives raw material from a producer and delivers products to a customer. All operations take place in different locations, and the goal is to minimize the cumulative production-transfer cost, including the raw material and associated delivery costs. When all processes have the same duration, an $O(n)$ solution algorithm is developed. The work [8] studies the impact of multiple (sequential) scheduling stages, with emphasis on two-stage processes in a logistics system of a company. A forward and a backward approach for solving the sequential stages is taken, reaching heuristic solutions in both cases. The work in [9] studies a scheduling problem in the last-mile, the final node before the end customer of a supply chain. Assuming specific truck delivery times, the optimal routes for the last-mile are designed, assuming the last hop can be flexible. On the contrary, the work in [10] focuses on a single-stage scheduling problem, where tasks are delivered in batches. A branch-&-bound solution is proposed for minimizing the withhold and transfer costs. Compared to the proposed BPLS approach, the existing optimization approaches for logistics systems address specific scheduling problems in logistics systems, without providing holistic solutions. The proposed BPLS framework aspires to fill in this gap and on top allow the definition of additional quality of service related problems, e.g. setting quality of serive criteria such as expedited delivery with special packaging or lower cost bulk transfer, etc.

Very recent works study the scheduling and routing problems in modern logistics systems with cyber-physical feautures. The paper [11] enhances delivery operations in logistics systems by suggesting a two step approach that uses deep learning to perform delivery time estimation and the Dijkstra's algorithm in combination with Particle Swarm Optimization to dispatch optimal paths. Contrary to our work, it neither performs close-to real time scheduling and path adaptations based on emerging changes in traffic conditions and delays in transfers nor considers traffic priorities. Along the same lines, the vehicles routing problem is studied in the recent paper [12] considering eclectic vehicle fleets for the transfers and their charging constraints. Another work with application on logistics, [13], studies scheduling and routing of vehicles, but scheduling regards avoiding collisions when using automated guided vehicles contrary to our work that is about choosing which connections will be served by vehicles at a given time depending on load conditions and vehicle availability. In [14], the authors study the vehicle routing problem in logistics systems using multi-agent Reinforcement Learning to solve the Markov decision process corresponding to the economic scheduling problem of logistics transport vehicles. Significant improvements ($\sim$ 30%) are achieved with respect to the total vehicle mileage and the average carriage loading rate. However, it does not consider different priorities of packages as well as different capacities of intermediate storage places. Table 1 summarizes the features included in the aforementioned papers on logistics optimization in comparison to the proposed BPLS.

B. BACKPRESSURE AND LIMITATIONS FOR LOGISTICS SYSTEMS

The BP algorithm was first proposed in [15] considering distributed wireless communications networks and entails two stages, achieving joint optimization: a phase determining routing based on differential backlogs and a link scheduling phase where a maximum weight matching problem is solved. In logistics terms, routing refers to determining a path that a package will follow from its source to its destination, namely determining the whole path including the intermediate warehouses and branch shops stored. The BP algorithm makes dynamic decisions and does not determine the whole

TABLE 1. Summary of features of existing works in logistics optimization that are mostly related to our setting.

Feature/ Work	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	BPLS
Routing					✓	✓	✓		✓
Scheduling	✓	✓	✓	✓			✓	✓	✓
Delay-awareness	✓		✓		✓		✓		✓
Traffic priority									✓
Limited storage capacity									✓
Real-time Adaptation				✓		✓	✓	✓	✓
Cost minimization	✓	✓	✓	✓	✓	✓	✓	✓	✓

path initially, but at every time t, it chooses the next node of the network that the package needs to be sent at, therefore optimizing routing decisions dynamically according to the current system state (congestion level). Scheduling refers to whether this package should be sent at time t to the next (intermediate) destination or defer the transfer for another time.

The backpressure algorithm has the advantages of being throughput optimal, adaptable to time-varying network conditions and applicable without a-priori knowledge on the network load characteristics. All these features are especially attractive for freight networks, but also for other applications. It has been enhanced and adapted for diverse applications such as for traffic lights management [16], [17], for energy management in energy harvesting networks [18] and wireless energy exchange networks [19], and for traffic flows with diverse characteristics such as delay requirements [20], bandwidth allocation in multicast networks [21], etc. Despite the important advantages of throughput optimality and dynamic decision-making of BP, its deployment to other application areas, including logistics, can be impeded by the fact that it can lead to high delays in package transfer due to the emergence of routing loops [22], the slow-start problem, as well as the last packet problem in low traffic conditions [23]. BPLS solves these problems by ensuring that the full capacity of the transport means is always in use if loads are available and by in combination borrowing techniques for improving the delay of the conventional BP algorithm, which are explored below.

C. IMPROVING THE DELAY OF BACKPRESSURE

Several approaches aim to address the delay issues of the BP algorithm. Lately, [24] proposed a throughput-optimal biased backpressure algorithm for routing, where the bias is learned through a graph neural network, towards minimizing end-to-end delay. The approach aims to favor shorter paths by incorporating pre-defined biases in the backpressure computation, such as biases indicating shortest paths (in hops) to the destination. The authors in [23] apply the drift-plus-penalty technique to account for the lifetime of the data packets considered in a communication network and packets are discarded if they have not reached their destination within a specific time limit. The work in [25], suggests a variation of the backpressure algorithm aided by shortest-path routing that achieves reduced packet delays by enforcing traffic routing via shortest paths. In our previous work in [26], we propose a weighted backpressure algorithm that scales the congestion gradients with appropriately defined per-pair (link, destination) weights. This achieves performance-awareness with respect to a given measure, such as delay, which is linked to the definition of the weights. The work in [27] achieves delay improvements by using LIFO instead of FIFO queues. A priority mechanism is proposed in [20] via storing priority packets in different queues than the normal packets. Finally, [28] develops a loop-free backpressure algorithm using directed acyclic graphs. All features offered by the aforementioned works can be useful in various cases, but the corresponding approaches do not address holistically the emerging challenges in freight networks while taking into account specific features aligned to them such as limited capacities of both links and nodes and under-utilization costs, which is exactly where our proposed approach contributes.

D. CONTRIBUTIONS OF THIS WORK

To the best of our knowledge, the proposed BPLS framework is the first approach allowing to address holistically the emerging joint routing and scheduling problems in freight systems. The heart of BPLS lies at the BP algorithm that is typically used in communications networks but in our work is shown to be very promising for freight systems as well. The two stages of the BP algorithm, i.e., routing and scheduling, address the more fundamental operations required for package transferring in logistics applications, since for each packet one needs to determine the warehouse where it should be transferred next as well as if it will be transferred now or wait to be transferred later, given the availability of the transport means (e.g., the available space in trucks, trains or planes) and of the storage places. The conventional BP algorithm's operation is adapted to the particular characteristics of freight systems to cover delay requirements and account for limited storage space as well as priority handling. We demonstrate its potentials, both theoretically via analysis and practically via simulations and the presentation of an operational implementation.

III. BACKPRESSURE-STYLE PACKET TRANSFER ALGORITHM FOR LOGISTICS SYSTEMS (BPLS)

A. ADAPTATION OF THE ORIGINAL BACKPRESSURE ALGORITHM FOR LOGISTIC SYSTEMS

We propose a backpressure-style decision-making algorithm for package transfer in logistics systems that performs (i) routing of packages, i.e., chooses the next warehouse along the package's path towards the destination, and (ii) scheduling of packages, i.e., chooses which links will have a non-zero capacity in the sense that the trucks (or other transportation means employed) will move along them and carry package traffic. In particular, we have enhanced and adapted the original backpressure algorithm so as to exploit its high throughput properties while tackling its delay and loops-related limitations for freight companies. More specifically:

- Each warehouse organizes its stored packages in two types of queue structures, one for emergency packages and one for normal packages. In this way, flows of different priorities can be easily distinguished and handled base on their own needs in terms of delay. This is a similar approach as the one of [20].
- Following the approach of [25], the queue structures are further differentiated in relation to the hop-distances of the warehouses to the final destinations of the packages in order to avoid routing loops that waste the network capacity and increase delays.
- Based on the paradigm of [29], our proposed backpressure-style algorithm uses pressure functions when defining the queue differentials aiming to account for the limited storage space of the associated warehouses.
- Contrary to the classical backpressure algorithm, BPLS chooses as many queues to serve as required until there is either no more enough free capacity in the transport means or no more enough storage space in the receiving warehouse or no more available packets to serve. This is an important enhancement of the original BP algorithm for logistics systems as it is not cost-efficient (or even acceptable) to move half-empty transport means if there is available load waiting in warehouses.

B. SYSTEM MODEL

1) FREIGHT NETWORK AS A FLOW GRAPH

We consider a freight network describing the operations of the logistics ecosystem, represented as a directed graph $G = (V, E)$ with V the set of nodes ($|V| = N$) and E the set of directed links ($|E| = L$). The nodes correspond to warehouses or premises of potentially different logistics companies. The links represent the capability to transfer loads/packages from one node to another.

We define the capacity, $c(i, j, t)$, of a link $(i, j) \in E$ between nodes $i, j \in V$ at time t, expressed in m^3. In particular, if $c(i, j, t) = 0$, there is no possibility of package transfer between i and j at time t and if $c(i, j, t) > 0$ some type of transport means (e.g., trucks) with aggregated capacity $c(i, j, t)$ are available between i and j at time t.

We compute the hop distance between all pairs of nodes-warehouses, denoted as $hops(i, j)$ for a pair of warehouses i and j, e.g., by applying the Dijkstra's algorithm on G [31]. This distance may be considered constant for the purposes of our study because it varies rather slowly in the actual logistics networks, e.g., monthly or even yearly, since the corresponding changes are associated with adding/removing warehouses and/or carrier branches.

2) PACKET TRAFFIC FLOWS: DEFINITION, GENERATION AND TRANSFER

We define a flow to represent packet traffic sent from a specific source node to a particular destination node. There can be multiple flows between the same source-destination pair with different characteristics, e.g., priorities, handling requirements, etc. More specifically, we consider two types of priorities for the flows, namely, emergency and normal. Emergency flows consist of packages that should be transferred the quickest possible from source to destination. Normal flows would also prefer but do not necessitate small delays.

Nodes may generate new packet traffic for some destinations, e.g., representing new packets handled by customers to warehouses. The newly generated traffic in m^3 from node i, at time t, and that should arrive via at most h hops to the destination is denoted as $a_i^{emg,h}(t)$ if belonging to an emergency flow or as $a_i^h(t)$ if belonging to a normal flow. Moreover, transport means (e.g., trucks) transfer packet traffic from a warehouse i to a warehouse j over link (i, j), if its capacity allows, and assume $r^{emg}(i, j, t)$ and $r(i, j, t)$ as the amounts of emergency and normal packets, respectively, expressed in m^3, that are transferred over link (i, j) at time t. Of course, the capacity constraint $r^{emg}(i, j, t) + r(i, j, t) \leq c(i, j, t)$ should be satisfied.

3) NODE QUEUES WITH FINITE CAPACITY

To handle flows of different priorities, each node/warehouse maintains two types of queues, namely H emergency and H normal queues with H the maximum hop distance for all node-pairs in G. H can be trivially set to $N - 1$, as the maximum possible diameter in a network with N nodes. Let $Q_i^{emg,h}(t)$ and $Q_i^h(t)$ be respectively, the emergency and normal queue of node i containing packages to be transferred in at most h-hops to their final destination. Note that with $Q_i^{emg,h}(t)$, $Q_i^h(t)$, we abusively denote both the queue structures and the aggregated space filled by the packets currently stored in the queues in m^3 without loss of accuracy.

The length of each queue Q_i^f ($f \in \{(emg, h), h\}$) is updated with time as follows:

$$Q_i^f(t+1) = \max\{Q_i^f(t) - \sum_{j \in N_i} r_{(i,j)}^f(t), 0\} \tag{1}$$

$$+ \sum_{j: i \in N_j} r_{(j,i)}^f(t) + a_i^f(t), \tag{2}$$

where we denote by N_i the set of one-hop neighbors of i. Each location (warehouse, branch, etc.) i is assumed to have an aggregated capacity C_i to store packets for all queues, expressed in m^3.

4) LINK FORMATION

A link with non-zero capacity can only be formed if there is an available transport means (e.g., trucks) at its one endpoint able to reach the other one and with free space so as it can get loaded with packets. And at each time t, the availability of transport means varies since different vehicles, trucks, ships, containers, etc., can be at different places and filled with different loads over different times. Thus, at every decision time interval there might be only specific sets of links possible to be formed and carry traffic.

To express this link formation process more formally, assume that $Y(t)$ is a time-varying set of sets of links with non-zero capacity. A set $I \in Y(t)$ is a subset of E containing links that can sent concurrently packets, based on the availability of the transport means. In particular, different $I \in Y(t)$ correspond to different set of links that can be formed based on the possible routes that the available transport means can follow. For better illustration purposes let us examine a toy example. Assume two trucks with capacities tc_1, tc_2 (in m^3). At time t, the truck 1 can move from warehouse 1 to 2 and the truck 2 from warehouse 2 to 3 or from 2 to 4. Then, $Y(t) = \{I_1 = \{(1, 2), (2, 3)\}, I_2 = \{(1, 2), (2, 4)\}\}$. The capacity of each link at time t will be equal to the capacity/free space of the corresponding available transport mode, i.e., for I_1, $c(1, 2, t) = tc_1$, $c(2, 3, t) = tc_2$, $c(2, 4, t) = 0$ and for I_2, $c(1, 2, t) = tc_1$, $c(2, 3, t) = 0$, $c(2, 4, t) = tc_2$.

In addition, we assume that the system is in its steady state and that the ergodic limits of the arrival processes $a_i^{emg,h}(t)$, $a_i^h(t)$, lie in the capacity region of the network. Finally, each time slot t corresponds to a decision interval. The duration of the time slot can vary depending on the goals of each problem and the variability of the underlying specific systems.

C. BPLS ALGORITHM

In this section, we describe the proposed backpressure-based algorithm for logistics applications (BPLS). Specifically, below we present all the computing and decisioning steps that should be followed for every time t.

1) BPLS ACTIONS FOR EVERY DECISION INTERVAL t

For each node/warehouse $i \in V$, we determine its free storage space (in m^3) at time t as

$$C_i^{\text{free}}(t) = C_i - \sum_{h=1...H} (Q_i^{emg,h}(t) + Q_i^h(t)). \tag{3}$$

For each link (i, j) in E we compute the optimal differential backlog at time t, $\Delta Q^*(i, j, t)$, as follows:

If the emergency queues of node i are not empty, we will first process packets from the emergency queues and packets from the normal queues will be transferred only if available space remains. In this case, we define:

$$\Delta Q^*(i, j, t) = \max_{h=1...H} \{\max\{P_i^{emg}(Q_i^{emg,h}(t)) - P_j^{emg}(Q_j^{emg,h-1}(t)), 0\}\}, \tag{4}$$

with $P_i^{emg}(.)$ representing the pressure function of node i for emergency queues. The pressure function may obtain diverse forms, and later in this subsection we provide indicative examples.

Otherwise, if the emergency queues of node i are empty, packets from the normal queues will be served. We define as:

$$\Delta Q^*(i, j, t) = \max_{h=1...H} \{\max\{P_i(Q_i^h(t)) - P_j(Q_j^{h-1}(t)), 0\}\}, \tag{5}$$

with $P_i(.)$ the pressure function of node i for normal queues.

Let $h^*(i, j, t)$ be the optimal number of hops that achieves $\Delta Q^*(i, j, t)$ for link (i, j) at time t. For brevity, we will denote $h^*(i, j, t)$ as h^* in the following.

Once $\Delta Q^*(i, j, t)$ is computed for all links $(i, j) \in E$, we solve a maximum weight matching problem to determine the optimal set of links that will carry packets at time t. The maximum weight matching problem can be written as:

$$\max_{\forall I \in Y(t)} \sum_{(i,j)\in I} c(i, j, t)\Delta Q^*(i, j, t). \tag{6}$$

Let us assume that I^* is the solution of the above problem. If a link is selected for packet transfer, which means it belongs to I^*, the selection of packets to be transferred on it is performed as follows:

1) If the priority queues of node i are non-empty, then (i, j) will first serve packets in $Q_i^{emg,h^*}(t)$, which achieves the maximum $\Delta Q^*(i, j, t)$. The number of packets served from the selected queue will be equal to $\min\{Q_i^{emg,h^*}(t), c(i, j, t), C_j^{\text{free}}(t)\}$. If $c(i, j, t) > Q_i^{emg,h^*}(t)$ and $C_j^{\text{free}}(t) > Q_i^{emg,h^*}(t)$, then the link can serve more packets such that the available space, e.g., of a truck does not remain partially unused. To do so, the link first ranks all remaining priority queues (apart from h^*) according to the differences $P_i^{emg}(Q_i^{emg,h}(t)) - P_j^{emg}(Q_j^{emg,h-1}(t))$. Assuming an ordering from the first to last is $h_1, h_2, \ldots, h_{H_{emg}-1}$, where H_{emg} is the number of emergency queues (accounting also for the one served already) and if h_k ranks higher than h_l, this means that $P_i^{emg}(Q_i^{emg,h_k}(t)) - P_j^{emg}(Q_j^{emg,h_k-1}(t)) > P_i^{emg}(Q_i^{emg,h_l}(t)) - P_j^{emg}(Q_j^{emg,h_l-1}(t))$. Then (i, j) starts serving packets from queues ranked higher, namely, first from the queue with index h_1, then with h_2, etc., until the capacity of the link is exhausted or the free storage space of node j is exhausted or there is no remaining packet to be served. If node i has served all packets from the emergency queues but there is still available space in the link and the receiving node j, it will serve packets from normal queues. In this case, following a similar procedure, the normal queues are ranked based on the difference $P_i(Q_i^h(t)) - P_j(Q_j^{h-1}(t))$ with higher priority determined by higher position of the queue in the ranking. The link serves packets from normal queues starting with those having higher rank if available link capacity remains and node j has still free storage space.

2) If the emergency queues of node i are empty, then link (i,j) will serve packets from normal queues and more specifically from queue $Q_i^{h^*}(t)$ achieving maximum $\Delta Q^*(i,j,t)$. The number of packets served from the selected queue will be equal to $\min\{Q_i^{h^*}(t), c(i,j,t), C_j^{\text{free}}(t)\}$. If $c(i,j,t) > Q_i^{h^*}(t)$ and $C_j^{\text{free}}(t) > Q_i^{emg,h^*}(t)$, then more packets from normal queues will be served to exploit all available space. To do so, similarly to the previous case, the link first ranks the remaining normal queues according to the differences $P_i(Q_i^h(t)) - P_j(Q_j^{h-1}(t))$ with higher values indicating higher priority. The link will serve packets starting from queues higher in the ranking as long as available link capacity remains and node j has still free storage space.

Then, the amount of traffic to be transferred over the link (i,j) in m^3 from an emergency queue with hop-index h is given by:

$$r^{emg,h}(i,j,t) = \sum_{p \text{ served from } Q_i^{emg,h}(t)} l(p), \tag{7}$$

where $l(p)$ is the space in m^3 occupied by packet p.

Similarly, the amount of traffic to be transferred over the link (i,j) in m^3 from a normal queue with index h is given by:

$$r^{h}(i,j,t) = \sum_{p \text{ served from } Q_i^{h}(t)} l(p). \tag{8}$$

The queue's occupancy update for the emergency queues takes place according to:

$$Q_i^{emg,h}(t+1) = \max\{Q_i^{emg,h}(t) - \sum_{j \in N_i} r^{emg,h}(i,j,t), 0\} + \sum_{j:i \in N_j} r^{emg,h+1}(j,i,t) + a_i^{emg,h}(t). \tag{9}$$

Similarly, the update of normal queues is as follows:

$$Q_i^{h}(t+1) = \max\{Q_i^{h}(t) - \sum_{j \in N_i} r^{h}(i,j,t), 0\} + \sum_{j:i \in N_j} r^{h+1}(j,i,t) + a_i^{h}(t). \tag{10}$$

2) PRESSURE FUNCTIONS

The pressure functions are fundamental for taking into account the constrained capacity of warehouses. According to [29], they should satisfy two requirements, namely, (i) they should ensure fairness under low traffic conditions, i.e., their marginal values at zero should be the same over all nodes; and (ii) they should tend to be linear as node capacities increase to infinity so as to ensure the stability properties of the original backpressure algorithm in this case. A possible definition satisfying these two requirements and which we employ in this work is the following:

$$P(Q; C, m, C_\infty) = \min\left\{1, \frac{\frac{Q}{C_\infty} + (2 - \frac{C}{C_\infty})(\frac{Q}{C})^m}{1 + (\frac{Q}{C})^{m-1}}\right\}, \tag{11}$$

with parameter C the capacity of the warehouse and parameters m, C_∞ determining the form of the pressure function. Parameter m determines the transition from the linear regime, while C_∞ determines the slope of the pressure in low-traffic regime and is such that for a node with capacity value equal to C_∞, the pressure is linear. We assume that all node capacities are lower than C_∞ and $m > 1$. Here, we set both $P_i(Q)$ and $P_i^{emg}(Q)$ equal to $P(Q)$ (Equation (11)) for all nodes $i \in V$.

IV. EVALUATIONS

In this section, we perform evaluations and comparisons of the proposed algorithm based on simulations. The main goal of the evaluations is twofold. On the one hand, we aim to showcase and compare the performance of the proposed BPLS algorithm for transferring packets in supply chain systems and on the other hand to provide guidelines to freight companies on using BPLS for discovering the limits of their systems in terms of exploiting their traffic-carrying capacity as well as in terms of handling the emergency traffic under specific guarantees in delay and service rate. Knowledge of these limits is essential for deciding infrastructure updates such as buying or building more storage space, or increasing the last-mile service resources, etc.

Towards this target, our evaluations focus on the performance assessment of the proposed BPLS for different source rates and different node capacities as well as its comparison with the traditional BP algorithm applied to supply chain systems. Also, to discover the distinct features of BPLS's performance with respect to the two traffic types, namely, emergency and normal flows. Note that the presented evaluation of scalability of the proposed algorithm is quite more demanding than in a real case scenario of an operational freight company. Essentially our evaluation setting determines a complete supply chain ecosystem with multiple logistics-related SMEs or larger companies and freight sub-contractors.

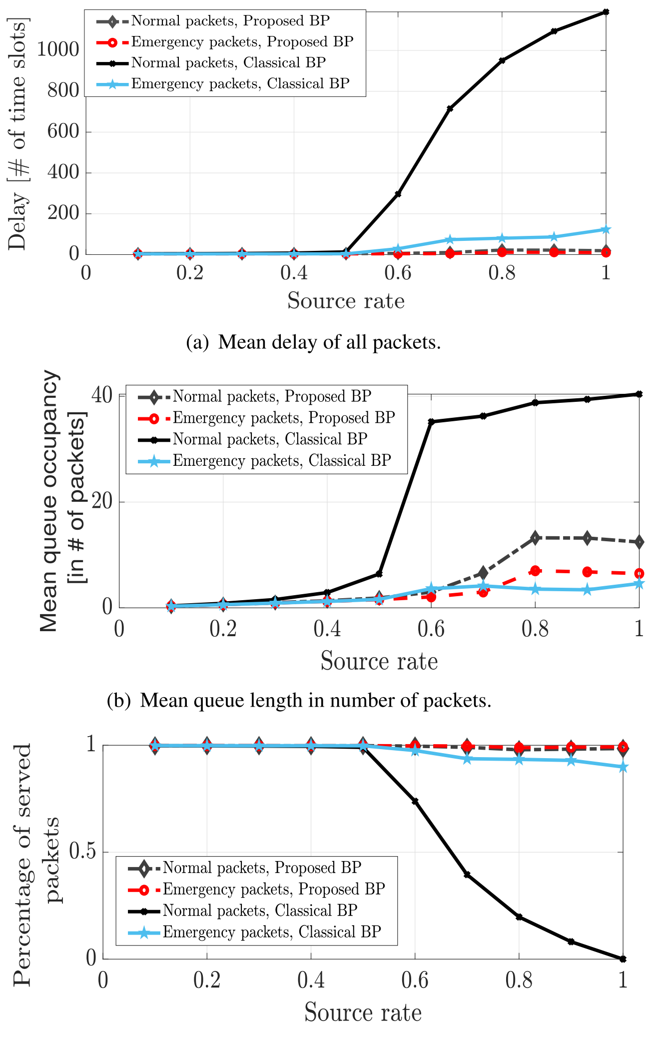
We assume the indicative network of [Fig. 3, [30]] because it exhibits a relevant complexity and allows for the study of all parameters of interest in non-degenerate and tractable means. All nodes except 1 and 14, are sources of normal packets for sink node 1 and of emergency packets for sink node 14. Each source produces packets independently of the others. The source rate corresponds to the probability that a source of a normal or an emergency flow produces a packet of this flow. Specifically, we consider that at each time slot, a source may produce at most one normal packet and at most one emergency packet each one with probability given by the corresponding source rate. Except from acting as sources of new traffic, the nodes of the graph act also as relays or intermediate warehouses where packets can remain temporarily stored, until being scheduled. We study three key performance indicators (KPIs) for both normal and emergency packets, namely, mean delay in number of time steps, mean number of served packets and mean queues occupancy in number of packets. Delay accounts for all packets including both those already served and those currently stored in queues. The capacity of all links is set to 5 m^3 for all time steps and the packet size is randomly and uniformly chosen within [0, 1] m^3.

Figures 1, 2 illustrate the performance of the proposed BPLS for both emergency and normal traffic as well as compare BPLS with the traditional version of the BP algorithm. In Fig. 1, the node capacity is set to 20 m^3, whereas in Fig. 2, the node capacity is set higher to 500 m^3. Note that the lower the node capacity the lower the traffic volume in the logistics network as the sources producing capability is limited not only by the source rate but also by the source node's available storage space. As a result, the traffic volume in Figure 2 is higher than in Figure 1 leading to much higher queue occupancy values (note that the node capacity is given in m^3, whereas the mean queue occupancy in the figures is in number of packets). In these two figures, we have not applied the pressure function when computing the BPLS differentials. The pressure functions are applied in Figures 3 and 4, where their effect in the KPI values for low and high node capacities is quantified. The pressure functions for emergency and normal queues are considered the same with $C_\infty = 100$ and $m = 2$, while the value of C is set as the capacity of each corresponding warehouse.

Under low traffic conditions BPLS maintains low time delays and queue lengths and high service rates for both types of traffic, emergency and normal. In addition, as it is shown closer in Figure 3, for higher source rates (but still under an overall low traffic regime due to the limited node capacity), the time delays and queue occupancy values for the emergency traffic are much lower than for the normal traffic and similarly the service rate for the emergency traffic is higher than for the normal traffic. As the traffic becomes more dense due to the increased node capacity value in Figure 2, BPLS ensures always low delays and queue lengths for emergency traffic but these increase significantly for normal traffic under higher source rates. This comparison is shown closer in Figure 4. This is because both the emergency and the normal traffic volumes increase analogously while the emergency traffic has priority in filling the storage space of the transport means. Thus, the normal traffic takes only the remaining space which leads to its increased waiting times.

The traditional BP algorithm leads consistently to higher delays and lower service rates than BPLS and this is due to serving only one queue per active link at every decision round. However, by splitting the emergency and normal traffic into two different queues with different priorities, it can still distinguish between the two and favor emergency traffic. But since the traditional BP algorithm does not exploit the available transport capacity at every time slot in its totality it cannot function effectively for the provision of prompt delivery services by freight companies. Importantly, from Figure 1, it can be observed that the traditional BP gives higher delay values for the emergency traffic than those given by BPLS for the normal traffic.

From Figure 3 we observe that using the pressure function when computing the BP differentials significantly improves the KPI values for both normal and emergency traffic. However, if comparing it with Figure 4, it can be stated that this is true only for low capacity values. Table 2 illustrates the exact values for delay obtained from BP and BPLS with and without pressure for both emergency and normal traffic referring to a node capacity of 20 m^3. It becomes clear that BPLS significantly improves BP especially for normal traffic and under the use of the pressure function where the improvement is around 120 times. For emergency traffic and under the use of the pressure function, BPLS reduces delay by 17 times compared to BP.



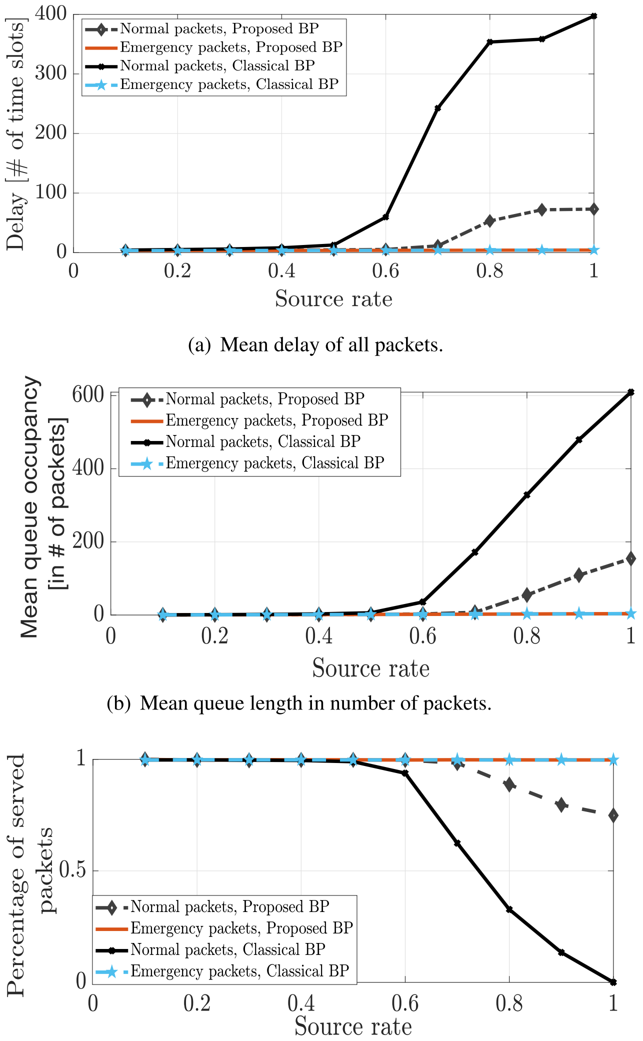
(a) Mean delay of all packets.

(b) Mean queue length in number of packets.

(c) Percentage of served packets.

FIGURE 1. **The node capacity is set to 20 m^3 for all nodes.**

Figures 5 and 6 present the differences in delay and queue occupancy values, respectively, if not using pressure minus if using pressure both for emergency and for normal traffic. We observe that there is positive difference, i.e., an improvement when applying the pressure functions, for

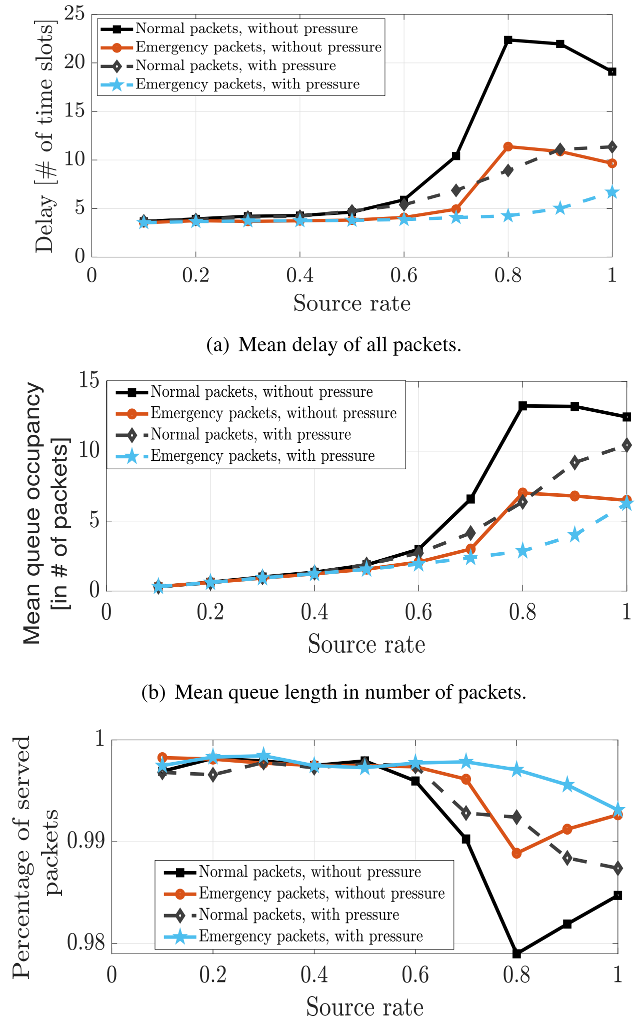


(a) Mean delay of all packets.

(b) Mean queue length in number of packets.

(c) Percentage of served packets.

FIGURE 2. The node capacity is set to 500 m^3 for all nodes.



(a) Mean delay of all packets.

(b) Mean queue length in number of packets.

(c) Percentage of served packets.

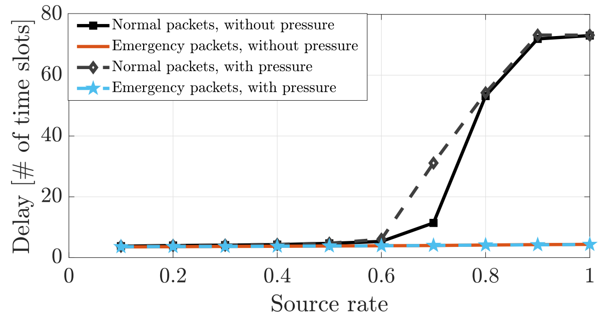
FIGURE 3. Comparisons with and without pressure. The node capacity is equal to 20 m^3 for all nodes.

TABLE 2. Illustration of the delay values for node capacity 20 m^3 for BP, BPLS without pressure (NP) and BPLS with pressure (P). E stands for emergency packets and N for normal.

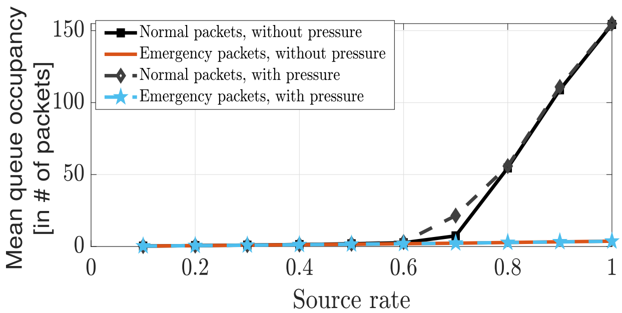
Source rate/ Alg.	BP (N)	BPLS (N, NP)	BPLS (N, P)	BP (E)	BPLS (E, NP)	BPLS (E, P)
0.2	5	3.94	3.87	3.61	3.75	3.66
0.4	8.1	4.28	4.21	3.74	3.74	3.74
0.6	296.2	5.90	5.39	28.9	4.90	3.87
0.8	950.2	22.37	8.91	80.27	11.38	4.25
0.8	1189.2	19.10	11.35	123.62	9.66	6.68

lower node capacity values up to 200, whereas there is no improvement for node capacity values higher than or equal to 300. Service rates (Figure 7) present a more varying behaviour: for emergency traffic there is not a clear tendency of improvement but also the difference with and without pressure is not significant (less than 4%); for normal traffic there is an improvement only when node capacity values lie under 200. By definition of the pressure functions, the traditional BP queue differentials can be obtained back for node capacities tending to infinity. Thus, node capacities higher than 300 can be considered as large enough for the traffic conditions under our considered setting.

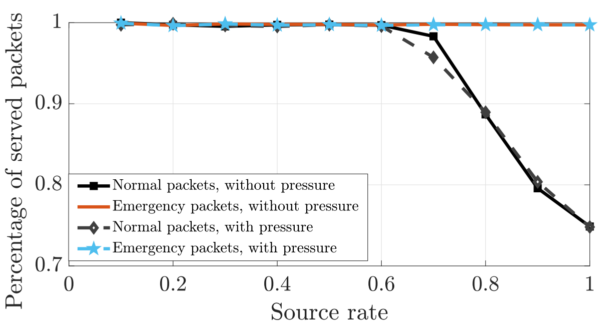
Figures 8, 9, 10 summarize the KPI values versus the node capacity for different source rates. We observe two distinct trends for the normal and the emergency flows. In the case of emergency traffic, the delay and queue lengths initially increase with the node capacity up to a top peak at the node capacity value equal to 200, and then decrease fast reaching up the levels corresponding to low network traffic, i.e., for low node capacity and source rates values. As expected, higher source rates lead to higher delay and queue length values. On the contrary, for the normal flows, the delay and queue length values initially increase up to a top peak and then stabilize around these high values. The service rates for the emergency flows are not illustrated since they remain very



(a) Mean delay of all packets.

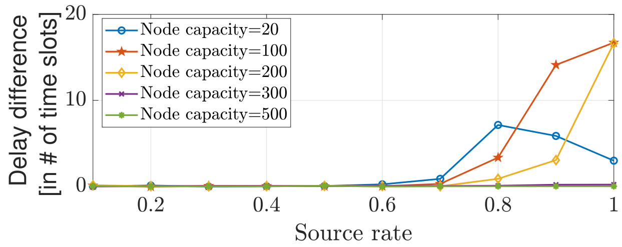


(b) Mean queue length in number of packets.

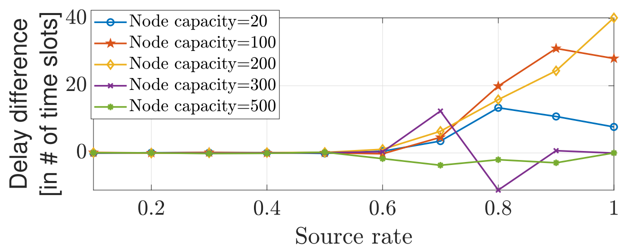


(c) Percentage of served packets.

FIGURE 4. **Comparisons with and without pressure. The node capacity is equal to 500 m^3 for all nodes.**

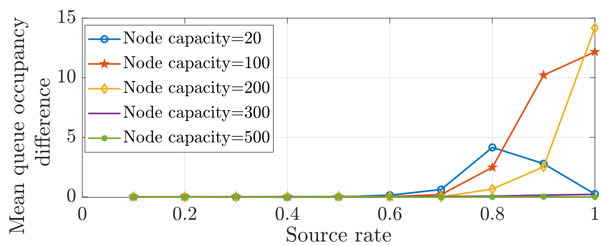


(a) Emergency flows.

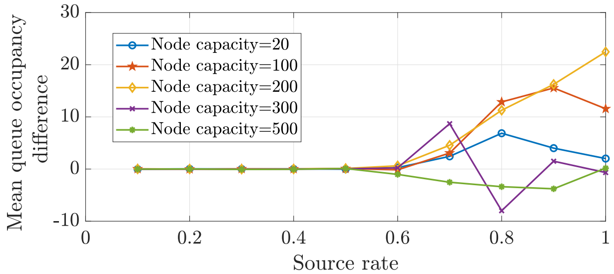


(b) Normal flows.

FIGURE 5. **Delay without pressure minus delay with pressure vs source rates for different node capacity values.**



(a) Emergency flows.



(b) Normal flows.

FIGURE 6. **Queues occupancy without pressure minus queues occupancy with pressure vs source rates for different node capacity values.**

close to unity. On the contrary, the service rates for the normal traffic follow the opposite trend of the delay and queue lengths values, i.e., they initially decrease up to a minimum value and then stabilize around this low value.

A. MAIN OUTCOMES OF THE EVALUATIONS

The main outcomes of the above evaluation, which can be used for designing and applying best practices in the general case of a logistics ecosystem can be summarized as follows:

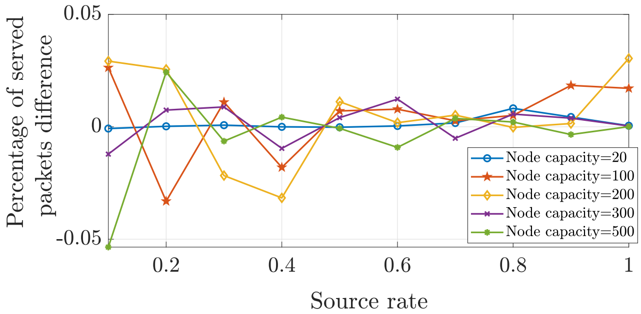
1. The BPLS algorithm ensures that emergency traffic experiences consistently lower delays than the normal traffic for all source rates and node capacities.

2. When the traffic volume in the network increases the delays and queue lengths of both normal and emergency traffic flows increase and the service rates decrease.

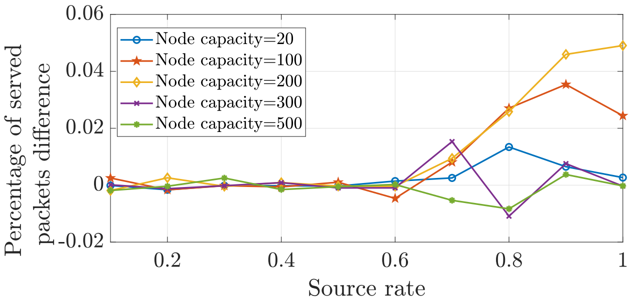
3. When node capacities increase, the KPIs of normal traffic stabilize and those of the emergency traffic improve significantly reaching the levels of low traffic conditions.

4. Under the traffic conditions of our case studies, node capacity values equal to 300 lead to similar behavior as infinite node capacity values, therefore demosntrating how the BPLS algorithm can be used to achieve more efficient, scalable and stable operation of a logistics network without sacrificing unnecessary resources.

5. The pressure functions improve significantly the KPIs for low node capacities and higher source rates but do not bring additional benefits for spacious storages.

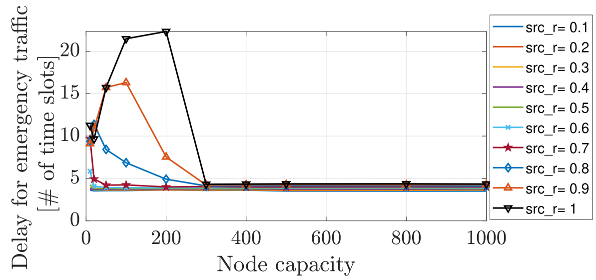


(a) Emergency flows.

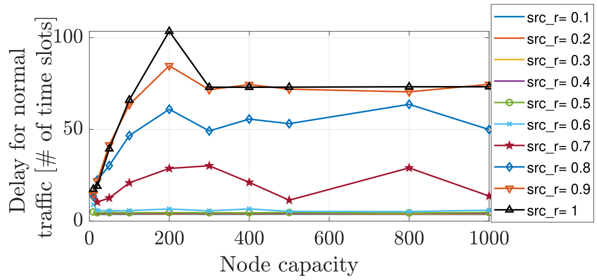


(b) Normal flows.

FIGURE 7. **Percentage of served packets with pressure minus percentage of served packets without pressure vs source rates for different node capacity values.**



(a) Mean delay of all packets for emergency flows.



(b) Mean delay of all packets for normal flows.

FIGURE 8. **Mean delay vs node capacity values for different source rates.**

6. The traditional BP algorithm is not effective for logistic systems as it fails to exploit the available transport capacity in its totality. On the contrary, our approach emerges as quite more appropriate, capable of addressing multiple performance goals.

V. OPERATIONAL IMPLEMENTATION AND EVALUATION

In this section, we present an operational information system and its evaluation, which is based on BPLS for its scheduling-routing component. Its evaluation was performed with industrial stakeholders, namely independent companies, subcontractors, etc., all related in different capacities with the logistics ecosystem in Greece.

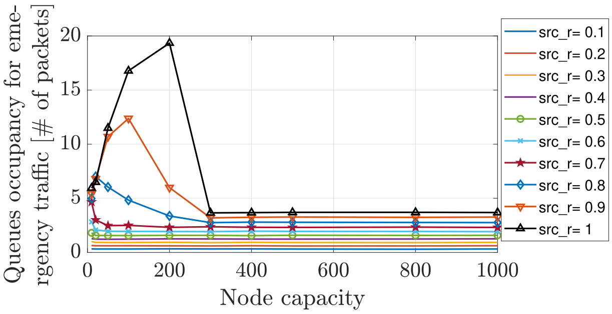
A. SYSTEM DEVELOPMENT

The backpressure scheduling and routing algorithm was instantiated in a logistics information system for the Greek logistics sector. The system comprised of a web platform that allowed logistics companies to initially register their transportation network (i.e., collaborating companies and transit hubs) and then submit transportation requests of individual items and/ or commercial pallets. Therefore, the freight network $G(V, E)$ was formulated as a cumulative network flow graph of all received inputs. Upon user specified time frames, the system executes the backpressure algorithm (BPLS) to compute the optimal groupings of individual transportation requests into scheduled shipments between the transportation network nodes. Logistics companies' employees may review the algorithm recommendations and accept or reject them. A relevant snapshot of the corresponding interface is shown in Figre 11(a). Following final acceptance of the algorithm recommendations, the system allocates the shipments to the company's transportation fleet (in cases of transit transports) or couriers (in cases of last mile delivery). Furthermore, the system calculates and displays the expected shipments' incoming deliveries and outgoing departures per transportation network node. Logistics companies' employees may also track and trace each shipment and individual item as well as review valuable statistical reports pertaining to the operational and cost efficiencies of their transportation network. A relevant snapshot of the corresponding interface is shown in Figure 11(b).

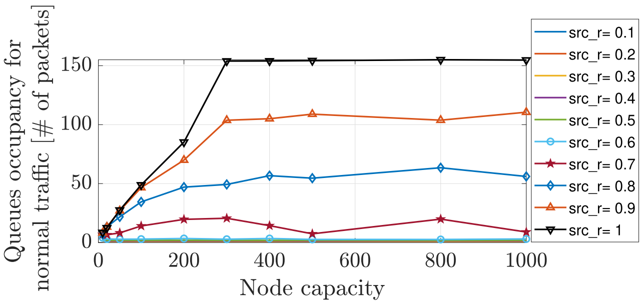
The web platform was developed using ReactJS and used MariaDB as its database management system. We also developed a RestAPI gateway with corresponding endpoints based on NodeJS that handled all interactions between the front-end and back-end system components effectively managing all communication, authentication, load balancing, and security handling requests. A more detailed presentation of the system architecture and functionality is available in [32].

B. ADOPTION PERCEPTIONS FROM INDUSTRIAL STAKEHOLDERS

To evaluate the acceptance and business value of the information system by the wider logistics industry we organized a workshop in October 2023. In total, 17 experienced professionals from several logistics companies participated in the workshop. The information system evaluation methodology included the following steps: (a) demonstration of the core system functionality based on real-world application

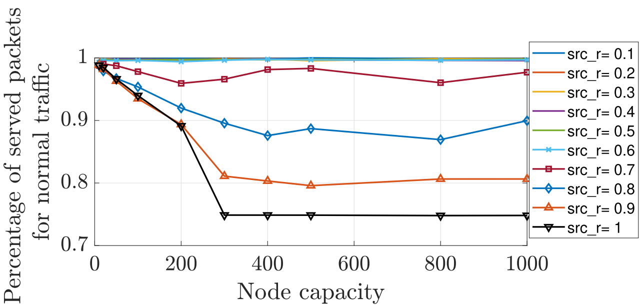


(a) Mean queues occupancy for emergency flows.



(b) Mean queues occupancy for normal flows.

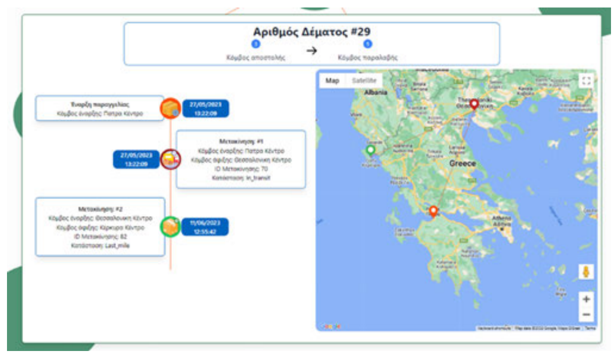
FIGURE 9. Mean queues occupancy vs node capacity values for different source rates.



(a) Percentage of served packets for normal flows.

FIGURE 10. Percentage of served packets vs node capacity values for different source rates.

(a) Backpressure algorithm (BPLS) recommendations



(b) Track and trace functionality.

FIGURE 11. Screenshots of the operational information system operating on the decisions made by BPLS. The shown text is in Greek, as the system has been initially developed for Greek companies.

scenarios, (b) extensive discussion with the companies' representatives in order to capture their perceptions regarding the challenges and ways of utilizing the information system in their corporate environment, and (c) completion of an evaluation questionnaire consisting of closed and open-ended questions following the prescriptions of the IS Success Model [33]. The evaluation model measures the participants' adoption perceptions towards the system under the prism of six dimensions, namely system quality, information quality, service quality, intention to use, user satisfaction, and net benefits. All questionnaire items were measured using a Likert scale anchored from 1 (strongly disagree) to 7 (strongly agree).

Regarding the system quality, more than 80% of the participating companies considered the information system easy to use and easy to learn and interact with. In addition, more than 70% of the companies considered that the information system has an attractive design, a satisfactory response time to every placed request, and user adaptable. Similar perceptions were exhibited in the evaluation of the information quality of the system. Specifically, more than 80% of the workshop participants characterized the information they receive from the system as clear, understandable, and consistent. Moreover, more than 70% of participants characterized the information generated by the system as complete, up-to-date, and accurate.

Regarding the evaluation of the service quality dimension, more than 80% of the participating companies in the workshop recognized that the information system satisfactorily covers their scheduling and routing needs of their shipments/products. Moreover, more than 70% of participants agreed that the system provides quality services for their business, helps them to better manage their customers and orders, and does not impose any security challenges for their corporate data.

Interestingly, most participants (over 80%) indicated that they are willing to pay a reasonable cost for the purchase and installation of the information system on their premises. A one-time purchase cost payment is the preferred way of procuring the system compared to the alternative of paying a monthly fee to an online service provider. Over 70% expressed the willingness to use/ adopt the system when it is commercially available. Finally, over 70% of participants reported that the information system may have a positive contribution to the more efficient operation of their company and the wider logistics chain, as well as contribute to the reduction of their operating costs. Similar perceptions were reported regarding the ability of the information system to enhance the sustainability and resilience of the supply chain.

VI. CONCLUSION

Logistics networks are important for modern economies but very sensitive to changes of the demand and the environment they operate, calling for holistic, efficient and dynamically adaptable optimization approaches. In this paper, we proposed such a framework capitalizing on the BP scheduling-routing technique and properly expanded it to adapt to all fundamental operations required in freight management. Our framework, BPLS takes as input the underlying topology, the capacity values of nodes/links, data on backlog and package load at each node, and makes dynamic, optimal routing and then scheduling decisions by solving a maximum weight matching problem. We have demonstrated BPLS' operation via simulation, emphasizing on its efficiency and stability properties under increasing load conditions. We have shown that by the considered adaptations to the traditional BP algorithm for freight systems, the delay can be reduced up to $110\times$ for normal traffic and $17\times$ for emergency traffic compared to traditional BP. In addition, we have incorporated an implementation of BPLS in an operational information system and assessed its potentials with multiple interested stakeholders. Through simulations and the actual evaluation, we were able to show how the framework can be used to provide long-term and short term decisions for optimizing freight networks at small or large-scale. Future work will involve further expanding the framework to include additional logistics operations, e.g., broadcast deliveries, and the further development of features of the information system for market uptake.

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