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Research Article

A Multilayer Model Predictive Control Methodology Applied to a Biomass Supply Chain Operational Level

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Forest biomass has gained increasing interest in the recent years as a renewable source of energy in the context of climate changes and continuous rising of fossil fuels prices. However, due to its characteristics such as seasonality, low density, and high cost, the biomass supply chain needs further optimization to become more competitive in the current energetic market. In this sense and taking into consideration the fact that the transportation is the process that accounts for the higher parcel in the biomass supply chain costs, this work proposes a multilayer model predictive control based strategy to improve the performance of this process at the operational level. The proposed strategy aims to improve the overall supply chain performance by forecasting the system evolution using behavioural dynamic models. In this way, it is possible to react beforehand and avoid expensive impacts in the tasks execution. The methodology is composed of two interconnected levels that closely monitor the system state update, in the operational level, and delineate a new routing and scheduling plan in case of an expected deviation from the original one. By applying this approach to an experimental case study, the concept of the proposed methodology was proven. This novel strategy enables the online scheduling of the supply chain transport operation using a predictive approach.

1. Introduction

The use of renewable energy sources has been promoted as a way to avoid the increase of carbon dioxide concentration in the atmosphere. Legislative guidelines such as the Kyoto Protocol were created with this purpose [1]. Also, the continuous rising of fossil fuels prices has triggered the interest in these sources of energy [2, 3]. Among the available options, forest biomass has gained interest in the last years [1, 4–6].

The biomass supply chain involves several stakeholders, like raw material suppliers, transportation companies, and production facilities, among others, which work together in order to bring the materials from their source to the consumers [7]. Regarding the processes, this supply chain encompasses the harvesting and collection, chipping, transportation, storage, and final conversion. Biomass can be used to provide heat, electricity, and biofuels [8–11]. Also, compared to other renewable sources of energy, biomass has the possibility of storage and, consequently, producing energy on demand [12]. In the renewable energy context, the biomass is considered as a "carbon neutral" source having a neutral balance in the carbon cycle [13]. In this sense and when compared to fossil fuels, forest biomass can contribute to decreasing carbon emissions [12] and the dependence on imported energy [2].

The transportation is the operation that requires the highest parcel of costs, being responsible for 25–40% of the total value [14]. Besides the economic aspect, this drive intensive characteristic emphasizes the energetic and environmental impact of transportation [15, 16]. As such, this work will focus on the transportation process.

Forest biomass has also some drawbacks: it is a seasonal energy source, has low energy density, is usually spread over large areas, and is composed of a set of interconnected stakeholders, making the decision process more difficult [2, 7, 12, 17, 18]. Associated with this, forest biomass supply chains present a variability and uncertainty that turns the planning of their operations more complex. The management procedure in a supply chain is usually differentiated into three levels, namely, strategic, tactical, and operational [19]. In this work, only the operational level is focused on. It must be noted that the processes dynamics are stochastic in nature. During operation, several adverse situations may occur such as natural phenomena, equipment breakdown, and low quality of material, which disturb the system performance and, consequently, invalidate the original delineated plan [12, 15, 20].

As such, the sustainable and robust management of these supply chains at a cost-effective manner is essential to the expansion and growth of these systems [21]. Thus, it is important to efficiently use the resources at the minimum cost possible [22] trying also to reduce the impacts and a continuous feedstock supply [7]. This is also the main challenge of supply chains [9, 15], where complex decision-making processes are needed to achieve short-, medium-, and long-term goals [23].

There are several planning tools available in the literature to optimize the operational performance of biomass supply chains. In [24], a flow-shop approach to handle operations scheduling problems is proposed. The strategy was tested and demonstrated through a small real example and verified improvements compared to the traditional decision-making process. Also regarding schedule optimization, [25] proposed an approach for planning of sequential tasks scheduling in the harvesting and handling operations in geographically dispersed fields. In [26], the authors applied the classical vehicle routing problem to the biomass collection problem in order to determine the routes with minimal costs to the vehicle fleets involved in the biomass supply chain. In [27], three mixed integer programming formulations were presented to solve the truck scheduling problem. For more detailed information, [28] presented a survey on the models developed for biomass supply chains from an operations research perspective, and [18] presented the modelling approaches to optimize economic, social, and environmental criteria in these supply chains. Furthermore, other optimization procedures have been described in the literature for not only the operational but also tactical and strategic levels [29–31].

Despite the available planning tools, the management of these supply chains continues to be executed based on the empirical knowledge and experience of the decision-maker [24]. In case of deviation from the plan and due to these supply chains interlaced nature, such as synchronized schedules and time windows constraints, it becomes very complex to assess the repercussions of the deviation and to replan based on the current conditions.

In this work, a methodology that allows following the biomass supply chain's operational level during a working day, regarding the transportation process and continuously predicting if the initially proposed schedule will be attained, is proposed. In case of deviation from that goal, the proposed framework makes use of the model predictive control (MPC) approach to automatically update the plan to a viable solution that aims to satisfy the demand within the proposed time frame at the lowest cost possible. With this proposal, it is intended to make the decision-making problem automatic and reactive to possible disturbances that might occur in the system with repercussions in the different levels. This contrasts with the static approach commonly found in the literature.

The paper is organized as follows: Section 2 presents the biomass supply chain, describing its processes and the decisions taken in the different management levels; Section 3 details the operational model based on the developed multi-layer model predictive control strategy; Section 4 illustrates the proposed methodology through a simple example; and, finally, Section 5 presents the main conclusions and insights into future work.

2. Problem Statement

Forest-based supply chains are complex systems with several processes and stakeholders involved. Although some processes are common to all these chains, the biomass supply chain has specific requirements and phases not present in the remaining ones. The biomass supply chain starts in the forest area, within the forest stands, where the trees and branches are harvested and forwarded into piles disposed at the roadside. These wood sources are then transformed into small wood chips by the chipping process. Those wood chips are loaded into a truck which will transport them to a mill. In the case of a biomass for bioenergy supply chain, the wood chips arriving to the power plant are converted into energy to the energy market. It should be noted that the chipping process occurs simultaneously to the truck loading process as the chipper machine is itself assembled to the truck. Also, intermediate storage stages can be considered.

Periodically, the power plant demands a certain amount of energy to be delivered at the end of the week. Based on that, the management team has to define the amount of wood that needs to flow inside the supply chain to comply with the demand. This management is divided into several levels, mostly differentiated by the time scale. The tactical level, usually concerning decisions with times from weeks to months, addresses issues of resources dimensioning, that is, the number of resources to be used and the amount of material that flows inside the system. On the other hand, the operational level, as the name indicates, addresses decisions related to routing and scheduling of operations at smaller time scales. At a higher time scale, from months to years, there is also the strategic management level. However, this level is more related to forest management issues. In the present work, only decisions regarding the operational level during a working day will be considered. In this sense, decisions related to material flow and pile-client association are already provided as a result of the tactical level optimization. The operational level, here considered, will deal with the trucks' fleet routing and scheduling questions.

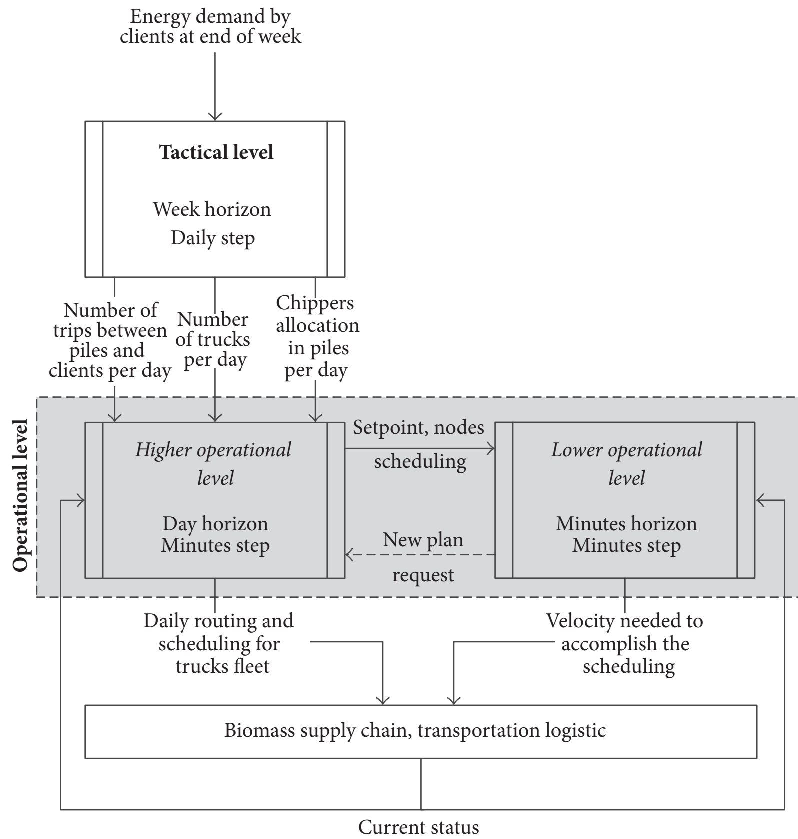

Figure 1: Multilayer operational level proposed methodology.

The management of the operational level is usually performed in a static way, using planning tools to generate an initial plan at the beginning of the day. However, no monitoring of the processes' evolution is verified. Consequently, if there are deviations from the plan, no corrective actions are applied during that day and will accumulate for the following day, possibly leading to an unfeasible solution to the weekly goal.

In this work, a tool that considers the online replanning of the biomass supply chain transportation process is proposed, inspired by the model predictive control technique. The objective is to create a framework that deals with the system evolution during the day, with the possibility of taking the advantages of the MPC technique to forecast possible deviations from the plan and in an automatic and efficient way reacting beforehand and replanning all the involved decisions.

3. Proposed Methodology

Due to its complexity, the overall architecture of significant size supply chains should be described by means of multilayer hierarchical connection between the most fundamental elements. This is true in all its different dimensions: corporative, economical, and logistic. Regarding the latter, strategic, tactical, and operational levels are stacked one after the other, where the operational level is the ground level. Those three levels are highly intertwined and information flows among them. The tactical level is based on the long-term business vision provided by the strategic component and the operational level behaviour defined in a shorter time scale as a function of the tactical level decisions.

The current work addresses uniquely the biomass supply chain operational level, particularly the transportation logistic problem. The overall supply chain regulation paradigm here proposed, with the information flow between the tactical and operational levels, is revealed at Figure 1.

In the current supply chain control methodology, it is assumed that the tactical level provides the information that will steer the decision-making process that will take place in the operational level. This information regards the number of trips between piles and clients and the number of trucks and chippers available.

The tactical level operates at a daily time frame, where the control actions are planned according to the current system states. The planning process is many times carried out aiming to minimize the costs regarding the raw material transportation and both the chipping machines and trucks usage [32–34]. All these variables are defined, per day, along a time horizon of one week. At the beginning of each day, new tactical actions are planned according to the current system states. This information is then conveyed to the operational level whose main objective is to establish the set of working schedules and deliver them to the field working teams.

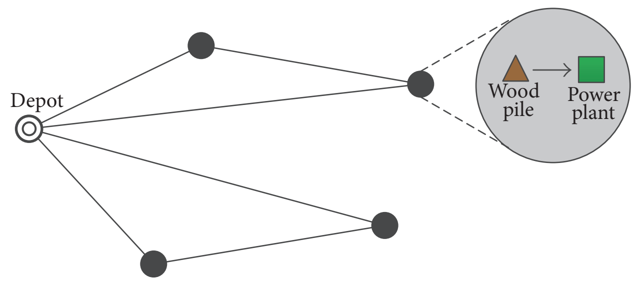

Figure 2: Example of geographic dispersion of nodes.

In order to define both the routing and scheduling of the trucks fleet, the operational level must have a deep insight about the supply chain structure and its timing requirements. Conceptually, the actual supply chain problem is composed of nodes scattered along a given geographical area. All the trucks depart, at the beginning of the day, from the same node, designated by depot. Moreover, they should also arrive to this same node when their working schedule ends. Besides the depot, the supply chain network is composed of a set of nodes, denoted by working nodes, which should be visited during the daily schedule. Each working node in the networks can be further decomposed into a lower level structure constituted by one wood pile, one client, and a job. This concept is illustrated in Figure 2, where two distinct routes are considered. Both depart and arrive to the depot, while traversing two working nodes.

Also in Figure 2, one of the nodes is expanded in order to show its internal activity. This activity assumes the following steps: the truck moves to the wood pile, where it is loaded with wood chips. After the loading process, it carries on toward the client for the unloading process. After this task has been accomplished, the truck leaves the working node toward the next one. Notice that the pairing between wood piles and clients has already been performed, in an optimal context, by the tactical level [34].

Delivering a proper working plan to the field operatives is the responsibility of the operational level. As can be seen from Figure 1, the operational level is divided into two distinct layers: a higher layer and a lower layer. The higher layer operational level component is committed to making schedules and routes taking into consideration some important operational constraints. First, and for each working node, the loading and unloading time windows must be known. That is, each network working node has an admissible time interval, where it is expected to be visited by a truck. For example, the chipping machines are scheduled to be in a particular wood pile during some time window and the clients are only able to process unloading tasks in an alternative time span. For this reason, a truck must arrive at a node at the time instant that permits concluding its intrinsic job. It should be noted that the expected loading, driving, and unloading times for a given working node are known. Moreover, during the present work, it is considered that, after entering the node, the situation is deterministic. That is, the exit time is equal to the arrival time plus the time expended during the loading, driving, and unloading tasks.

The working plan is delivered, at the beginning of the day, to each field operative element. Each schedule sheet provides information to the truck driver regarding the nodes to be visited, their order of appearance, and an estimation of the arrival time. The routing problem faced by the higher layer operational level boils down to a classical travelling salesman problem (TSP) with variable number of salespersons. In this case, each truck can be viewed as a different salesman and the set of cities to be visited are the network nodes. It is well known that those classes of problems are NP-hard and the complexity in finding a solution increases quickly with the number of nodes in the network. In fact, if there are N nodes in the network, then the number of possible paths is equal to the factorial of $(N-1)$. For this reason, the performance of any search algorithm will be severely degraded by the addition of new working nodes in the network.

The lower layer operational level controller will be responsible for closely monitoring the process evolution by means of measuring the relevant state variables such as the position and state of each vehicle and the nodes visited. The trucks' geographical positions are assumed to be provided by a global positioning system (GPS). It is also assumed that the nodes' geographical locations are equal to the one of the wood piles. Hence, the positions of all the nodes in the network are known.

From the available field data, the lower layer operational controller will be able to forecast possible unaccomplished jobs due to truck delays. It is then possible to define a feedback control strategy aiming to maintain the initial target set of jobs even in the presence of disturbances. Those disturbances can span from simple delays in the delivery to a particular machine breakdown or adverse weather conditions, among others. This type of anticipative reaction from a closed loop system is highly desired, since it prevents large deviations in the system state variables. In control theory, this type of paradigm is known by model predictive control (MPC) and, as will be seen in Section 3.2, it is embedded in the lower layer of the operational level controller. If the lower layer predicts that the job is impossible to be accomplished, a new routing and scheduling plan is requested to the higher layer of operational level. Section 3.1 will be devoted to describing and analysing this higher layer by presenting its mathematical formulation.

Before ending, it is worth noticing that if no solution can be achieved by the operational level, then, at the end of the working day, a report is provided to the tactical level with information regarding the jobs that were unaccomplished. The tactical level will use this information to correct the setpoints delivered to the next days, hence avoiding cumulative deviations at the end of the week. However, this tactical replanning is out of the scope of the current work.

3.1. Operational Level: Higher Layer Control. Daily, the tactical level delivers both the wood pile/client pairs and the available resources to the operational level. The former will become the nodes in the operational network and the latter regards the maximum number of available machines that can be used during the tasks execution. The operational level is decomposed into two hierarchical sublevels: a higher layer, which is responsible for defining the trucks fleet routing and scheduling, and a lower level, which keeps track of the generated schedule and predicts the impact of truck delays in the supply chain. This section is devoted to describing the higher layer of the operational level control.

The routing and scheduling result from an optimization process that takes place at this level, particularly by solving a minimization mixed integer programming problem that describes the behaviour of the supply chain at this level. For this reason, the higher layer operational level model will be presented as an optimization problem.

Let $q \in \mathbb{N}^*$ be the number of working nodes and let $q+1$ be the total number of network nodes including the depot. As previously referred, the depot is a very special node, since all the vehicles are supposed to depart from it and are expected to return to it after the last task takes place. Let this node take the index 0. The set $\mathcal{Q} = \{0, \ldots, q\}$ contains the reference to each network node beginning with the depot. Also, let m be the number of trucks available in a given working day and let $\mathcal{K} = \{1, \ldots, m\}$ be the set of those machines.

Each working node can be in one of three possible states: unvisited, partially visited, or fully visited. The first state is achieved when no vehicle has arrived to it or departed from it, and the second state is achieved when a truck has entered the node but has not left it yet. Finally, the node is said to be fully visited when a previously arrived truck leaves toward a new node. In other words, it is considered that a node is fully visited when a particular truck enters it and departs from it. It is worth noticing that each node is supposed to be visited only once and that the depot is the only node that remains partially visited from the beginning of the truck tours up to the end. Moreover, it will be assumed that the depot can only change its state to "fully visited" when the number of trucks arriving at it will be equal to the number of vehicles that have departed from it. That is, the net flow of trucks in this node must be equal to zero.

When a given node $i \in \mathcal{Q} \setminus \{0\}$ is traversed by one of the m trucks, it will become a fully visited point and will be added to the set $\mathcal{P}$. According to what has been previously stated, the last node to be included in $\mathcal{P}$ will always be the depot. Moreover, let $\mathcal{J}$ be the set of the "partially visited nodes" and let $\mathcal{L}$ be the set of "unvisited nodes." In this context, $\mathcal{Q} = \mathcal{P} \cup \mathcal{J} \cup \mathcal{L}$. Moreover, define the set $\mathcal{R} = \mathcal{L} \cup \mathcal{J}$ as the set of nodes that remain to be "fully visited," that is, the nodes that are in the state of being "partially visited" or "unvisited." The higher layer operational supervisor will be filled with the actual network status, at an asynchronous rate T, triggered by demand of the lower layer operational supervisor whenever collapse in one of the jobs is expected. If this is the case, the higher operational supervisor will compute and submit an alternative working plan considering the new system state. For this reason, the content of the above defined sets can be changed. If the system state sampling occurs at nT, with $n \in \mathbb{N}$, then the sets $\mathcal{P}(n)$, $\mathcal{J}(n)$, and $\mathcal{L}(n)$ contain the "fully visited," "partially visited," and "unvisited" notes at that time instant.

Whenever a particular vehicle arrives at a node, this point will become a partially visited node and will be the new starting point for this truck. Let $s_k \in \mathcal{R}(n)$ be this new starting node for truck $k \in \mathcal{K}$. Then, $\mathcal{S}(n) = \{s_1, \ldots, s_m\}$ represents the set of the starting nodes associated with each truck. Due to the node's number of visits constraint, $s_i = s_j$ if and only if $i = j$.

For the current problem formulation, it is supposed that, at a given time instant, one is able to locate all the resources in the network. That is, the nodes position, their relative distances, and the trucks' positions are known. Moreover, the absolute time is known with a resolution of one minute. Let $t \in [0, 1439]$ be this time where 0 regards 0 h 00 m and 1493 regards 23 h 59 m. Also, let us assume that the distance d_{ij} between two distinct nodes in the graph, $i, j \in \mathcal{Q}$, is known and that the average time, required to perform the trip between those two points, is constant and equal to γ_{ij}. In order to perform the required task in node i, the truck must spend some time on it. Let the required working time at node $i \in \mathcal{Q} \setminus \{0\}$ be constant and equal to α_i.

In this frame of reference, the current decision variables are $x_{ij}^k(n) \in \{0, 1\}$, which take the value of 1 if, from the present time instant n up to the end of the working day, it is expected from vehicle k to visit node $j \in \mathcal{L}(n) \cup \{0\}$ after finishing the task at node $i \in \mathcal{P}(n)$. The value of zero will be used to denote otherwise. Moreover, the expected time at which the activity performed by truck k starts at node $i \in \mathcal{L} \cup \{0\}$, from the present time instant n upwards, is denoted by $t_i^k(n)$ and is also a decision variable. For the depot node, this starting activity concerns the truck's departure time. However, for the remaining nodes, this variable indicates the truck's arrival time. Due to imposed time window constraints at the working nodes, this $t_i^k(n)$ must be within the time interval that spans from $\hat{\eta}_i \in [0, 1439]$ up to $\check{\eta}_i \in [0, 1439]$ with $\hat{\eta}_i < \check{\eta}_i$. These lower and upper time intervals depend on the chipping machine schedule for that node and on the last available unloading time slot at the client.

An important aspect of the schedule plan is to derive the time at which each of the vehicles is expected to arrive at the depot. Thus, an additional decision variable $\tau^k(n)$ is associated with each truck and denotes the time at which it arrives at the depot. This variable has to be less or equal to the maximum working hours per day of truck k. Let w^k be that value.

In order to find the best working plan, at a given time instant nT, the system model is formulated as a linear programming problem, where the cost function is described in (1). This cost function has two terms: the leftmost represents the total distances travelled by the set of all vehicles and the rightmost is the total time required to perform the full set of operations.

$$\min \left(\sum_{i \in \mathcal{R}(n)} \sum_{j \in \mathcal{R}(n)} \sum_{k \in \mathcal{K}} d_{ij} \cdot x_{ij}^k(n) + \sum_{i \in \mathcal{R}(n)} \sum_{k \in \mathcal{K}} t_i^k(n) \right). \quad (1)$$

Aiming to model the supply chain operational behaviour, a set of constraints are added to the above linear programming problem. For example, the following equation addresses the case where it is required that all trucks, belonging to $\mathscr{K}$, must always leave the actual entering working node.

$$\sum_{i\in\mathscr{L}(n)\cup\{s_k\}} x_{ij}^k(n) = \sum_{i\in\mathscr{L}(n)\cup\{0\}} x_{ji}^k(n) \quad \forall j \in \mathscr{L}(n),\ \forall k \in \mathscr{K}. \tag{2}$$

That is, for each node j, in the set of nodes that remain to be fully visited, if a truck is entering this node from any node not fully visited, excluding the depot, then it must leave to any of the remaining nodes.

Moreover, each node can only be visited one time during the working day. This condition is imposed by the following expression:

$$\sum_{j\in\mathscr{L}(n)\cup\{0\}} \sum_{k\in\mathscr{K}} x_{ij}^k(n) = 1 \quad \forall i \in \mathscr{L}(n). \tag{3}$$

The next pair of constraints implies that the already visited nodes cannot be visited again; that is, none of the trucks can leave from those nodes to another and cannot go from another to those nodes.

$$\begin{gathered}\sum_{j\in\mathscr{Q}} \sum_{k\in\mathscr{K}} x_{ij}^k(n) = 0 \quad \forall i \in \mathscr{P}(n), \\ \sum_{i\in\mathscr{Q}} \sum_{k\in\mathscr{K}} x_{ij}^k(n) = 0 \quad \forall j \in \mathscr{P}(n).\end{gathered} \tag{4}$$

The following inequality refers to the start condition of the trucks. This forces each truck to leave from its starting point.

$$\sum_{j\in\mathscr{L}(n)\cup\{0\}} x_{s_k j}^k(n) \le 1 \quad \forall k \in \mathscr{K}. \tag{5}$$

Furthermore, since all the trucks must end at the depot,

$$\sum_{i\in\mathscr{L}(n)\cup\{s_k\}} x_{i0}^k(n) \le 1 \quad \forall k \in \mathscr{K}. \tag{6}$$

An additional decision variable associated with node $i \in \mathscr{Q}$ and denoted as $u_i(n)$ is also added in order to prevent trajectory loops. Those cycles are avoided by means of the following constraint:

$$u_i(n) - u_j(n) + l \cdot \sum_{k\in\mathscr{K}} x_{ij}^k(n) \le l - 1 \quad \forall i, j \in \mathscr{L}(n), \tag{7}$$

where l represents the number of nodes present in set $\mathscr{L}(n)$ at sampling time n.

In order to define the time at which each task takes place $t_i^k(n)$, it is necessary to attend the travel time between nodes i and j, γ_{ij}, the time spent in node i, α_i, and the upper time window associated with that node, $\check{\eta}_i$. That is,

$$\begin{aligned} & t_i^k(n) + (\gamma_{ij} + \alpha_i) - t_j^k(n) \\ & \quad \le (\check{\eta}_i + \gamma_{ij} + \alpha_i) \cdot (1 - x_{ij}^k(n)) \\ & \qquad \forall i \in \mathscr{L}(n) \cup \mathscr{S}(n),\ j \in \mathscr{L} \setminus \{0\},\ k \in \mathscr{K}. \end{aligned} \tag{8}$$

The following constraints indicate the nature of decision variables:

$$\begin{gathered} \hat{\eta}_i \le t_i^k(n) \le \check{\eta}_i \quad \forall i \in \mathscr{Q}, \\ u_i(n) \ge 0 \quad \forall i \in \mathscr{Q}, \\ x_{ij}^k(n) \in \{0,1\} \quad \forall i, j \in \mathscr{Q},\ \forall k \in \mathscr{K}. \end{gathered} \tag{9}$$

Finally, the time at which the truck returns to the depot must be constrained to be within the interval:

$$t_i^k(n) + (\gamma_{i0} + \alpha_i) \cdot x_{i0}^k(n) \le \tau^k(n) \le w^k \quad \forall i \in \mathscr{L}(n),\ k \in \mathscr{K}. \tag{10}$$

The above-defined problem will be solved once at the beginning of the working day and whenever there is a demand for a new plan from the lower layer operational controller. The following section will describe, in further detail, the operation of this lower level operational component.

3.2. Operational Level: Lower Layer Control. During the working day, the position of each truck is checked by means of a GPS tracking system. Thus, the truck's relative position regarding the nodes is known. It will be assumed that this information is regularly sampled with a period T_s equal to 10 minutes. This time period was chosen based on the dynamic system characteristics. At each sampling time, nT_s for $n \in \mathbb{N}$, it is considered to have full information concerning the current system state.

The purpose of the lower layer operational control is to keep track of the vehicles and to provide information to the driver regarding the expected average speed he is expected to follow. By forecasting each truck position in the network, this layer is able to provide speed estimates in order to accomplish the working plan. Those predictions are generated according to a model of the truck's position.

This philosophy is in line with the concept of model predictive control (MPC). In particular, the aim of this work is to provide an alternative formulation of the MPC paradigm in the context of supply chains regulation. The MPC unveils its full power if a sufficient accurate system process model is available. This model is used to perform system predictions, leading to an anticipative controller reaction if relevant system state deviations are likely to occur. Classically, the MPC is formulated as a quadratic optimization problem subject to actuators constraints, where the decision variables are the sequence of possible actuation which minimizes the prediction error. The objective function usually encompasses a term that penalizes any setpoint deviations and a second term that leads to control effort minimization. According to the MPC strategy, only the first computed control action is placed into the actuators. When the system status is updated, a new set of control actions is calculated based on this new information.

The MPC model can be translated into the current supply chain control problem. First, according to the current position and time of a particular truck and by resorting to the truck's position model, it will be possible to predict if it will

Table 1: Geographical distance (km) between the considered nodes.

	Vila Real	Mirandela	Bragança	Chaves	Braga
Vila Real	0	59.4	118	66.6	105
Mirandela	59.4	0	61.3	51.5	159
Bragança	118	61.3	0	110	217
Chaves	66.6	51.5	110	0	128
Braga	105	159	217	128	0

arrive to the next node at the time defined by the higher layer operational plan. The desired truck speed, which will be sent to the truck driver, will be computed during this step, taking into consideration the route speeds limits. If the lower layer controller predicts that the time provided by the working plan will not be attained, an alert will follow to the upper level to generate a new scheduling plan. Information regarding the predicted delay in the task accomplishment will be provided.

Following the MPC concept, the objective function to minimize in the lower level takes two terms into consideration: a first term that aims to minimize the remaining distance to the destination node (the quadratic formulation is used to avoid the overpassage of the destination node) and a second term that penalizes the control effort, that is, penalizes abrupt changes in the velocity. The objective function considered in this level is presented in the following equation:

$$\begin{aligned} \min \quad & \left[d_{jp}^{k}\left(n+h \mid n\right)\right]^{2} \\ & + \sum_{i=1}^{h}\left[v^{k}\left(n+i\right)-v^{k}\left(n+i-1\right)\right]^{2}, \end{aligned} \tag{11}$$

where v^k refers to the velocity of truck k, h refers to the control horizon, and n is the current time sample. Note that the number of available trucks is not a decision variable of this level, being provided by the tactical level as depicted in Figure 1. In this formulation, the control horizon is considered as equal to the prediction horizon. This allows better distributing the control actions along the horizon and avoiding future deep changes. In this work, h is assumed to be variable regarding each truck and task and is computed by

$$h = \left\lceil \frac{t_i^k\left(n\right) - nT_s}{T_s} \right\rceil. \tag{12}$$

The predictive component is incorporated into the objective function by means of the remaining distance to travel regarding the next node j based on the current position p of a truck k, $d_{jp}^k(n)$. This distance is computed according to the remaining distance to node j, at the previous time instant, plus the distance travelled in that time interval. Mathematically, this can be formulated as

$$d_{jp}^{k}\left(n+h \mid n\right) = d_{jp}^{k}\left(n\right) - T_s \cdot \sum_{i=1}^{h} v^{k}\left(n+i\right). \tag{13}$$

Note that v^k has to be a positive value; that is,

$$v^k \geq 0 \quad \forall k \in \mathcal{K}. \tag{14}$$

In order to provide a proof of concept of the proposed control methodology, a case study will be considered in the next section.

4. Illustrative Example

In this section, a biomass supply chain example is considered to demonstrate the applicability and advantages of the proposed methodology. It should be noted that the dimension of the problem can be easily scalable, and a small scale example is here presented for simplicity of analysis. A total of 5 nodes including the depot are considered, representing a set of cities in the North of Portugal: Vila Real (depot), Mirandela, Bragança, Chaves, and Braga. The distances between each pair of network nodes are presented in Table 1.

Two trucks will be considered during a working day, and each truck spent approximately 45 minutes within the node to complete the defined job (loading the wood chips, drive toward the power plant, and unload). The initial travel time is considered as equal to the time needed to travel the presented distance assuming a constant mean speed of 60 km/h.

The schedule definition process has two stages: a setup stage, where the initial plan is established, and a tracking stage, where the above plan is followed in terms of completion. The former is handled by the higher layer, described in the previous section, and the latter by the lower layer of the operational level control. The setup stage can occur in any time period before the instant at which the lower layer takes charge. For example, considering the above problem definition and assuming that the lower layer should start at 8:00, the initial plan produced by the higher layer optimization problem must be generated at any time instant prior to 8:00. For example, let us assume that, at 7:00, the higher layer was executed and was able to generate the routing and scheduling plan for the two trucks as depicted in Figure 3. Each coloured triangle represents a particular truck route. The time tags added to each node indicate the expected truck's arrival time to the respective node. This is true for all nodes with the exception of the depot, where the time schedule, printed in white background, is the departure time and the remaining coloured tags represent the depot arrival time for the respective truck.

From Figure 3, it is possible to conclude that the higher layer initial schedule assumes that one of the trucks performs the route that visits the nodes 1-4-5-1 and the other executes the sequence 1-2-3-1. Both trucks depart from the depot at the same time, in this case 8:00, but will arrive at the depot at different time instants. The first will be ending its work schedule at 14:29 and the second around one hour earlier.

Table 2: Control of the average speed (km/h) and the expected delay (min) according to systems states update.

Sample n	Computed speed (km/h)							Delay (min)
	$n+1 \mid n$	$n+2 \mid n$	$n+3 \mid n$	$n+4 \mid n$	$n+5 \mid n$	$n+6 \mid n$	$n+7 \mid n$	
0	58	58	57	57	57	57	57	0
1	57	57	57	57	56	56		0
2	62	62	62	62	62			0
3	76	76	76	76				0
4	80	80	80					8
5	80	80						18

Figure 3: Routing and scheduling solution provided at the beginning of the day. Each coloured triangle represents a truck's route.

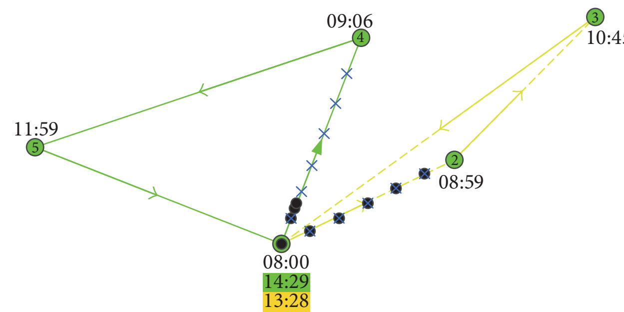

Figure 4: Trucks' position evolution during the working schedule (the blue crosses indicate the trucks' expected position and the black dots the trucks' actual position).

Figure 5: Routing and scheduling solution provided by the higher operational layer due to a predicted delay greater than the threshold.

Exactly at 8:00, the lower level operational layer controller will be activated. This layer will sample the trucks' positions, with a sampling period of 10 minutes. Based on this data and resorting to the trucks movement dynamic model, a set of desired truck velocities are computed in order to attain the target nodes at the time instants closest possible to the ones delivered by the initial schedule. The predicted delay at a particular node will be the difference between the expected time of arrival to that node and the time initially scheduled. If this delay is above a predefined threshold, then the lower layer is resumed and the higher layer is asked to provide an alternative schedule plan in order to mitigate further impacts of this delay in the supply chain tasks.

In order to illustrate the behaviour of the lower layer and its connection to the higher layer, consider the situation where both trucks depart from the depot at 8:00. The lower layer will be tracking the position of the trucks at regular time intervals and will be providing suggestions to each truck driver regarding the actual expected speed for the rig. Figure 4 depicts the evolution of both trucks' positions during the first six samples. As can be observed, the truck whose route is represented with the dashed line has a position progress that consistently provides confidence on the accomplishment of its task. However, regarding the other truck, something went wrong after 20 minutes of its departure, since the estimated arrival time at node 4 is constantly postponed. This increasing delay can be due to several situations such as a truck's mechanical malfunction, route problems, and traffic jams. In this case study, let us consider that a malfunction has occurred.

Table 2 presents the predicted speeds computed by the lower layer operational controller for the truck that presents problems, namely, the truck represented by the solid line. The one-step-ahead speed prediction will be the one delivered to the truck driver. Moreover, the expected time delay, considering the system states update at each sampling time, is also presented.

As can be observed from the table, at sample time $n = 5$, the accumulation of expected delays is near 20 minutes. Assume, for the sake of simplicity, that 10 minutes is the threshold level limit from which a new schedule should be generated. In this context and assuming that the faulty truck cannot carry on due to some malfunction, the higher operational layer control is triggered and the schedule plan presented in Figure 5 is delineated. It is worth noticing that this new plan is generated assuming that the operational trucks will finish their current tasks.

Moreover, the truck's driver is only informed about the next job at the end of the previous job. This allows changing the plan internally without the knowledge of the driver. This will avoid constant changes in the overall schedule.

With the presented approach, the operations occurring during the day are closely monitored and corrective actions are automatically applied beforehand to avoid deviations in the tasks accomplishment and, consequently, their propagation. Thus, the proposed methodology has been proven to be advantageous when compared to the traditional used strategies.

5. Conclusions

Biomass supply chains are complex systems, where their interconnected character hinders the disturbance propagation analysis along the processes. This task is even more complicated when no decision support tool is available. In this work, a methodology based on model predictive control was proposed to control the operational level of a biomass supply chain regarding the transportation operation. The proposed approach allows following the system state during the working day. At each time step, it predicts if the planned schedules and, consequently, the final goal of client satisfaction will be achieved. At each iteration and considering the current status of the system, if necessary, an alternative control sequence is generated to overcome possible deviations from the previous plan. With this approach, the system is automatically controlled reacting to disturbances in the plan accomplishment, avoiding errors accumulation. In order to test the feasibility of the proposed method, an application example was presented. The simulation results show that the system is able to react to delays, replanning the operations in order to comply with the daily goal. Due to the nature of these systems and their discrete event behaviour, in future work, it is intended to propose a hybrid event driven MPC approach.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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