Production optimization in the time of pandemic: an SIS-based optimal control model with protection effort and cost minimization

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Abstract

The COVID-19 pandemic wreaks havoc in supply chains by reducing the production capacity of some essential suppliers, closure of production facilities or the absence of infected workers. In this paper, we present three decision support models for a plant manager to help in deciding on (a) the level of protection of the workforce against the spread of the virus in the absence of regional protection measures, (b) on the duration of the protection, and (c) the level of protection of the workforce with regional protection measures enforced by health authorities. These decision models are based on a SIS epidemiological model which takes into account the possibility that a worker can infect others but also that even when recovered can be infected again. The first and third models prescribe how, in time, the protection effort in terms of prophylactic measures must be deployed. The second model extends the first one as it also determines the length the

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protection effort must be deployed.

The proposed models have been applied to the case of a meat processing plant that must satisfy the demand of a large-scale retailer. Clearly, to achieve production targets and satisfy customers' demand, plants in this labor-intensive industry rely on the number of healthy workers and the service level of suppliers. Our results indicate that these models provide managers with the tools to understand and measure the impact of an infection on production and the corresponding cost. Along the way, this work illustrates the ripple effect as suppliers affected by the pandemic are unable to fulfill the processing plant requirements and so the retailer's orders. Our findings provide normative guidance for supply chain decision support systems under risk of pandemic induced disruptions using a quantitative model-based approach.

Keywords: COVID-19, decision support, supply chain, production optimization

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1. Introduction

COVID-19 is a highly contagious virus-induced communicable disease, transmitted via droplets and contaminated objects during close unprotected contact between an infector and infectee (World Health Organization, 2020c). As workers in a facility get infected, production level drops and demand from customers downstream goes unfulfilled (Singh et al., 2020). The effects of infection spread on production and operations can be severe, particularly in those sectors where large pools of workers are mandated or intensive contacts are required (Hille, 2021). Supply chains and the industries linked to them also feeling the impact (Alvarez et al., 2020; Ivanov and Dolgui, 2020b; Ivanov, 2020). The infection spread can be curbed through the implementation of prophylactic measures such as social distancing and the use of protection equipment (Paul and Chowdhury, 2020). Therefore, such measures, in addition to protecting workers, represent an important lever to ensure production continuity and demand satisfaction (van Hoek , 2020; Ivanov and Dolgui, 2020b).

We consider a production facility manager who must ensure that the facility (hereafter called a plant) is able to deliver the products or services required by her customers according to their demand over a given planning horizon in the context of a pandemic. In a labour-intensive plant, the production level is directly function of the number of workers present, and dependent upon the provision by suppliers of the necessary inputs and raw materials. If suppliers are also affected by the pandemic, their ability to provide the necessary inputs may be jeopardised in a ripple effect as illustrated in Dolgui et al. (2017); Hosseini and Ivanov (2019); Ivanov and Dolgui (2020b); Ivanov (2020) and Ivanov and Dolgui (2021). To provide guidance to managers, and following the approach taken in various works (Paul and Chowdhury, 2020; Craighead et al., 2020), we adopt a modeling approach of how infection spreads among workers in time in a single closed environment. The proposed decision support models are applied to the case of a meat supply chain including a livestock supplier, a meat processing plant and a large-scale retailer. In Europe, the meat industry employs a million workers and is highly labor intensive. Many processing disruptions occur in the meat supply chain because of labour shortage in the sequel of absenteeism entailed by sickness (Fabris, 2020). For instance, labour availability was reduced by up to 30% in French meat processing facilities in the regions of the country worst hit by COVID-19 (OECD, 2020). As such, the meat industry is one of the most prominent applications of our models.

The infected workers are absent and hence cannot contribute to the production level (there is no teleworking possibility). In this context, the plant manager has two decisions to make. She must decide on the amount of effort she must dedicate to the protection of workers, and also decide when to stop such effort. We present first the plant manager's decision model on the protection effort to deploy so that there are enough workers to satisfy as much as possible the demand. She must, in particular, balance the penalty cost for not matching the supply with the demand with the cost incurred by the effort for implementing prophylactic measures. Although we do not detail the prophylactic measures available, we consider that there is a wide range of measures from which the plant manager can choose (Haug et al., 2020, presents a comprehensive list of such measures coded according to the Complexity Science Hub COVID-19 Control Strategies List). The cost corresponding to these measures can be evaluated *ex ante* and the corresponding deployment and enforcement is under the manager's responsibility.

How the infection spreads in a closed environment, how someone who recovers can be infected again is not well known and the debate as to how best to limit the spread of infection is still ongoing (Morawska et al., 2020; Rothan and Byrareddy, 2020). We start from the premises that a manager can, through proper effort in prophylactic measures, limit the propagation of infection among her workers (Courtemanche et al., 2020). Even if not yet sick, workers who commute from their communities to their place of work can bring the virus to the manufacturing facility (as a "contact") and contaminate co-workers (West et al., 2020). To model how such contamination spreads, most of the recent research (Acemoglu et al., 2020a,b; Gaeta, 2020) is based on a SIR (Susceptible-Infected-Recovered) setup, yet evidence that "people who have recovered from COVID-19 and have antibodies are protected from a second infection" is not only lacking (World Health Organization, 2020b), but there are indications to the contrary (World Health Organization, 2020a). Hence, it seems more reasonable and realistic to rely on a SIS framework (susceptible-Infected-Susceptible) in which, after recovery, people are susceptible to being infected again (Bailey et al., 1975).

The considered decision problems are formulated using optimal control models in continuous time (Gersovitz and Hammer, 2004; La Torre et al., 2020). The optimality conditions give rise to a system of forward-backward ordinary differential equations (ODE) in the state and co-state variables, with the addition of an algebraic equation describing the maximum principle. More specifically, the state variable has an initial condition while the co-state variable has a final condition. The sweep algorithm, one of the most widely used algorithms to deal with this forward-backward setting (McAsey et al., 2012), is then used to solve the proposed models.

Even though based on theoretical grounds and a stylised model, this study provides indications for managers and scholars as to the interactions between a manager's decisions related to the effort to invest in implementing prophylactic measures and a facility's production level in a pandemic context.

The study refines and advances the one presented in (Brusset et al., 2022). The differences can be summarized as follows:

- We model the spread of the disease by means of a nonlinear SIS model. We do not perform any linearisation but, instead, we consider the whole dynamics of the epidemics. The resulting optimal control model is nonlinear by construction, and so does not admit a closed-form solution. We proceed by simulating the optimality conditions which, in this context, read as a system of backward-forward ODE with initial and terminal conditions. We implement an ad-hoc numerical procedure based on the sweep algorithm;

- We introduce an exogenous service level which represents the ability of the suppliers to provide the plant with enough inputs and raw materials for production. The latter is 100% initially and can evolve in time with the propensity of suppliers to see their own production be affected by the pandemic. This might affect the amount of produced goods by the plant (see Ivanov, 2020, for a numerical study of the ripple effect of a pandemic on a supply chain);

- We present an extension of the first proposed nonlinear model to identify the endogenous optimal lockdown time T. By means of a numerical algorithm, we generate the cost curve as function of T and determine a numerical approximation of the global minimiser;

- We present a second extension of the first proposed nonlinear model in which we consider the regional protection measures enforced by health authorities.

The remainder of this paper is organized as follows. After presenting the epidemiological setup in section 2, we present in section 3 a first model in which the optimal effort in terms of social distancing and prophylactic measures is evaluated. The next section (section 4), is the model to obtain the optimal effort and the optimal time during which the prophylactic effort must be kept up. We then report computational experiments and results in section 5. Thereafter, in section 6, we present a third extension of the model and its results where the impact of regional authorities' effort in controlling the epidemic is taken into account. We provide some managerial insights based on the findings derived from the computational results in section 7 before concluding.

2. The Epidemiological setup

To understand how a pandemic works and how a single infected worker who comes in to work can generate in time a measurable and quantifiable impact on the production level of a plant, it is necessary to introduce here some elements of the results achieved in the science of epidemiology as applied to epidemics and pandemics.

A generic Susceptible-Infected (SI) epidemic model takes the form (Bailey et al., 1975):

$$\begin{cases} \dot{I}(t) = f(I(t), S(t)), \\ \dot{S}(t) = g(I(t), S(t)), \\ I(0) = I_0, S(0) = S_0, \end{cases} \tag{1}$$

where $I(t)$ is the number of infected people and $S(t)$ is the number of susceptible people at time t. As N is the total population on the homogeneous geographical site[1], $S(t) = N - I(t)$. In the sequel of this paper we model the evolution of the epidemic by means of a classical SIS model where both private and public actors strive to control infection in the population. Regional authorities are the public actors which have the responsibility for protecting the population in a specific region against infection. Such authorities will deploy general prophylactic measures, while private actors such as plant managers will deploy an effort within the premises of their plants. Such a model reads as:

$$\begin{cases} \dot{I}(t) = \gamma(1 - \beta_L(t) - \beta_G(t))S(t)I(t) - \alpha I(t), \\ \dot{S}(t) = -\gamma(1 - \beta_L(t) - \beta_G(t))S(t)I(t) + \alpha I(t), \\ I(0) = I_0, S(0) = S_0, \end{cases} \tag{2}$$

where γ is the infection rate at the regional level, $\beta_L(t)$ is the time dependent amount of effort in implementing prophylactic measures at the plant level, $\beta_G(t)$ is the time dependent amount of effort in implementing prophylactic measures at the regional level and α is the recovery rate. Note that if there is no effort in implementing prophylactic measures at the regional level and the plant, that is $\beta_L = 0$ and $\beta_G = 0$, then the disease infection rate coincides with γ. Note also that the greater the effort β_L the smaller will be the infection rate, $\gamma(1 - \beta_L(t) - \beta_G(t))$. By assuming that $\beta_G = 0$ and using the substitution $S(t) = N - I(t)$, the model (2) can be rewritten as it

[1] Workers on site move around without limits in random ways thus coming across all other workers on the premises.

follows:

$$\begin{cases} \dot{I}(t) = \gamma(1-\beta_L(t))(N-I(t))I(t) - \alpha I(t), \\ I(0) = I_0. \end{cases} \tag{3}$$

This equation can be solved in closed-form and its expression depends on the integrals over time of β_L. When β_L is supposed to be constant, the expression of I reads as:

$$I(t) = \frac{I_0(\gamma(1-\beta_L)N-\alpha)}{\gamma(1-\beta_L)I_0 + e^{-(\gamma(1-\beta_L)N-\alpha)t}((\gamma(1-\beta_L)N-\alpha) - I_0\gamma(1-\beta_L))}$$

3. Decision support model for optimal effort

The proposed model aims at investigating how to maintain production in a labor-intensive plant in an epidemic context through the optimal effort in implementing prophylactic measures. Indeed, in such a context, the plant manager, as decision maker, tries to control epidemic spread among workers within the plant through the deployment and enforcement of prophylactic measures at plant level at time t, $\beta_L(t)$ in an effort to minimize the number of workers getting infected so that the plant can meet the demand addressed to it. The plant manager strives to balance the cost incurred by the implementation of prophylactic measures with the penalty for not matching the demand and epidemic social cost.

Markedly, the plant manager has no power to influence the effort β_G in general prophylactic measures decided at the regional level and, therefore, such an effort, β_G, is assumed to be exogenous. The number of infected workers is time-dependent and relies on the efforts in implementing prophylactic measures invested at time t, $\beta_L(t)$ and $\beta_G(t)$. In order to account for the dynamics of the control effort and the number of infected workers, the decision support problem is formulated using control theory.

To facilitate the reading of this paper, we group in Table 1 the notation used.

It is worth noting, at this level, that in this first decision support model (also referred to as first optimal control model), we consider the case where there is no regional protection effort enforced by the health authorities. An extension of this model that incorporates regional protection effort will be presented and discussed in section 6.

The objective function of the proposed model can be spelled as follows:

$$\begin{aligned} TC &= \min_{I(t),\beta(t)} \int_0^T \left[cx(t) + \frac{c_A}{2}\left(x(t)-a\right)^2 + \frac{c_\beta}{2}\beta_L^2(t) + \frac{\bar{c}_\beta}{2} I^2(t) \right] dt + \frac{\phi}{2} I^2(T) \\ &= \min_{I(t),\beta(t)} A + B + C + D + E, \end{aligned} \tag{4}$$

where

$A = \int_0^T cx(t)dt$	is the total production and shipping cost,
$B = \int_0^T \frac{c_A}{2}\left(x(t)-a\right)^2 dt$	is the total penalty cost for not matching the demand and the supply,
$C = \int_0^T \frac{c_\beta}{2}\beta_L^2(t)dt$	is the total cost incurred by the effort for implementing prophylactic measures,
$D = \int_0^T \frac{\bar{c}_\beta}{2} I^2(t)dt$	reflects the social cost of the epidemics over the planning horizon,
$E = \frac{\phi}{2} I^2(T)$	reflects a penalty cost of having infected workers at the end of the considered planning horizon. Hence this term favors the continuity of production in the subsequent planning horizon.

Table 1: Table of notations

N	total number of workers in the plant
T	length of the planning horizon
α	recovery rate from infection
γ	infection rate in absence of effort for implementing prophylactic measures at the regional level
c	production and shipping cost per unit
a	demand in units which has to be met per period
c_A	per unit penalty cost for not matching the supply with the demand per period
c_β	total cost of implementing prophylactic measures per period
$\bar{c}_\beta$	social cost of the epidemic per period
ϕ	penalty cost of still having infected workers at the end of the planning horizon
θ	per-capita productivity ($0 < \theta \leq 1$)
I_0	number of infected workers at the beginning of the planning horizon
$L(t)$	delivery reliability (percentage of the ordered quantity delivered on time) in period t from uptstream suppliers ($L(t) \in [0, 1]$), also named service level
$\beta_L(t)$	control variable expressing the effort for implementing prophylactic measures at time t ($\beta_L(t) \in [0, 1]$)
$\beta_G(t)$	exogenous time dependent parameter expressing the effort for implementing prophylactic measures at the regional level ($\beta_G \in [0, 1]$)
$I(t)$	number of infected workers in period t
$S(t)$	number of susceptible (healthy and so available) workers at time t ($S(t) = N - I(t)$)
$x(t)$	produced and shipped quantity in period t

While assuming that $\beta_G = 0$, the constraint system of this first model is described as follows:

$$\begin{cases} \dot{I}(t) = \gamma(1-\beta_L(t))I(t)(N-I(t)) - \alpha I(t), \\ I(0) = I_0, \\ 0 \le I(t) \le N, \\ 0 \le \beta_L(t) \le 1, \\ x(t) = \theta L(t)(N-I(t)), \end{cases} \tag{5}$$

Note that the produced and shipped quantity at time t, $x(t)$, depends on the number of healthy workers at time t, $N-I(t)$, the per-capita productivity, θ, and the delivery reliability of the upstream suppliers at time t, $L(t)$.

Theorem 1. *Let $(I(t), \beta_L(t), \lambda(t))$ be the optimal solution to the above optimal control model Eqs. (4)-(5). Then a necessary and sufficient optimality condition is expressed by the following system of FOCs:*

$$\begin{cases} \dot{\lambda}(t) & = cL(t)\theta + c_A\theta L(t)[\theta L(t)(N-I(t)) - a] - \bar{c}_\beta I(t) \\ & -\lambda(t)\left[\gamma(N-2I(t)) - \frac{\gamma^2}{c_\beta}\lambda(t)I(t)(N-I(t))(N-2I(t)) - \alpha\right] \\ \dot{I}(t) & = \gamma I(t)(N-I(t)) - \frac{\gamma^2\lambda(t)}{c_\beta}I^2(t)(N-I(t))^2 - \alpha I(t) \\ \beta_L(t) & = \frac{\lambda(t)\gamma I(t)(N-I(t))}{c_\beta} \\ I(0) & = I_0 \\ \lambda(T) & = \phi I(T), \end{cases}$$

where $\lambda(t)$ is the co-state variable used in the Hamiltonian associated with the formulated problem.

The proof of the above Theorem can be found in the Appendix. To find the optimal control effort we apply one of the most widely used algorithms to deal with this forward-backward setting, namely the sweep algorithm. A detailed version of the sweep algorithm is presented in McAsey et al. (2012). The implemented forward-backward sweep method is presented in the appendix.

4. The optimal effort and protection duration

In this section, we wish to understand how long the plant manager must keep up the prophylactic measures. To do so, we investigate an extension of the first optimal control model in which the finite planning horizon T is no longer exogenously chosen but, instead, is optimally and endogenously determined by the model itself. That is, we evaluate the optimal length of time over which the effort in terms of prophylactic measures must be kept up. In addition, we suppose that ϕ, the penalty for infected workers at the end of the finite horizon T is a function of T and takes the form $\phi = \frac{\bar{\phi}}{T}$ where $\bar{\phi}$ is an exogenous parameter that serves as a proxy for the plant manager's concern for long run health outcomes tied to the epidemic outbreak. If $T \to 0$ the short and long run coincide and thus an infinitely large weight is attached to the final damage, if $T \to +\infty$ the long run is infinitely far away and thus the weight attached to the final damage is null. For positive but finite values of T, instead, a positive and finite value is attached to the final level giving rise to a clear trade off between the discounted sum of the instantaneous losses (which are minimised with $T \to 0$) and the discounted final number of infected people (which is minimised when

$T \to +\infty$) ensuring thus that optimality will require that the plant manager will enforce epidemic mitigation policies for a positive and finite amount of time. For any fixed $T > 0$, the optimal control model to be solved reads as:

$$C(T) = \min_{I(t),\beta(t),T} \theta c \int_0^T L(t)(N - I(t))dt + \frac{c_A}{2} \int_0^T (\theta L(t)(N - I(t)) - a)^2 \, dt \\ + \frac{c_\beta}{2} \int_0^T \beta_L^2(t)dt + \frac{\bar{c}_\beta}{2} \int_0^T I^2(t)dt + \frac{\bar{\phi}}{T} \frac{I^2(T)}{2} \tag{6}$$

subject to

$$\begin{cases} \dot{I}(t) = \gamma(1 - \beta_L(t))(N - I(t))I(t) - \alpha I(t), \\ I(0) = I_0, \\ 0 \leq I(t) \leq N, \\ 0 \leq \beta_L(t) \leq 1, \\ x(t) = \theta L(t)(N - I(t)). \end{cases} \tag{7}$$

The model determines the control effort and the protection duration that optimally balance the production and shipping cost, the penalty cost for not matching the demand, the cost for implementing prophylactic measures, and the epidemic social cost. An extended version of the sweep algorithm has been used to solve the proposed model as detailed in the appendix. It is easy to notice that

$$\lim_{T \to 0^+} C(T) = +\infty$$

due to the fact the first four terms in the expression of C tend to zero when $T \to 0^+$ while the fifth one diverges to $+\infty$. Furthermore, one can easily observe that

$$\lim_{T \to +\infty} \frac{\bar{\phi}}{T} \frac{I^2(T)}{2} = 0$$

due to the fact that $I(T)$ is bounded by N for any T and that the first order derivative of the first four terms in the expression of $C(T)$ is positive. This is enough to conclude that there exists a $T_{min} > 0$ where C attains its global minimum. This result is discussed in more details using the numerical simulations presented in the next section.

5. Experimentation and numerical results

We illustrate our first optimal control model and solution approach with the synthetic case of a three-stage localised meat supply chain so as to be able to infer descriptive and normative results in the sense of Bertrand and Fransoo (2002). This chain includes a livestock supplier and a meat processing plant serving a large-scale retailer.

To do so, we focus in sub-section 5.2 on investigating the optimal effort for implementing prophylactic measures in the meat processing plant and its impact on demand satisfaction and the total cost over a planning horizon of 30 days and compare it to the case where the plant manager decides not to do anything in terms of protecting the workers against the possibility of infection, named the "doing nothing case".

In a second step, in sub-section 5.2.2, we conduct a sensitivity analysis in order to investigate the effect of some parameters of the model, namely the penalty cost for not matching the supply with the demand c_A, the cost of implementing prophylactic measures c_β, the social cost of the epidemics $\overline{c}_\beta$, and the penalty cost for having infected workers at the end of the planning horizon ϕ, on the protection effort policy that should be adopted by the plant manager. We do so under two scenarios:

- Scenario 1: the livestock supplier is not impacted by the pandemic; he is able at any time t to deliver the required quantity on time and in full which translates into $L(t) = 1, \forall t \in [0, 1]$
- Scenario 2: the livestock supplier is also within a zone of infection; his service level drops to 50% which translates into $L(t) = 0.5, \forall t \in [0, 1]$

In sub-section 5.3, we look at the case where the plant manager will jointly determine the optimal protection effort to deploy and the duration of this protection effort in time to still achieve the demand satisfaction targets.

Based on the conducted experimentation, we draw conclusions which can be generalised for managers and decision makers in similar settings. We now specify the data that we have used throughout this study.

5.1. Data description

Most of the data used for the meat supply chain is based on the case study presented in Mohebalizadehgashti et al. (2020) and updated data presented in Novek et al. (1990). As far as the SIS epidemic model parameters are concerned, they have been extracted from the model of the second wave of COVID-19 outbreak presented in Faranda and Alberti (2020). The daily demand of the large-scale supplier is equal to 15 tonnes. 80 production workers are employed in the meat processing plant. The per-capita productivity is assumed equal to 0.187 tonne per day per worker. The production cost of one tonne of meat is estimated based on the purchasing cost of livestock, the meat yield of livestock, and the labor cost. The shipping cost per tonne is estimated based on a transportation distance of 60 km between the meat processing plant and the central warehouse of the large-scale retailer using a reefer trailer. The per unit penalty cost for not matching the supply with the demand is assumed equal to the per unit production and shipping cost. The cost for implementing prophylactic measures is roughly evaluated based on the quantity of hydroalcoholic gel, masks, social distancing measures, and training required to protect the workers in the plant over the planning horizon.

The livestock supplier is considered through his reliability to deliver the required quantity of livestock on time . Such reliability will also be named in what follows the service level.

Indeed, if the meat processing plant holds a livestock risk mitigation inventory, the latter will serve to satisfy the plant's requirement on time and in full but only for a limited time, after which the supplier's lack of service will impact the plant's production (Ivanov, 2020). So, without loss of generality, we consider here that the meat processing plant uses a just-in-time ordering policy, and that lead time for delivery to the meat processing plant is null.

The parameters of the meat supply chain case are summarised below:

$$N = 80, \quad a = 15, \quad T = 30, \quad \theta = 0.187, \quad \alpha = 0.37, \quad \gamma = 0.5,$$
$$c = 4000, \quad c_A = 4000, \quad c_\beta = 75, \quad \bar{c}_\beta = 300, \quad \phi = 300.$$

5.2. Results from the first optimal control model

We study here the optimal effort model over the planning horizon. In subsection 5.3, we study the model where the manager evaluates also the length of time during which the prophylactic effort has to be maintained within this planning horizon.

5.2.1. The importance of adopting an optimal protection effort policy

In order to assess the importance of adopting an optimal protection effort policy, we compare it with the doing-nothing case, in which the plant manager decides to forfeit protection effort, that is $\beta_L(t) = 0, \forall t \in [0, T]$.

In the doing-nothing case, the number of infected workers can be determined using the following expression:

$$I(t) = \frac{I_0(\gamma N - \alpha)}{\gamma I_0 + e^{-(\gamma N - \alpha)t}\left((\gamma N - \alpha) - I_0\gamma\right)}. \tag{8}$$

The corresponding expression of $x(t)$ is then provided by:

$$x(t) = \theta L(t)(N - I(t)). \tag{9}$$

We then plug these two expressions into the objective function (4), in order to get an estimate of the total cost (TC) and different cost terms, namely A, B, C and D (as defined earlier in Section 3).

Figure 1 presents the optimal protection effort, the resulting share of infected workers, and the share of infected workers obtained for the doing-nothing case, when $I_0/N = 0.1$, $I_0/N = 0.2$ and $I_0/N = 0.3$ for both, scenario 1 and 2.

First, we observe that, in both scenarios, regardless of the initial number of infective workers, the effort in implementing prophylactic measures is monotonically decreasing over time. Moreover, as expected, one can see that the higher the initial number of infected workers, the higher the protection effort to contain the epidemic outbreak.

Noticeably, the protection effort is lower in scenario 1 than in scenario 2. Hence, the optimal protection effort is not only affected by the initial number of infected workers in the plant but also by the reliability of the supplier to deliver the ordered quantity on time and in full. If the supplier's service level is affected, the effort for implementing prophylactic measures in the plant must then be intensified in order to counterbalance the impact of this supply disruption on production and hence the meat processing plant's ability to match the supply and the demand.

The share of infective workers resulting from an optimal protection effort policy goes through a minimum. Remarkably, the share of infective workers at the end of the planning horizon is independent of the the initial share of infective workers. Obviously, the higher is the protection effort, the lower is the share of infective workers.

Moreover, we can see that the three curves portraying the share of infective workers in the doing-nothing case are also converging towards the end of the planning horizon. Indeed, according to (8), the share of infective workers should converge very rapidly to 0.26 as t increases. This also explains why, over the planning horizon, the share of infective workers is increasing when the initial share of infective workers is 0.1 and 0.2 while it is decreasing when the initial share of infective workers is 0.3.

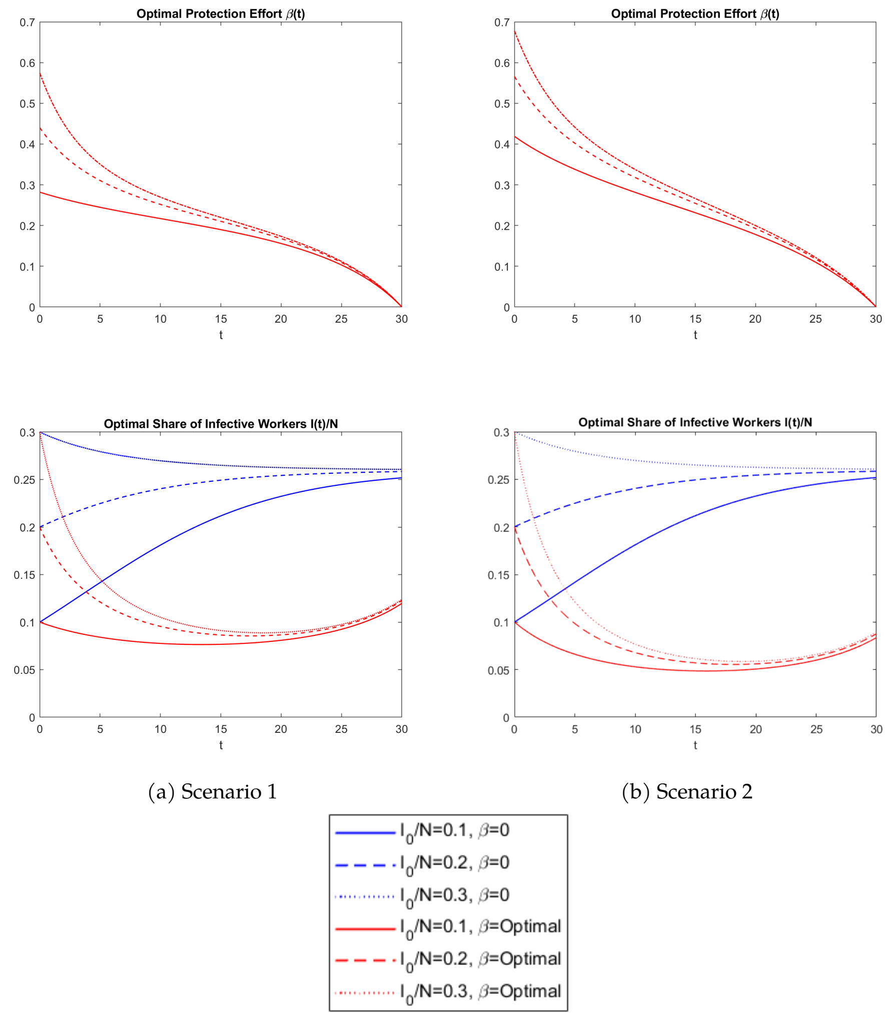
Table 2 compares the cost terms A, B, C, D and the total cost (TC) obtained for each scenario under optimal protection effort policy with those obtained in the doing-nothing case while assuming that the initial share of infective workers is 0.1. Expectedly, the produced quantity of meat is always higher in scenario 1, where the supplier is able to deliver the required livestock on time and in full. Moreover, note that the demand is better satisfied in scenario 1 than in scenario 2, even though scenario 1 involved a lower effort for implementing prophylactic measures than scenario 2.

Clearly, when the effort for implementing the prophylactic measures increases, the incurred cost increases while the social cost of epidemics decreases. Also, it is worth mentioning that the total penalty cost for having infected workers at the end of the planning horizon is very low with comparison to the other cost terms.

As the share of infective workers is obviously higher when no protection is afforded, the total cost of such a policy is higher than the one suggested by our model (in scenario 1, it is reduced by 23% while in scenario 2, it is reduced by 30%, see Table 2). This is due to the demand being better satisfied when optimal effort for implementing prophylactic measures is adopted (notice the lower total penalty cost for not matching the supply with the demand, B, under protection effort policy).

5.2.2. Sensitivity analysis

Figure 2a shows that an increase in the penalty cost for not matching the supply with the demand, c_A, entails an increase in the optimal protection effort. Again, as delineated by Figure 2b, this increase in protection effort is followed by a decrease in the share of infective workers. Moreover, we can note that, regardless of the penalty cost, c_A, the protection effort is relaxed



(a) Scenario 1 (b) Scenario 2

Figure 1: Share of infective workers: the optimal protection effort case vs. the doing-nothing case, for both scenario 1 and scenario 2.

Table 2: Cost distribution in hundred of thousands for scenario 1 and 2 and $I_0 = 0.1$: the optimal protection effort case vs. the doing-nothing case

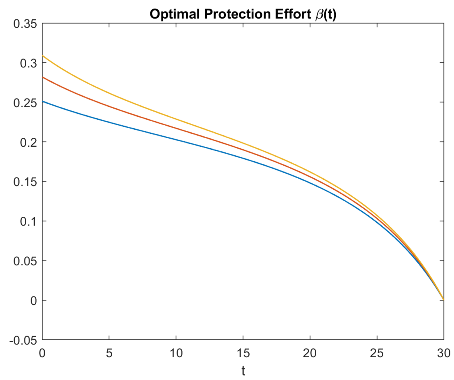
Scenario	Protection effort	A	B	C	D	TC
1	yes	16.406	1.071	2.588	2.163	22.234
	no	14.390	5.711	0	11.942	32.064
2	yes	8.432	38.139	4.456	1.097	52.128
	no	7.195	48.716	0	11.943	67.873

at the end of the planning horizon.

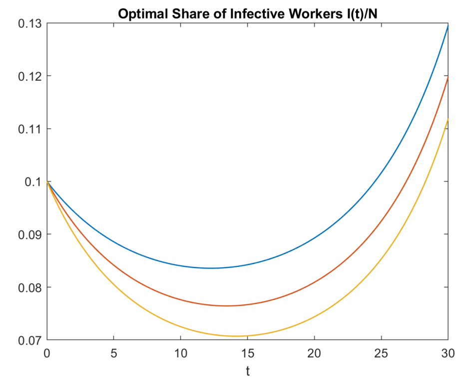
The inverse effect can be observed when c_β varies in Figure 3. Expectedly, the protection effort decreases as the associated cost increases.

Figure 4 presents the effect of a change in the social cost of the epidemics, $\bar{c}_\beta$, on the protection effort. Noticeably, the protection effort varies, in this case, in the same way as when the penalty cost for not matching the supply with the demand, c_A, varies. However, one notes that when $\bar{c}_\beta$ decreases (increases) the effort starts at only a slightly higher (lower) level with comparison to a similar change of c_A.

We finally present the case when the cost ϕ evolves in Figure 5: all the curves overlap each other which means that only the last one appears (yellow curve). Therefore, a 50% decrease or increase in ϕ does not have any measurable effect on the protection effort. This can be explained by the fact that - all other parameters being equal - the penalty cost for having infected workers at the end of the planning horizon, remains, although after

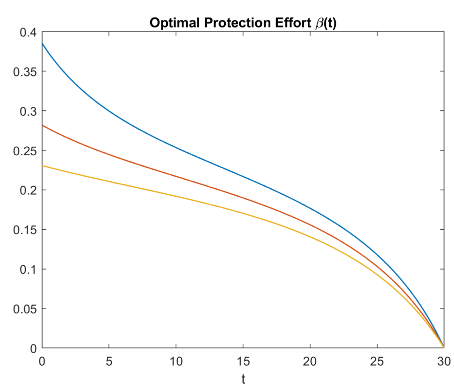


(a) Optimal effort

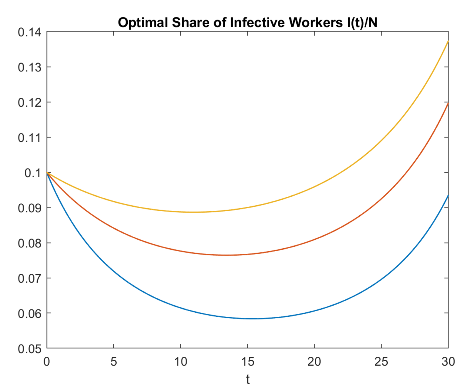


(b) Optimal Share of Infective Workers

Figure 2: Optimal protection effort and share of infective workers when c_A is either 50% above (yellow curve) or 50% below (blue curve) the central value (red curve).

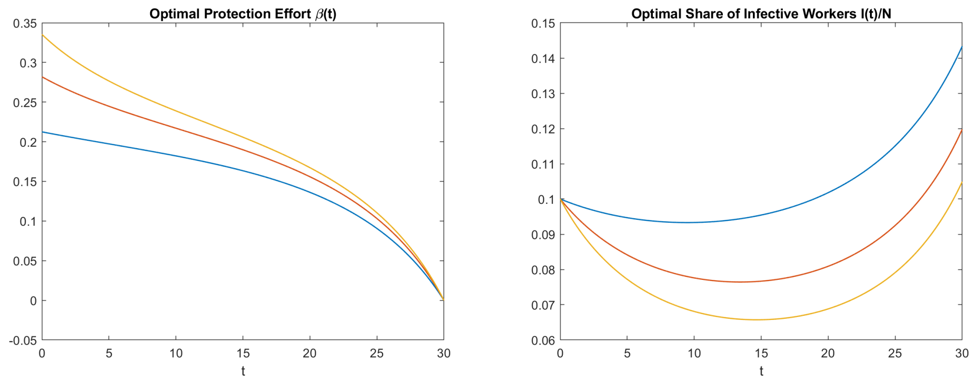


(a) Optimal effort



(b) Optimal share of infective workers.

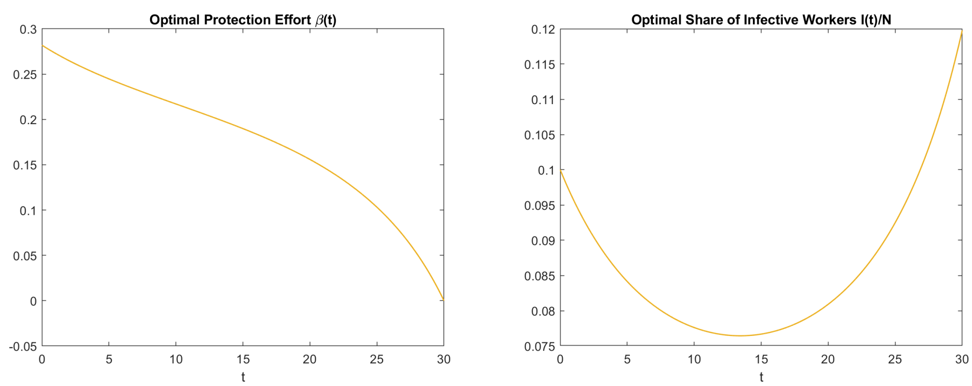
Figure 3: Optimal protection effort and share of infective workers when c_β is either 50% above (yellow curve) or 50% below (blue curve) the central value (red curve).



(a) Optimal effort

(b) Optimal Infective Workers.

Figure 4: Optimal protection effort and share of infective workers when when $\bar{c}_\beta$ is either 50% above (yellow curve) or 50% below (blue curve) the central value (red curve).



(a) Optimal Share of effort

(b) Optimal infective workers.

Figure 5: Optimal protection effort and share of infective workers when when ϕ varies: no change can be detected in either the optimal effort or the number of infectives.

an increase of ϕ by 50%, much lower than the other cost terms .

It is worth noting, at this level, that the results of the sensitivity analysis presented above are pertaining to scenario 1. The same sensitivity analysis has been also conducted for scenario 2 (where $L(t) = 0.5$). Conspicuously, the results are very similar, in general trends, to those obtained for scenario 1, and only vary in terms of starting values (See Figure C.12 in Appendix C for a quick comparison with scenario 2). Therefore, a change in the considered cost parameters triggers the same type of effect on the protection effort whatever is the service level of the supplier (100% or 50%).

5.3. *Estimating the protection duration for optimal control effort over the planning horizon*

We build upon the second decision support model where we want to evaluate the optimal duration for the protection effort. The corresponding function to be optimised is presented in (6) to jointly determine the optimal protection effort and the optimal protection duration, T_{Opt}. Figures 3 and 5 present how the optimal total cost varies as a function of the length of the optimal duration T_{Opt} for scenarios 1 and 2, the minima are $T_{Opt} = 14.5$ days in scenario 1 and 10 days in scenario 2. The shorter optimal protection duration in scenario 2 still generates a higher overall cost to the plant as reported in Table 3 because the lower service level of the supplier means that the plant cannot produce (column A) as can be understood by the penalty paid due to the unsatisfied demand (column B).

Figures 6 and 7 portray the optimal share of infective workers and the optimal protection effort during the optimal protection duration for scenarios 1 and 2, respectively. Again the effort for implementing prophylactic measures during the optimal protection duration is more intense in scenario 2 than in scenario 1. One can see from table 3 that the cost of the effort for implementing prophylactic measures is slightly higher by 5% in scenario 1 than in scenario 2, even though the duration is extended from 10 to 14.5 days, that is 45% longer.

Therefore, the optimal protection effort, the optimal share of infective workers and optimal protection time are impacted by the supplier's service level. Interestingly, the optimal protection time is longer when the supplier fully supplies the plant.

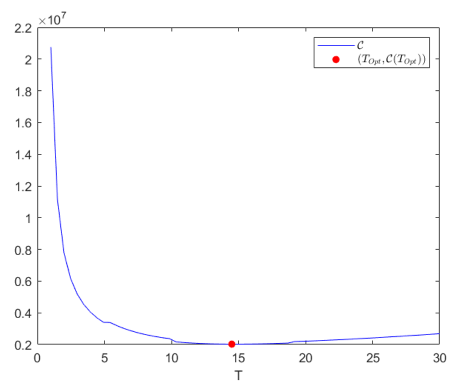
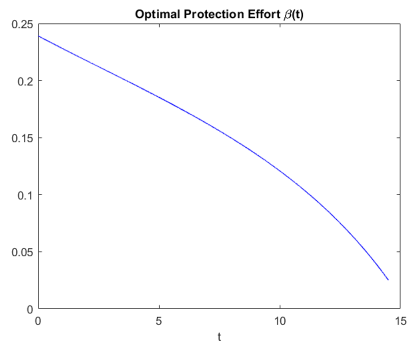
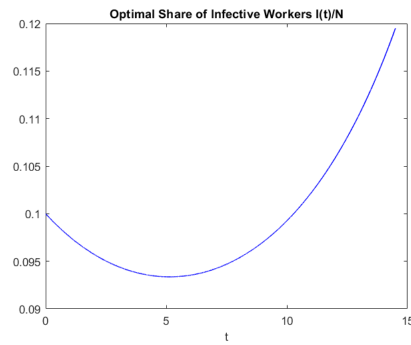


Figure 6: Total cost and endogenously determined optimal protection duration in scenario 1



(a) Optimal Protection Effort,



(b) Optimal Share of Infective Workers

Figure 7: Optimal share of infective workers and optimal protection effort within the optimal protection duration T_{Opt} for scenario 1

Table 3: Results obtained for scenario 1 and scenario 2 with optimal T and $I_0/N = 0.1$

	A	B	C	D	E'	TC	$I(T)/N$	T
Scenario 1	7.815	0.678	0.909	1.376	9.454	20.233	0.1198	14.5
Scenario 2	2.713	13.498	0.859	0.832	10.698	28.601	0.1056	10

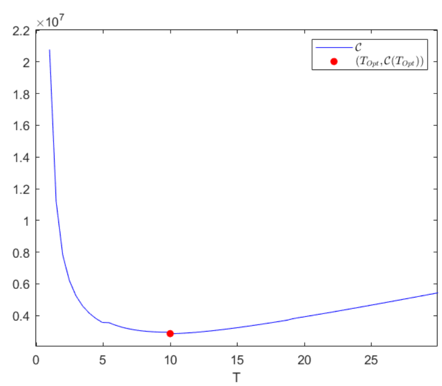
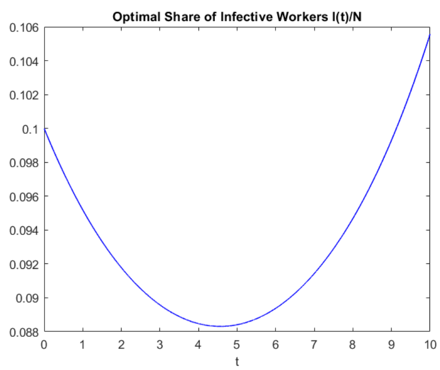
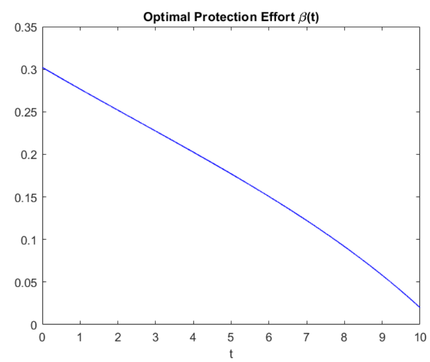


Figure 8: Total cost and endogenously determined optimal protection time in scenario 2



(a) Optimal Share of Infective Workers.



(b) Optimal Protection Effort.

Figure 9: Optimal share of infective workers and optimal protection effort within the optimal protection duration T_{Opt} in scenario 2

Observe in Table 3, that the share of infective workers at T_{Opt} at the end of Run 1 is slightly higher than the initial one. Assuming that the epidemic outbreak continues to spread with the same infection rate, we perform a second run of the decision support model for optimal effort and protection duration in order to decide on the protection strategy to adopt beyond T_{Opt}. In this second run, the value of the initial share of infective workers is set to the value of the share of infective workers at T_{Opt} obtained at the end of the first run. Hereafter, let us denote by $T1_{Opt}$ and $T2_{Opt}$ the optimal protection time obtained in the first and the second run of the model, respectively.

Table 4 depicts the results of the two successive runs of the decision support model for optimal effort and protection time obtained for scenario 1. The protection effort and the length obtained in the second run of the model are slightly higher than the ones of the first run.

If we suppose that the manager's planning horizon extends over 30 days, she might consider that the pandemic will extend over all this planning horizon, so we run the decision support model for optimal effort and protection time while enforcing the value of T to $T1_{Opt} + T2_{Opt}$ (so the model has been used only to determine the optimal protection effort). The obtained results are reported in table 5 and confirm that a better performance in terms of demand satisfaction and total cost would be achieved if the decision maker adopts a planning horizon of length $T1_{Opt} + T2_{Opt}$.

Hence, the manager's choice of policy depends upon her anticipation about the intensity of the pandemic. If she anticipates that the pandemic will extend beyond the 14.5 days of calculated optimal duration, it would be wiser to plan the optimal protection effort over a fixed longer period, based

Table 4: Results of two successive runs of the decision support model for optimal effort and protection time

Run	A	B	C	D	$A+B+C+D$	$I(T)/N$	T_{Opt}
1: $I_0/N = 0.1$	7.815	0.678	0.909	1.376	10.778	0.1198	14.5
2: $I_0/N = 0.1198$	8.292	0.820	1.236	1.674	12.022	0.1222	15.5

Table 5: Results with $T = T1_{Opt} + T2_{Opt}$

	A	B	C	D	$A+B+C+D$	$I(T)/N$	T
$I_0/N = 0.1$	16.406	1.071	2.588	2.163	22.228	0.1198	30

on an estimate of the intensity of the epidemic outbreak. This will result in an overall lesser cost than renewing the effort in consecutive periods to ensure that the workforce remains in optimal health to be able to meet the demand from downstream customers once social cost beyond the end of the protection duration.

6. An extended model with regional protection effort

In this section we consider the case where the plant is embedded in a region in which the health authorities, once a pandemic is detected, decide to engage in prophylactic measures to protect the general population. Such measures include social distancing, wearing a face mask in public places, and others as depicted in (Haug et al., 2020). The optimal control model with consideration of regional protection effort is as follows:

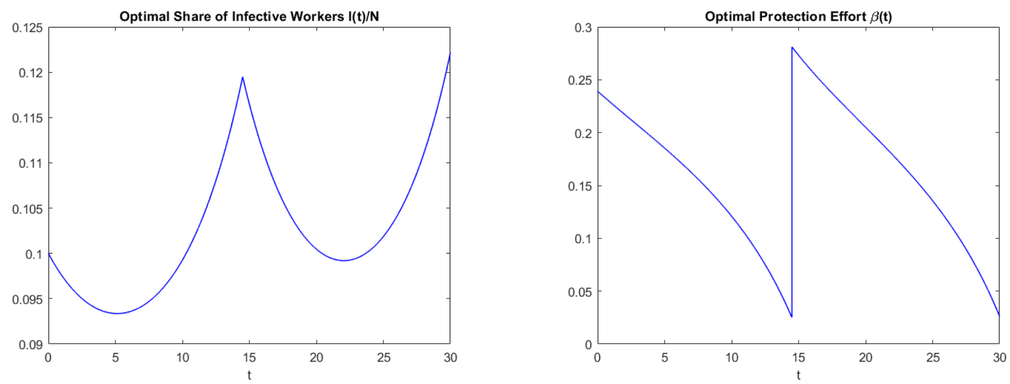


Figure 10: Optimal share of infective workers and optimal protection effort for two successive runs of the decision support model for optimal effort and protection time

$$TC = \min_{I(t),\beta(t)} \int_0^T \left[cx(t) + \frac{c_A}{2}\left(x(t)-a\right)^2 + \frac{c_\beta}{2}\beta_L^2(t) + \frac{\bar{c}_\beta}{2}I^2(t)\right]dt + \frac{\phi}{2}I^2(T) \quad , \tag{10}$$

subject to

$$\begin{cases} \dot{I}(t) = \gamma(1-\beta_L(t)-\beta_G(t))I(t)(N-I(t)) - \alpha I(t), \\ I(0) = I_0, \\ 0 \leq I(t) \leq N, \\ 0 \leq \beta_L(t) \leq 1-\beta_G(t), \\ x(t) = \theta L(t)(N-I(t)), \end{cases} \tag{11}$$

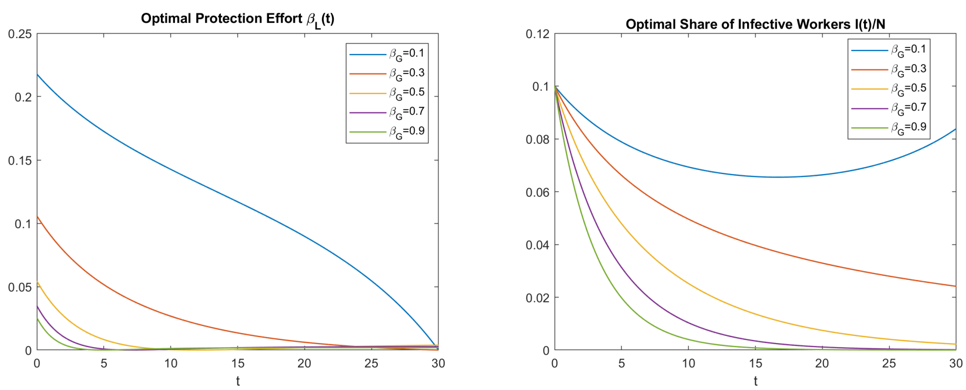
Recall that $\beta_G(t)$ is the time dependent amount of effort in implementing prophylactic measures at the regional level. The exogenous time dependent $\beta_G(t)$ is chosen by the regional authorities by putting in place epidemiological-macroeconomic policies of public health as presented in La Torre et al. (2021) and La Torre et al. (2022). The optimality conditions are presented in the following Theorem 2.

Theorem 2. *Let $(I(t), \beta_L(t), \lambda(t))$ be the optimal solution to the above optimal control model Eqs. (10)-(11). Then a necessary and sufficient optimality condition is expressed by the following system of FOCs:*

$$\begin{cases} \dot{\lambda}(t) & = cL(t)\theta + c_A\theta L(t)[\theta L(t)(N-I(t)) - a] - \bar{c}_\beta I(t) \\ & -\lambda(t)\left[\gamma(1-\beta_G(t))(N-2I(t)) - \frac{\gamma^2}{c_\beta}\lambda(t)I(t)(N-I(t))(N-2I(t)) - \alpha\right] \\ \dot{I}(t) & = \gamma(1-\beta_G(t))I(t)(N-I(t)) - \frac{\gamma^2\lambda(t)}{c_\beta}I^2(t)(N-I(t))^2 - \alpha I(t) \\ \beta_L(t) & = \frac{\lambda(t)\gamma I(t)(N-I(t))}{c_\beta} \\ I(0) & = I_0 \\ \lambda(T) & = \phi I(T) \end{cases}$$

In the extreme scenario in which $\beta_G(t)$ is maximum then the derivative of I is negative and therefore the total number of infected workers is decreasing no matter what is the manager's prophylactic effort $\beta_L(t)$. This is the situation witnessed in Europe. Let us point out here that if the regional authorities only engage in the maximum social distancing measure available which is a regional lockdown (case of Shanghai in April and May 2022), then our model does not make sense anymore as there are no workers in the plant and production drops to nil.

For further guidance as to the effect of the prophylactic effort provided by the regional authorities, we present in Figure 11 the impact of various intensities of effort β_G on the optimal effort and number of infectives inside the plant in scenario 1. As would be expected, as the intensity of regional authorities' effort in containing the epidemic increases, the manager will reduce her effort inside the plant. There is a substantial difference when regional authorities only engage in "token" prophylactic effort ($\beta_G = 0.1$) which leads the manager to maintain a substantial prophylactic effort and yet leaves the proportion of infectives at a comparatively high level at the end of the planning period. Note that similar optimal effort patterns have been observed for scenario 2 (See Figure C.13 in Appendix C for a quick comparison with scenario 2). Once again, under the same conditions, the optimal protection effort is higher in scenario 2 than in scenario 1.



(a) Optimal effort

(b) Optimal share of infectives.

Figure 11: Optimal protection effort and share of infective workers when β_G varies

7. Some managerial insights

Some managerial insights can be derived from the experimentation using plausible parameters in a three-stage supply chain involving a livestock supplier, a meat processing plant and a large-scale retailer.

First, the effort for implementing prophylactic measures at the meat processing plant to protect the workforce helps in maintaining satisfactory production level during an epidemic outbreak. As would be expected, we confirm that under an optimal protection effort policy, the demand is better satisfied. Because of the penalty cost incurred for not matching the supply with the demand, the total cost is lower than the one incurred by the doing-nothing case (that is, the cost of implementing prophylactic measures is lower than the penalty).

Second, the effort in implementing prophylactic measures is higher (all hands must be on deck) when the reliability of the supplier to deliver the required quantity on time and in full is affected by the epidemic context. This reduces the impact of supply disruption on demand satisfaction. However, clearly, even when an optimal protection effort is deployed the loss in production is not completely recovered because of the supply disruption. This highlights, in particular, the importance of multi-sourcing and holding risk mitigation stock as they can be used as levers to overcome, reduce or postpone the drop in supply during an epidemic outbreak.

Third, the plant manager should deploy the fullest protection effort possible strategy at the onset of the epidemic outbreak. The effect of an epidemic outbreak on production level is indeed lessened if prophylactic measures are implemented when the number of infective workers in the plant is still small. Surprisingly, our analyses shows that this effort will then be slightly reduced up, even if the pandemic is not over. In all cases, it is counter-productive to go without any prophylactic measures to protect workers against infection, whatever the proportion of workers infected when the pandemic is first observed in the plant.

Fourth, the supply chain's overall output is reduced if the supplier is also subject to pandemic induced disruptions (the ripple effect studied in Li et al., 2020; Ivanov and Dolgui, 2020a; Queiroz et al., 2020) but can still mitigate part of it by increasing prophylactic measures' effort at the level of the production plant according to our analysis.

Fifth, an increase either in the penalty cost for not matching the supply with the demand or, in the social cost of the epidemics, entails an increase of the protection effort. Therefore, a higher protection effort should be invested in plants producing more essential and vital products.

Sixth, protection measures enforced by health authorities help in sustaining production with less protection effort deployed in the plant.

8. Conclusion

We show in this paper how a plant manager can effectively address the risk of a loss in production incurred during a pandemic. The setting we consider here is that of a human labour intensive production facility so that any sick and hence absent worker directly impacts production. This plant receives its raw material from a supplier which may also be affected by the pandemic. The plant in turn supplies a market and any mismatch between the supply and the demand carries a penalty. The plant's manager, as decision maker, must decide on the effort in prophylactic measures to deploy in the plant so as to protect the workforce during the pandemic and so maintain production and ensure demand satisfaction.

First, we present a decision support model which not only takes into account the possibility that the workforce may be infected in various proportions as the pandemic starts but also considers that during the whole pandemic more workers could become ill. As time goes by, and based on a SIS model to represent the spread of the pandemic, the optimal protection effort is determined while trying to minimise the total cost, including the production and shipping cost, the penalty cost for not matching the supply with the demand, the cost of the effort for implementing prophylactic measures, the social cost of pandemics, and the penalty cost of having workers infected at the end of the planning horizon. To provide a backdrop, we compare the outcomes for two policies: when the decision maker immediately implements prophylactic measures to protect the workers inside her plant or when she does nothing. This first decision support model has been extended in two ways. First, it has been extended in order to jointly determine the optimal protection effort and the period of time over which the optimal protection policy should be implemented. Then, it has been extended to incorporate the regional protection effort enforced by health authorities.

To provide better insights and context, we have applied the proposed decision support models on the case of a meat processing plant which is supplied by a livestock breeder and has to satisfy the demand of a large-scale retailer. This case has been particularly motivated by the several examples of slaughterhouses not being able to comply with downstream demand during the pandemic because of infected workers and also because, in some cases, the workers complained from a lack of proper prophylactic measures to protect their health on the plant premises (Fabris, 2020).

Our work complements the stream of publications covering the impacts of the pandemic on supply chains. Most this literature considers the rippling effect of the pandemic on supply chains or the loss in terms of production in one node of the network. We provide here the plant manager with decision support models that can guide her to the best course of action during the pandemic period.

Appendix A. Proofs

In this Appendix we present the proof of Theorem 2. The one for Theorem 1 can be obtained by simply setting $\beta_G(t) = 0$.

The Hamiltonian associated with this problem is given below.

$$\begin{aligned} H(I(t), \beta_L(t), \lambda(t), t) \quad &= \quad cL(t)\theta(N - I(t)) + \frac{c_A}{2}\left[\theta L(t)(N - I(t)) - a\right]^2 \\ &\quad + \frac{c_\beta}{2}\beta_L^2(t) + \frac{\bar{c}_\beta}{2} I^2(t) \\ &\quad + \lambda(t)\left[\gamma(1 - \beta_G(t) - \beta_L(t))I(t)(N - I(t)) - \alpha I(t)\right] \end{aligned}$$

and the maximum principle leads to

$$\begin{cases} -\dot{\lambda}(t) &= \frac{\partial H}{\partial I} \\ &= -cL(t)\theta - c_A\theta L(t)[\theta L(t)(N - I(t)) - a] \\ &\quad + \bar{c}_\beta I(t) + \lambda(t)[\gamma(1 - \beta_G(t) - \beta_L(t))(N - 2I(t)) - \alpha], \\ \frac{\partial H}{\partial \beta_L} &= 0 = c_\beta \beta_L(t) - \lambda(t)\gamma I(t)(N - I(t)), \\ \dot{I}(t) &= \gamma(1 - \beta_G(t) - \beta_L(t))I(t)(N - I(t)) - \alpha I(t), \\ I(0) &= I_0, \\ \lambda(T) &= \phi I(T), \end{cases} \tag{A.1}$$

which, after simple algebra and using the expression

$$\beta_L(t) = \frac{\lambda(t)\gamma I(t)(N - I(t))}{c_\beta} \tag{A.2}$$

leads to the system of backward-forward ODEs in the FOCs. Sufficiency follows by noticing that the objective functional is convex.

Appendix B. Numerical Algorithm

The system (6) states the first order optimality conditions for problem (4). This system has an initial condition for the state variable $I(t)$ while a final condition for the costate variable $\lambda(t)$. It is therefore a system of forward-backward ODE in the state and costate variables, with the addition of an algebraic equation which describes the maximum principle (A.2). One of most widely used algorithm to deal with this forward-backward setting is the so-called sweep algorithm. The detailed implementation of the sweep algorithm is presented in McAsey et al. (2012). We have implemented the forward-backward sweep method for our system of first order optimality conditions which reads as follows:

1. Starting from the second equation of (6), we make an initial guess $\lambda^0 = \lambda_t^0$.
2. Let us iterated over $j \geq 0$: by using the spectral method, we solve:

   $$\frac{d\,I_t^{j+1}}{dt} = \gamma I_t^{j+1}(N - I_t^{j+1}) - \frac{\gamma\lambda_t^j}{c_\beta}(I_t^{j+1})^2(N - I_t^{j+1})^2 - \alpha I_t^{j+1}$$

   with the initial condition given by:

   $$I_0^{j+1} = I_0$$

   The first equation in (6) is reversed in time by means of the change of variable $\bar{t} = T - t$. This turns the problem into a forward problem, with initial condition given by the fourth equation in (6). Notably the initial condition in the time-reversed equation depends on T.

3. We then solve:

$$\frac{d\,\lambda_{\bar{t}}^{j+1}}{d\bar{t}} = -cL_{\bar{t}}\theta - c_A\theta L_{\bar{t}}[\theta L_{\bar{t}}(N - I_{\bar{t}}^{j+1}) - a] + \bar{c}_\beta I_t^{j+1})$$
$$+ \lambda_{\bar{t}}^{j+1}\left[\gamma(N - 2I_{\bar{t}}^{j+1}) - \frac{\gamma}{c_\beta}\lambda_{\bar{t}}^{j+1} I_{\bar{t}}^{j+1}(N - I_{\bar{t}}^{j+1})(N - 2I_{\bar{t}}^{j+1}) - \alpha\right]$$

with initial condition in $\bar{t}$ given by:

$$\lambda_0^{j+1} = \phi I_T^{j+1}$$

4. Finally we check for convergence by computing the difference between the values of I_t and λ_t in two subsequent iterations (i.e. $j+1$ and j). If the L^2-norm of the difference is negligibly small, we display the current function as solution, otherwise we continue iterating.

Points 1 and 2 are enough to numerically define the solutions to the considered problem. The optimal protection time is endogenously determined, and it requires an additional numerical step: Once we get a satisfactory numerical approximation of I_t and λ_t and hence of β_t, we evaluate the cost function for different values of T. We then select the cost-function minimizing value of T, as shown in Figure 3.

Appendix C. Complementary pictures regarding Scenario 2.

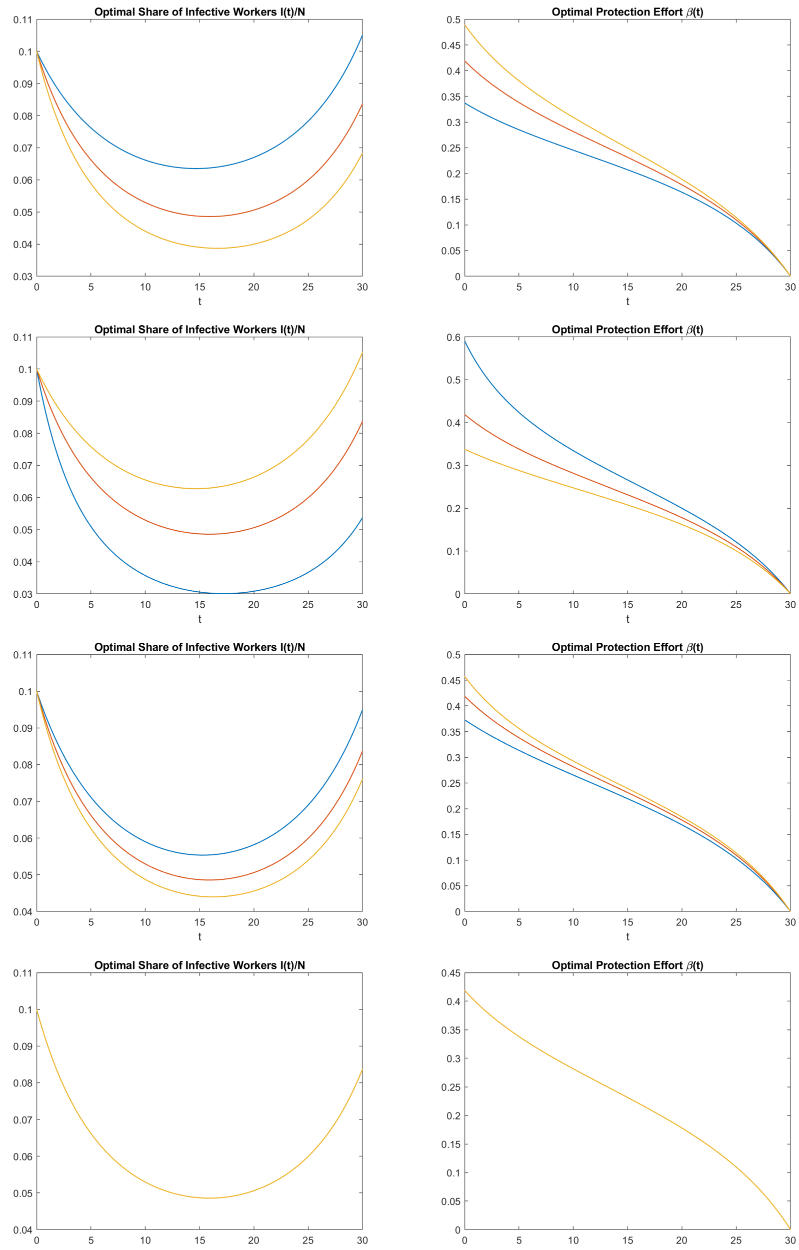


Figure C.12: From top to bottom sensitivity analysis on $x \in [c_A, c_\beta, c_{\bar{\beta}}, \phi]$. Everywhere the red curve represents the central value x, the blue curve represents 0.5x and the yellow curve represents 1.5x.

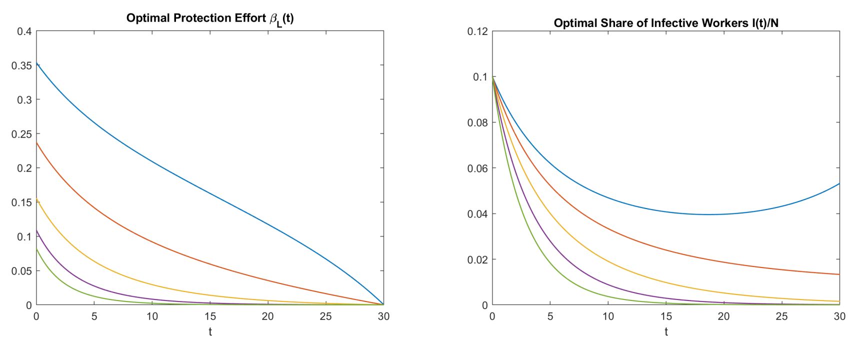


Figure C.13: Optimal protection effort and share of infective workers when β_G varies: same values and colour code as in the main text.

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