# A Dynamic Model of Workforce Management During Seasonal Epidemics

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**Abstract**
Seasonal epidemics pose a recurring threat to organizational stability by reducing workforce availability and disrupting operational continuity. This study presents a dynamic modeling framework that adapts the classical Susceptible-Infected-Recovered (SIR) model to organizational settings, allowing for the evaluation of managerial policies under varying levels of infectivity, disease severity, and sick leave culture. Simulation experiments demonstrate that proactive leave policies—particularly those targeting mildly infected employees who continue to work—can significantly reduce infection spread and cumulative workday losses. However, the effectiveness of such interventions is highly dependent on epidemic characteristics and cultural attitudes toward presenteeism. The findings underscore a critical trade-off between capacity reductions due to absenteeism and increased transmission risk from infected attendance, highlighting the importance of adaptive, data-driven workforce management strategies. By offering a decision-support tool for simulating diverse epidemic scenarios, this study equips organizations with actionable insights to safeguard employee health, maintain operational continuity, and enhance resilience against seasonal epidemic threats.

**Keywords:** epidemiological modeling, infection dynamics in workplaces, seasonal epidemics, workforce management

## 1. Introduction

Seasonal epidemics pose significant challenges to organizational stability, emphasizing the critical relationship between workforce health and operational capacity. Organizational environments such as offices, manufacturing plants, and healthcare facilities inherently involve extensive interpersonal interaction, creating ideal conditions for rapid disease transmission. Empirical evidence consistently identifies workplaces as significant sites for infection spread, accounting for approximately one-third of community influenza transmissions (Edwards et al., 2016). Such findings highlight organizational vulnerabilities during seasonal outbreaks and emphasize the necessity of effective managerial strategies to mitigate associated risks.

The rapid dissemination of infectious diseases within workplaces profoundly affects workforce dynamics and organizational capacity. Employees experience approximately 20–25% of their daily interpersonal contacts at work, significantly elevating infection risk (Edwards et al., 2016). During severe influenza seasons, infection prevalence among working-age adults can reach up to 14.3%, leading to substantial absenteeism and decreased operational capacity (Groenewold, 2019). Further exacerbating the situation is presenteeism—employees attending work despite exhibiting symptoms—which is reported among 60–80% of symptomatic workers (Blanchet Zumofen et al., 2023). Presenteeism notably accelerates disease transmission, highlighting the critical need for targeted managerial interventions.

Additionally, inadequate epidemic management within workplaces carries substantial economic consequences. Influenza epidemics alone account for up to 111 million lost workdays annually in the United

States, translating into approximately $7 billion in economic losses due to absenteeism and reduced workforce capacity (Asfaw et al., 2017). These financial implications underscore the critical necessity for dynamic, evidence-based managerial approaches specifically designed to mitigate infection risks and enhance organizational resilience.

Sick-leave behaviors also exhibit significant variation across cultural and regional contexts. Recent data illustrates marked disparities; for instance, 51% of South Korean workers did not utilize sick leave in the past year, compared to only 14% in Australia (Armstrong, 2023). Such differences substantially influence infection trajectories, underscoring the importance of incorporating cultural and regional variations into epidemic management models.

To address these challenges, this study presents a dynamic model based on the classical SIR epidemiological framework, specifically tailored for organizational contexts. The model explicitly integrates key epidemic characteristics and managerial policies, providing organizations with analytical tools to evaluate and strengthen resilience against seasonal epidemics. Ultimately, this approach offers actionable, evidence-based strategies to reduce infection spread, safeguard employee health, and maintain operational continuity.

### 1.1. Problem Definition

Seasonal epidemics significantly disrupt enterprise operations, primarily through rapid disease transmission and reduced workforce capacity. Organizational settings, characterized by close physical interactions, shared spaces, and common facilities, frequently become focal points for disease propagation. These environments inadvertently foster conditions conducive to disease spread, rapidly transforming workplaces into infection epicenters. Outbreaks driven by symptomatic employees engaging in presenteeism substantially accelerate infection transmission within organizations, compounding labor shortages and operational instability (Bamberg et al., 2010). This situation highlights the critical need for proactive workforce management strategies to safeguard employee health and ensure workforce continuity.

Organizational culture significantly impacts operational continuity during epidemics. Cultures with high absenteeism often experience direct production capacity losses, as fewer employees are available to perform essential tasks. Conversely, in cultures with high presenteeism, symptomatic employees continue attending work, significantly amplifying disease transmission. This widespread contagion affects a larger proportion of the workforce, escalating both the magnitude of the outbreak and workforce capacity losses (Blanchet Zumofen et al., 2023). Organizations thus face a critical trade-off: policies encouraging attendance may inadvertently increase outbreaks through higher intra-organizational transmissions, whereas policies emphasizing absenteeism to mitigate health risks can directly exacerbate workforce capacity losses. Effective organizational strategies must carefully balance these competing considerations to minimize both health-related risks and workforce capacity losses.

Given these complexities, targeted managerial interventions become essential. The effectiveness of these interventions is significantly influenced by workplace culture. Organizations characterized by prevalent presenteeism face heightened infection rates, complicating traditional management approaches. Therefore, context-specific managerial strategies are crucial to effectively mitigate disease transmission, strengthen workforce resilience, and sustain organizational continuity during seasonal epidemic threats.

### 1.2. Objectives

The primary objective of this study is to investigate and critically evaluate managerial policies aimed at effectively managing workforce dynamics during seasonal influenza-like epidemics. Specifically, this research assesses how various workforce management interventions perform under differing epidemic conditions and diverse cultural approaches to sick leave. The dynamic model developed in this study serves as a strategic decision-making tool, enabling organizations to simulate and evaluate the impacts of alternative managerial interventions on workforce availability and capacity during seasonal epidemics.

Additionally, the study quantitatively analyzes how different epidemic scenarios and infectivity profiles affect organizational workforce dynamics. Particular emphasis is placed on examining the influence of regional and cultural variations in sick-leave attitudes and practices, which significantly shape epidemic trajectories and workforce losses. By systematically integrating these cultural nuances into the dynamic model, this research provides detailed insights into workforce behavior across various sick-leave cultures. Ultimately, this work aims to offer actionable managerial recommendations to enhance organizational resilience, facilitate informed decision-making, and maintain effective workforce performance during seasonal epidemic disruptions.

### 1.3. Literature Review

Extensive research spanning epidemiology, organizational management, and economics highlights the profound impact of seasonal epidemics on workforce dynamics and organizational outcomes (Chiu et al., 2017; Fisman et al., 2024). Several studies within this literature specifically examine these effects in distinct occupational settings (Lui et al., 2022). Workplaces, characterized by frequent and prolonged interpersonal interactions, are recognized as critical environments for disease transmission. Empirical evidence consistently demonstrates that occupational settings significantly contribute to community-acquired infections, primarily driven by high contact rates that elevate transmission risks.

Epidemiological modeling has emerged as an essential tool for quantifying and managing infectious diseases in workplaces. Researchers frequently employ adaptations of the classical Susceptible-Infected-Recovered (SIR) model, integrating workplace-specific interactions, managerial interventions, and behavioral adjustments to enhance predictive accuracy and control effectiveness. For instance, Lee and An (2007) developed a system dynamics model utilizing an SIR structure to evaluate the consequences of absenteeism during pandemics, exploring interventions such as telecommuting and staggered shifts. Similarly, Thanner et al. (2011) employed the CDC's FluWorkLoss simulation tool to realistically forecast workforce availability during influenza pandemics, providing valuable guidance for operational continuity planning.

More specialized approaches have also been developed to address industry-specific challenges. Kluger et al. (2020) applied Monte Carlo simulations to evaluate hospital staff scheduling strategies, concluding that extended shifts and stable team rotations substantially reduce infection transmission among healthcare workers. Additionally, Zucchi et al. (2021) proposed a mathematical optimization model to integrate epidemiological factors into workforce scheduling, aiming to minimize disruptions caused by disease outbreaks. Further extending this line of inquiry, Aguilar et al. (2021) introduced an adaptive network-based SIR model, revealing that hybrid staffing policies significantly improve operational resilience and employee health protection. Blackburn and Moreno-Cruz (2021) integrated workforce characteristics into multi-group SIR models, demonstrating that workforce composition directly influences epidemic dynamics and emphasizing the critical role of employee heterogeneity in accurate disease modeling.

Other studies have explored advanced forecasting techniques and strategic vaccination planning. Osthus et al. (2017) incorporated deterministic SIR models combined with stochastic Bayesian inference methods, enabling real-time predictions of outbreak metrics, such as peak intensity and timing, thus guiding dynamic policy adjustments and resource allocation. Similarly, Doutor et al. (2016) investigated vaccination strategies through SIR models with seasonal variability, comparing optimal strategies aimed at full disease eradication with Nash-Equilibrium approaches where individuals independently assess vaccination benefits against costs. This work emphasizes the importance of balancing individual decision-making autonomy with public health objectives to achieve effective epidemic control.

Collectively, the literature underscores the necessity of dynamic and context-sensitive workforce management strategies during epidemics. Workplaces emerge as critical focal points for disease transmission, demanding targeted interventions addressing absenteeism, presenteeism, and cultural variations in sick-leave practices. The economic and operational impacts of epidemic-related workforce losses reinforce the importance of timely, evidence-based policy interventions informed by effective epidemiological modeling. Building on these foundations, the present study advances previous research by developing a dynamic, SIR-based workforce model explicitly designed to evaluate the effects of varying managerial leave policies on epidemic trajectories, organizational resilience, and organizational output.

## 2. Model Description

The infectivity of an epidemic is defined as the probability that contact between an infected individual and a susceptible individual results in disease transmission. This study focuses on influenza as the epidemic of interest. The analysis considers an infectivity period of 64 days. The base model simulation spans 100 days to comprehensively capture both the progression of the epidemic and the subsequent recovery phase. Immunity acquired after infection is assumed to last for one year (Zanobini et al., 2022), which exceeds the simulation period and thus eliminates the possibility of immunity loss within the modeled timeframe.

Infectivity in this model follows a seasonal epidemic pattern, mathematically represented by a sinusoidal function to realistically capture seasonal fluctuations in transmission factors (Grassly & Fraser, 2006). As a result, the simulation produces sinusoidal infection rates consistent with established findings in the literature (Altizer et al., 2006). Although more detailed models could segment the workforce by contact frequency, susceptibility, or demographic characteristics, the current model assumes a homogeneous workforce. This simplification improves model clarity and interpretability while preserving the ability to yield meaningful insights into epidemic dynamics.

External sources of infection are explicitly incorporated by assuming that each worker interacts with a fixed number of infected individuals outside the organization. This mechanism ensures that the epidemic can be propagated within the simulated environment, even in the absence of initial internal infections.

### 2.1. Causal Loop Diagram

The causal loop diagram representing the developed dynamic model for workforce management during seasonal epidemics is illustrated in Figure 2. The diagram comprises ten distinct feedback loops, categorized into balancing (B) and reinforcing (R) loops. Balancing loops B1–B6 (depicted in red) directly relate to stock variables and their corresponding outflows. These loops function to stabilize the system by ensuring that an increase in a stock variable prompts a corresponding increase in its outflow, thereby reducing the stock and preventing unbounded growth. For instance, an increase in the number of severely infected employees directly enhances the severe infection recovery rate, subsequently decreasing the population of severely infected individuals (B1).

An increased number of mildly infected workers exhibiting presenteeism leads to a rise in the infection fraction within the enterprise. This occurs because a higher proportion of infected active employees results in further infection spread within the organization, creating a reinforcing feedback loop (R2). In contrast, as workers become severely infected and take leave, fewer people remain available for contact within the enterprise, thereby reducing the infection rate (B7). Additionally, balancing feedback loop B8 emerges from the relationship between the fraction of actively working infected employees and workplace contact rates. This dynamic arises from behavioral adaptations among actively working employees, who adjust their interpersonal interactions in response to perceived infection risk. A higher perceived infection fraction typically motivates employees to reduce interpersonal contact, thereby lowering the infection rate and stabilizing the number of actively working mildly infected cases.

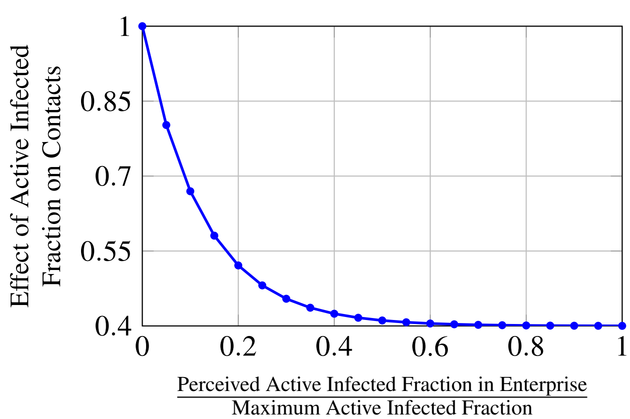
Finally, reinforcing loop R1 encapsulates the dynamics of employee absenteeism driven by infection rates. An increase in the susceptible population elevates the overall infection rate, leading to higher absenteeism as employees become more aware of disease risks. Since absent employees do not contribute to infection transmission within the organization, the outflow from the susceptible population decreases, dynamically influencing organizational resilience during epidemic periods.

### 2.2. Stock Flow Diagram

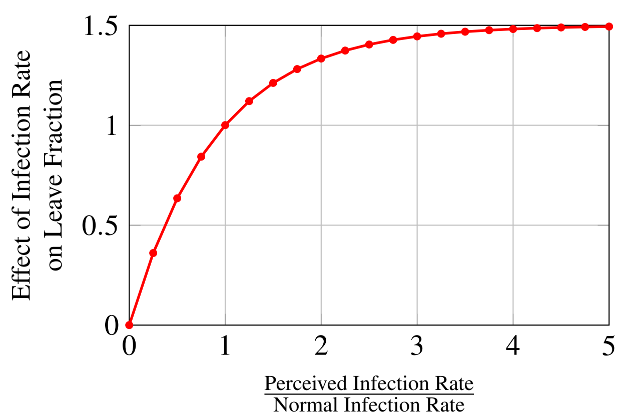
The stock-flow diagram illustrating the workforce dynamics model during seasonal epidemics is presented in Figure 3. This diagram extends the classical stock-flow structure of the SIR model by tailoring it specifically to workforce dynamics. The complete set of equations governing the stocks, flows, auxiliary variables, and corresponding parameter values are provided in Appendix A.

The infected employee population is divided into two distinct groups: mildly infected and severely infected workers. Severely infected employees, who represent a fixed fraction of all infections, are deemed unable to work and remain absent from the workplace, typically requiring longer recovery periods. In contrast, a portion of mildly infected employees take leave, with the leave fraction dynamically adjusting over time in response to perceived infection rates. Employees who take leave are assumed to recover more quickly than those exhibiting presenteeism.

Graphical functions representing behavioral responses to perceived infection conditions are shown in Figures 1a and 1b. Figure 1a illustrates the effect of the active infected fraction on interpersonal contacts within the organization. This relationship is modeled as a monotonically decreasing function governed by the perceived active infected fraction relative to its maximum value. As this perceived fraction increases, interpersonal contacts within the organization decline accordingly. Similarly, Figure 1b presents the effect of the infection rate on the leave fraction. This function follows a monotonically increasing relationship with respect to the perceived infection rate relative to the baseline infection rate. As perceptions of infection rate grow, employees become more likely to take leave instead of engaging in presenteeism. These behavioral adjustments are essential for realistically capturing organizational responses to epidemic threats.




(a) Effect of infected fraction on contacts.




(b) Effect of infection rate on leave fraction.

Figure 1: Graphical representations of behavioral response functions used in the seasonal epidemic model.

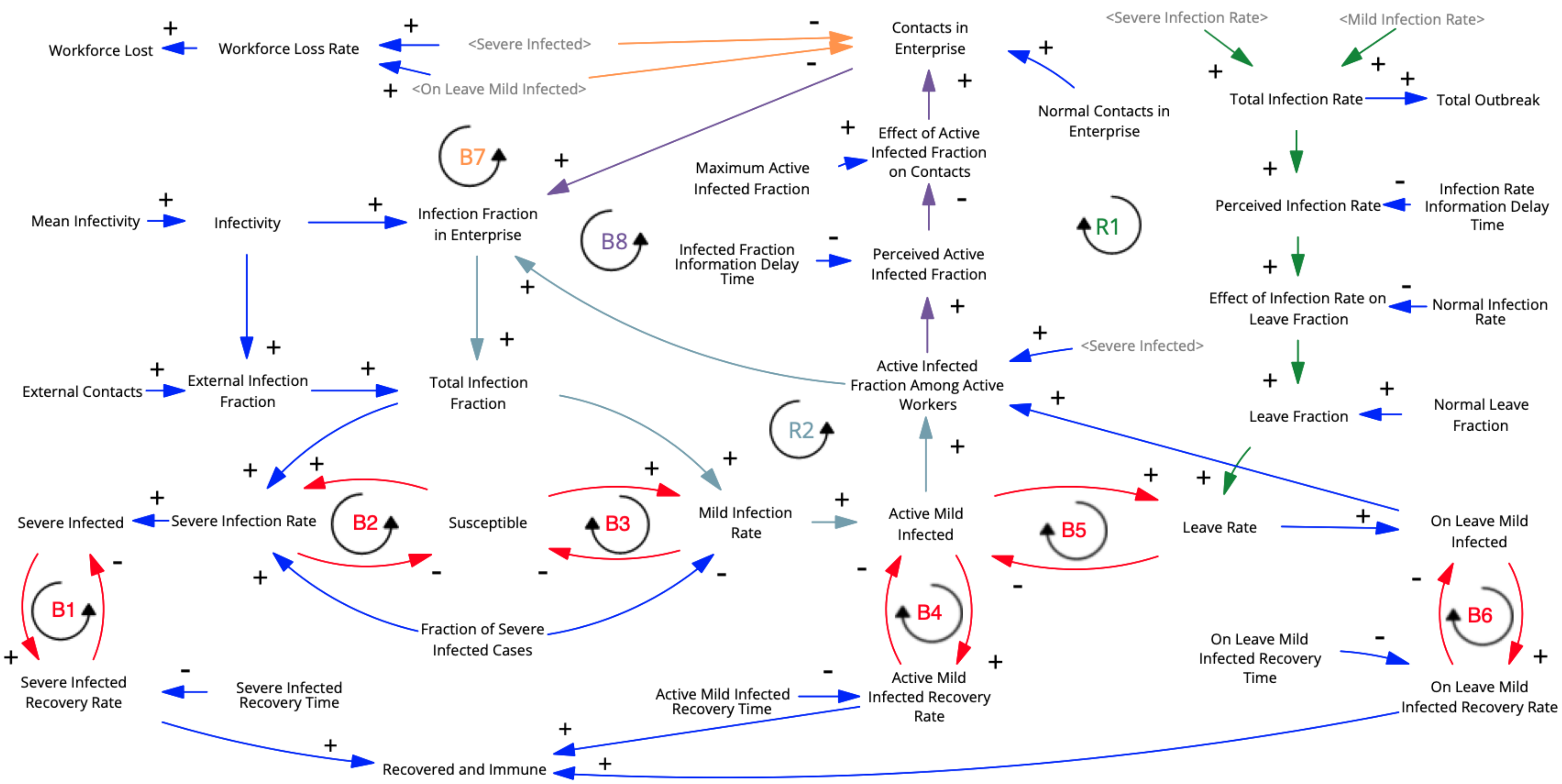



Figure 2: Causal loop diagram illustrating the base seasonal epidemic model.

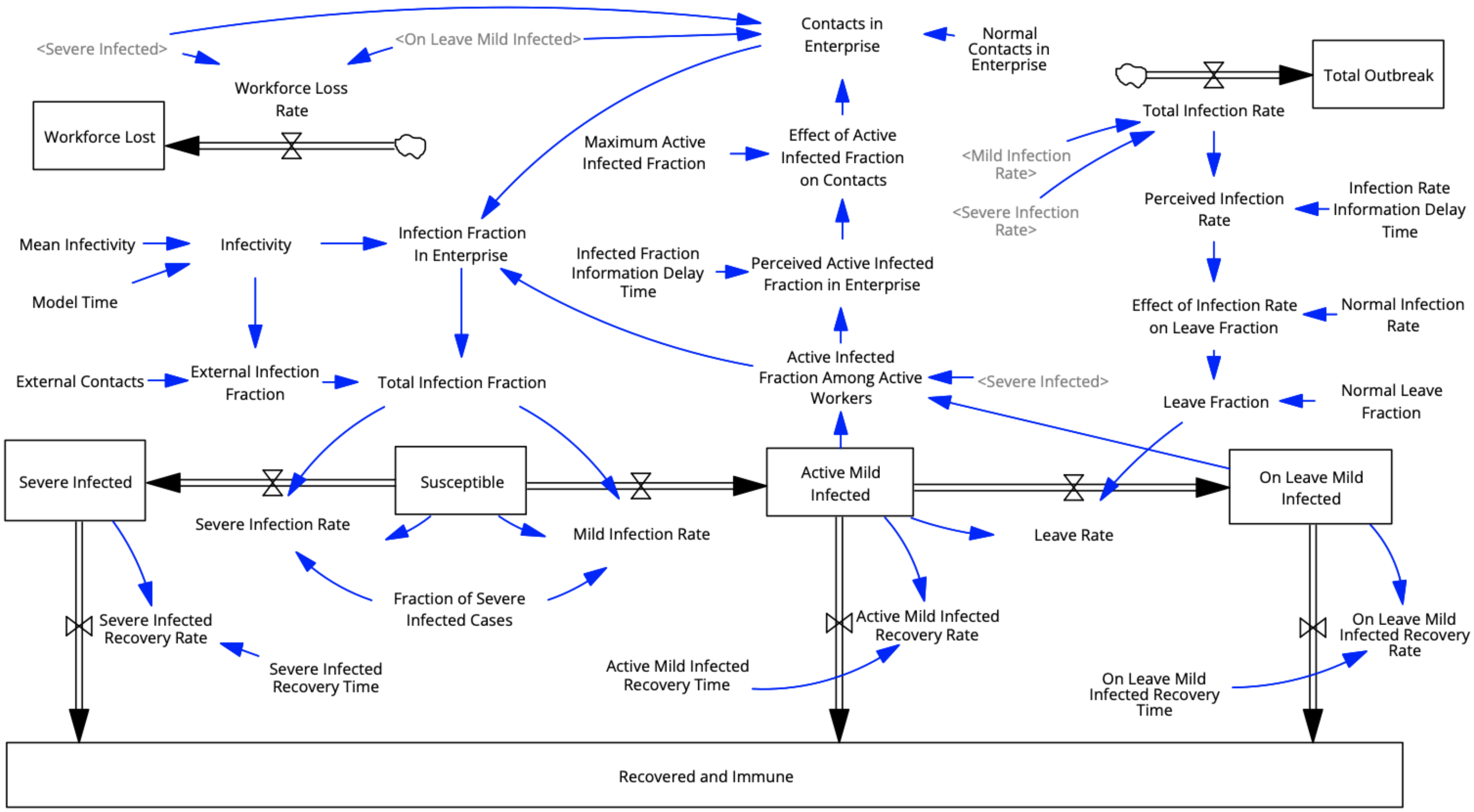



Figure 3: Stock flow diagram illustrating the base seasonal epidemic model.

## 3. Simulation Experiments

Prior to conducting the simulation experiments, rigorous verification and validation procedures were implemented to ensure the model's reliability and accuracy. Verification involved examining both direct and indirect causal relationships to confirm that the intended logic and causal loop structures were correctly implemented. Additionally, structural validation tests—such as extreme condition testing and dimensional consistency checks—were performed. The extreme condition tests ensured that the model behaved appropriately under boundary scenarios through varying parameter settings, while the dimensional consistency checks confirmed that all variable units were accurately represented (see Appendix B).

Following these validation steps, simulation experiments were carried out under various seasonal epidemic scenarios, where infectivity ($\beta$) is modeled as a sinusoidal function of time (see Equation 1). The base seasonal epidemic model offers comprehensive insights into workforce dynamics. Building upon this foundation, managerial policy experiments were conducted to evaluate the effectiveness of different policies under varying presenteeism cultures, aiming to mitigate infection spread and maintain organizational continuity. Each scenario was simulated over a 100-day period using Euler's integration method with a time step of $dt = 0.03125$.

$$\beta(t) = \begin{cases} \bar{\beta} \cdot \left(1 + \sin\left(2\pi \cdot \frac{t+48}{64}\right)\right), & t < 64 \\ 0, & t \geq 64 \end{cases} \tag{1}$$

To assess the impact of epidemics on the workforce, two key metrics were considered: total outbreak and workforce loss. The total outbreak refers to the cumulative number of employees infected over the course of the epidemic, while workforce loss quantifies the total number of workdays lost due to employee absences. The total outbreak is calculated by integrating the infection rate over time, whereas workforce loss is derived by integrating the number of severely infected employees and mildly infected employees on leave, as shown in Equations 2f and 2g, respectively.

### 3.1. Base Seasonal Epidemic Model

Simulation experiments were conducted using various parameter sets to investigate how cultural attitudes toward sick leave impact workforce dynamics during seasonal epidemics. These parameters included different normal leave fractions, mean infectivity levels ($\bar{\beta}$), and fractions of severe infections ($p_s$). Each parameter variation represents distinct epidemic scenarios characterized by specific infection transition probabilities, disease severities, and cultural norms regarding sick leave. Simulation outcomes summarizing the total outbreak size and workforce loss throughout the epidemic period are presented in Table 1.

In all simulation scenarios, the susceptible population initially begins to decrease at an accelerating rate, driven by a rising infection rate and the intensification of a feedback loop that amplifies infections within the organization (R2). As time progresses, balancing feedback loops related to decreasing infection rates due to reduced susceptibility (B2, B3), diminished interpersonal contacts within the enterprise (B7, B8), and rising absenteeism (R1) become increasingly influential, slowing the reduction of susceptible individuals. Notably, even after infectivity peaks and begins to decline, the number of mildly infected workers taking leave continues to rise due to sustained transmission within the organization and delayed perception of infection rates.

Comparisons across scenarios with varying epidemic severities and infectivity reveal that higher mean infectivity or a larger fraction of severe infections consistently result in greater total workforce losses, as anticipated. Furthermore, increasing the normal leave fraction typically reduces the total outbreak size, as fewer infected individuals remain present at work, thereby lowering the spread of infection.

In epidemics characterized by low mean infectivity ($\bar{\beta} = 0.010$) and a high fraction of severe infections ($p_s = 0.15$), total workforce losses exhibit an increasing trend as the normal leave fraction decreases. This increase is primarily driven by heightened infection spread due to presenteeism. However, lower levels of presenteeism do not always correlate positively with reduced workforce losses. For example, in low-severity scenarios ($p_s = 0.10$), cultures with lower absenteeism experience higher workforce losses, highlighting a trade-off between capacity losses from absenteeism and increased infection spread resulting from interpersonal contacts when infected employees remain at work. Similarly, in scenarios characterized by high mean infectivity ($\bar{\beta} = 0.010$) and high severe infection fraction ($p_s = 0.15$), the relationship between normal leave fraction and total workforce loss is complex and not unidirectional. This complexity underscores the importance of developing and evaluating potential workforce management policies tailored to specific epidemic conditions.

Scenarios with varying epidemic characteristics but identical sick leave cultures demonstrate smaller total outbreak sizes when the fraction of severe infections is higher. This outcome arises primarily because severely infected employees are compelled by their health conditions to remain absent, thereby limiting disease transmission within the enterprise. Conversely, higher mean infectivity consistently leads to larger outbreaks due to amplified transmission from mildly infected employees who continue to attend work.

The observed variability in total workforce losses across different epidemic scenarios and sick leave cultures underscores the importance of adaptive workforce management strategies. Effective management necessitates a balance between minimizing absenteeism-induced capacity losses and mitigating heightened infection risks stemming from presenteeism. These findings emphasize the need for epidemic-sensitive managerial policies that account for both epidemic characteristics and cultural attitudes toward sick leave.

Table 1: Simulation results for various epidemic scenarios in the baseline seasonal epidemic model.

| **Parameters** | | | **Results** | |
|---|---|---|---|---|
| Normal Leave Fraction | Mean Infectivity | Severe Infected Fraction | Workforce Lost | Outbreak |
| 0.3 | 0.010 | 0.05 | 882.5 | 421.9 |
| 0.3 | 0.010 | 0.15 | 1245.6 | 401.5 |
| 0.3 | 0.015 | 0.05 | 1351.0 | 597.3 |
| 0.3 | 0.015 | 0.15 | 1870.0 | 573.2 |
| 0.2 | 0.010 | 0.05 | 864.8 | 463.0 |
| 0.2 | 0.010 | 0.15 | 1272.9 | 438.7 |
| 0.2 | 0.015 | 0.05 | 1318.2 | 649.2 |
| 0.2 | 0.015 | 0.15 | 1903.9 | 623.0 |
| 0.1 | 0.010 | 0.05 | 780.9 | 526.5 |
| 0.1 | 0.010 | 0.15 | 1273.2 | 497.2 |
| 0.1 | 0.015 | 0.05 | 1165.4 | 722.1 |
| 0.1 | 0.015 | 0.15 | 1867.5 | 695.1 |

### 3.2. Managerial Policy Experiments

To mitigate the adverse effects of seasonal epidemics on organizational output, an effective managerial policy involves proactively granting leave to mildly infected employees, in addition to those already taking leave independently. Implementing this policy requires human resources departments to continuously monitor the proportion of infected employees within the active workforce and allocate leave accordingly. Clearly defined thresholds should be established to effectively manage the balance between workforce capacity loss due to absenteeism and increased infection spread caused by presenteeism. Specifically, organizations should define a minimum infected fraction threshold to initiate proactive leave-granting. This threshold should be set sufficiently high to prevent unnecessary absenteeism during periods of low infection risk yet allow timely interventions when infected fractions indicate significant potential for increased transmission. Additionally, a leave-granting coefficient was introduced to systematically evaluate different levels of leave allocation tailored to various epidemic scenarios, reflecting the aggressiveness of leave-granting decisions. The stock-flow diagram illustrating managerial policy implementation is presented in Figure 4, and additional equations and variables introduced in the policy implementation model are detailed in Appendix C.

Simulation experiments were conducted using combinations of three mean infectivity parameters (0.10, 0.15, 0.20), three severe infection fractions (0.05, 0.10, 0.15), and three normal leave fractions (0.1, 0.2, 0.3). For each of these 27 scenarios, policy experiment results were obtained for combinations of 31 minimum infected fraction thresholds for granting leave and 201 granting leave coefficients. To evaluate policy effectiveness, percentage changes in total workforce loss relative to base scenarios were calculated. These percentage changes are visualized in the heatmaps presented in Figure 5, with the best workforce loss reductions marked by green circular indicators. Negative percentage changes signify improvements, indicating reduced workforce loss compared to the corresponding base case.

Simulation results indicate that proactive managerial leave decisions substantially reduce the total outbreak across all epidemic scenarios. Targeted policies are particularly effective in managing the trade-off between controlling infection spread within organizations and minimizing workforce losses due to absenteeism. For instance, in epidemics characterized by moderate mean infectivity ($\bar{\beta} = 0.015$) and a high fraction of severe infections ($p_s = 0.15$), optimal managerial policies reduced total workforce loss by 16.9% and total outbreak size by 34.5% in environments with moderate levels of presenteeism.

The heatmaps reveal that managerial policies yield greater workforce loss reductions as disease severity increases. This outcome arises because higher fractions of severe infections lead to greater average losses of workdays, amplifying the impact of presenteeism-induced workforce losses. Consequently, proactively granting leave becomes increasingly critical in epidemics with higher severity levels.

Another key observation is that managerial policies become less effective—and may even be counterproductive—at higher levels of mean infectivity. This is primarily because a significant portion of infections originates from interactions outside the organization. In epidemics with high infectivity, external contacts continue to drive substantial disease transmission, resulting in widespread outbreaks regardless of policy implementation. Furthermore, managerial policies do not consistently result in greater reductions in workforce losses in cultures with high presenteeism. In epidemics where the expected workdays lost per worker due to absenteeism are lower, implementing leave policies may actually increase workforce losses, as the benefit of limiting transmission within the organization by granting leave is diminished.

Nevertheless, despite generally positive outcomes, in 4 out of 27 cases, not granting managerial leave proved more beneficial, as granting leave further exacerbated organizational capacity losses. Additionally, complex and unidirectional response patterns observed in workforce loss percentage changes suggest the need for adaptive strategies tailored specifically to different epidemic characteristics. These findings underscore the critical trade-off organizations face between absenteeism-related capacity losses and infection risks heightened by presenteeism. Ultimately, this emphasizes the necessity of context-specific human resource policies designed to maintain both organizational continuity and employee health during seasonal epidemics.

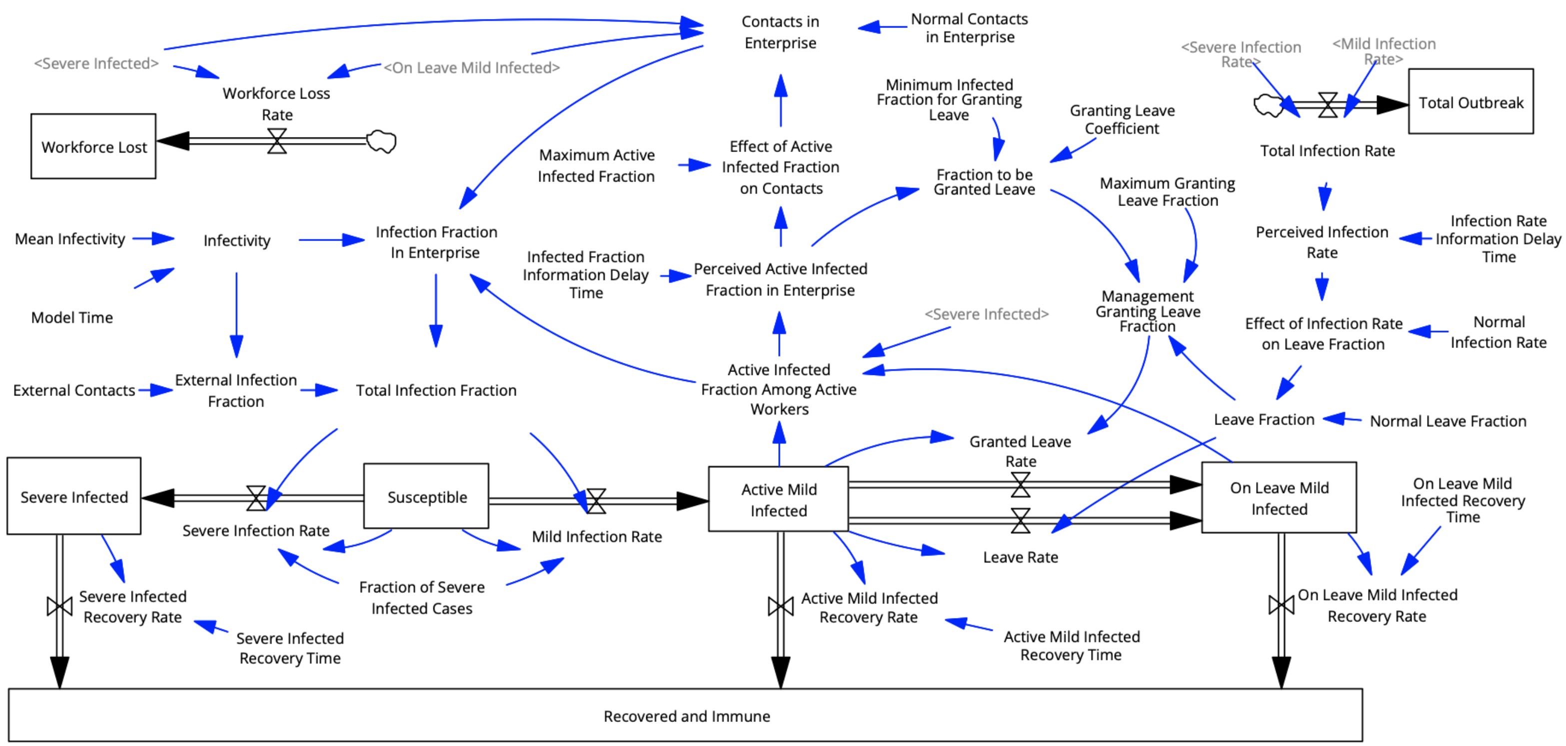



Figure 4: Stock flow diagram illustrating the managerial policy implementation in a seasonal epidemic model.

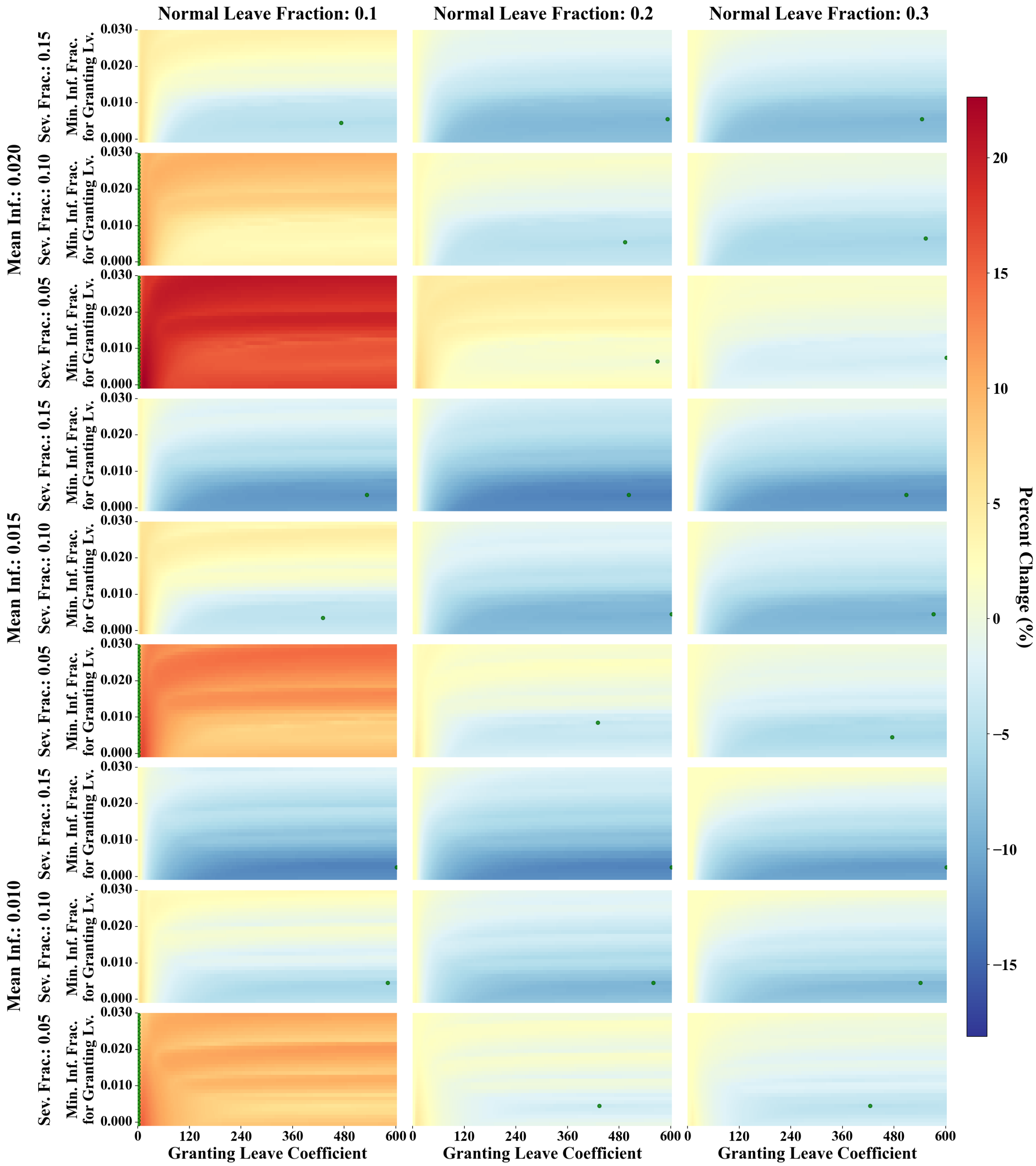



Figure 5: Heatmaps illustrating the percentage change in total workforce loss relative to the corresponding base scenarios under varying managerial leave policies. Each row represents an epidemic scenario defined by a unique combination of mean infectivity ($\bar{\beta}$) and fraction of severe infections ($p_s$), while each column corresponds to a different normal leave fraction. Green circular markers indicate the policy settings that yield the greatest reduction in total workforce loss compared to the base case.

## 4. Discussion and Conclusions

This study presents a dynamic model developed to analyze the impact of seasonal epidemics on workforce dynamics within organizational settings. By adapting the classical SIR epidemiological model to an enterprise context, we explored how variations in sick leave cultures, mean infectivity levels, and disease severity influence workforce availability and organizational output. Our findings highlight the inherent trade-off organizations face between workforce losses due to high absenteeism and those resulting from increased infection transmission driven by presenteeism. To effectively manage this challenge, we propose implementing structured managerial policies aimed at reducing workforce disruptions and maintaining organizational resilience during epidemic seasons.

A significant contribution of this study is the emphasis placed on tailoring managerial policies to diverse epidemic scenarios and varying absenteeism cultures, while simultaneously considering internal organizational dynamics and external epidemiological factors. The model underscores the critical role that managerial decision-making plays in shaping epidemic outcomes within organizations. Experimental results demonstrate the necessity of adaptable strategies, indicating that managerial policies must be explicitly tailored to epidemic characteristics and organizational sick leave cultures to achieve optimal outcomes. Such adaptability not only helps enterprises maintain operational continuity but also enhances employee well-being, thereby promoting a healthier and more resilient workforce. Integrating considerations of both employee health and workforce capacity ensures that organizations are better equipped to mitigate the economic and operational impacts arising from future outbreaks.

The proposed model serves as a comprehensive decision-support tool for enterprises navigating the complexities posed by seasonal epidemics. By capturing causal relationships between internal workforce dynamics and epidemic characteristics, the model enables organizations to evaluate the effectiveness of various intervention strategies. This analytical capability supports the development and refinement of targeted managerial policies, facilitating proactive workforce management tailored specifically to distinct epidemic scenarios. Ultimately, the findings of this study establish a foundation for evidence-based managerial decision-making, providing enterprises with essential strategies to minimize disruptions and enhance long-term organizational resilience in response to health-related challenges.

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## Appendix A. Stock-Flow Diagram Parameters and Equations

$$\text{Susceptible}(t+dt) = \text{Susceptible}(t) + dt \times (-\text{Severe Inf. R.} - \text{Mild Inf. R.}) \tag{2a}$$

$$\text{Severe Inf.}(t+dt) = \text{Severe Inf.}(t) + dt \times (\text{Severe Inf. R.} - \text{Severe Inf. Rec. R.}) \tag{2b}$$

$$\text{Active Mild Inf.}(t+dt) = \text{Active Mild Inf.}(t) + dt \times (\text{Mild Inf. R.} - \text{Leave R.} - \text{Active Mild Inf. Rec. R.}) \tag{2c}$$

$$\text{On Leave Mild Inf.}(t+dt) = \text{On Leave Mild Inf.}(t) + dt \times (\text{Leave R.} - \text{On Leave Mild Inf. Rec. R.}) \tag{2d}$$

$$\text{Recovered and Immune}(t+dt) = \text{Recovered and Immune}(t) + dt \times (\text{Active Mild Inf. Rec. R.} + \text{On Leave Mild Inf. Rec. R.} + \text{Severe Inf. Rec. R.}) \tag{2e}$$

$$\text{Total Outbreak}(t+dt) = \text{Total Outbreak}(t) + dt \times (\text{Mild Infection Rate + Severe Infection Rate}) \tag{2f}$$

$$\text{Workforce Lost}(t+dt) = \text{Workforce Lost}(t) + dt \times (\text{Severe Infected + On Leave Mild Infected}) \tag{2g}$$

$$\text{Total Inf. R.} = \text{Severe Inf.} + \text{On Leave Mild Inf.} \tag{2h}$$

$$\text{Mild Inf. R.} = \text{Susceptible} \times \text{Total Inf. Fraction} \times (1 - \text{Fraction of Severe Inf. Cases}) \tag{2i}$$

$$\text{Severe Inf. R.} = \text{Susceptible} \times \text{Total Inf. Fraction} \times \text{Fraction of Severe Inf. Cases} \tag{2j}$$

$$\text{Leave R.} = \text{Leave Fraction} \times \text{Active Mild Inf.} \tag{2k}$$

$$\text{Active Mild Inf. Rec. R.} = \frac{\text{Active Mild Inf.}}{\text{Active Mild Inf. Rec. Time}} \tag{2l}$$

$$\text{On Leave Mild Inf. Rec. R.} = \frac{\text{On Leave Mild Inf.}}{\text{On Leave Mild Inf. Rec. Time}} \tag{2m}$$

$$\text{Severe Inf. Rec. R.} = \frac{\text{Severe Inf.}}{\text{Severe Inf. Rec. Time}} \tag{2n}$$

$$\text{External Inf. Fraction} = \text{Infectivity} \times \text{External Contacts} \tag{2o}$$

$$\text{Inf. Fraction in Enterprise} = \text{Infectivity} \times \text{Contacts in Enterprise} \tag{2p}$$

$$\text{Total Inf. Fraction} = \text{External Inf. Fraction} + \text{Inf. Fraction in Enterprise} \tag{2q}$$

$$\text{Active Inf. Fraction Among Active Workers} = \frac{\text{Active Mild Inf.}}{1000 - \text{On Leave Mild Inf.} - \text{Severe Inf.}} \tag{2r}$$

$$\text{Perceived Active Inf. Fraction in Enterprise} = \text{DELAY3I}(\text{Active Inf. Fraction Among Active Workers}, \text{Inf. Fraction Information Delay Time}, \text{Active Inf. Fraction Among Active Workers}) \tag{2s}$$

$$\text{Effect of Active Inf. Fraction on Contacts} = f\left(\frac{\text{Perceived Active Inf. Fraction in Enterprise}}{\text{Maximum Active Inf. Fraction}}\right) \tag{2t}$$

$$\text{Contacts in Enterprise} = \text{Normal Contacts in Enterprise} \times \text{Effect of Active Infected Fraction on Contacts} \times (1 - ((\text{Severe Inf.} - \text{On Leave Mild Inf.})/1000)) \tag{2u}$$

$$\text{Perceived Inf. R.} = \text{DELAY3I}(\text{Total Inf. R.}, \text{Inf. R. Information Delay Time}, \text{Total Inf. R.}) \tag{2v}$$

$$\text{Effect of Inf. R. on Leave Fraction} = g\left(\frac{\text{Perceived Inf. R.}}{\text{Normal Inf. R.}}\right) \tag{2w}$$

$$\text{Leave Fraction} = \text{Normal Leave Fraction} \times \text{Effect of Infectivity on Leave Fraction} \tag{2x}$$

$$\text{Infectivity} = \text{IF THEN ELSE}(\text{Model Time} < 64, \bar{\beta} + \bar{\beta} \times \sin(2 \times \pi \times (\text{Model Time} + 48/64)), 0) \tag{2y}$$

$$\text{Model Time} = \text{TIME BASE}(0\ ,\ 1) \tag{2z}$$

Table 2: Model parameters and initial stock values for base seasonal epidemic model.

| Variable | Value | Unit |
|---|---|---|
| Severe Infected Recovery Time | 12 | day |
| Active Mild Infected Recovery Time | 6 | day |
| On Leave Mild Infected Recovery Time | 3 | day |
| Infection Rate Information Delay Time | 3 | day |
| Infected Fraction Information Delay Time | 3 | day |
| Mean Infectivity ($\bar{\beta}$) | 0.01 | worker / contact |
| Fraction of Severe Infected Cases ($p_s$) | 0.05 | - |
| Normal Leave Fraction | 0.2 | - |
| Maximum Active Infected Fraction | 1 | - |
| Normal Infection Rate | 20 | worker / day |
| Normal Contacts in Enterprise | 20 | contact / (worker $\times$ day) |
| External Contacts | 0.4 | contact / (worker $\times$ day) |
| Initial Susceptible | 1000 | worker |
| Initial Severe Infected | 0 | worker |
| Initial Active Mild Infected | 0 | worker |
| Initial On Level Mild Infected | 0 | worker |
| Initial Recovered and Immune | 0 | worker |

## Appendix B. Dimensional Consistency Test Table

Table 3: Dimensional consistency test table for base seasonal epidemic variables and parameters.

| Variable | Unit | Variable | Unit |
|---|---|---|---|
| Susceptible | worker | Severe Infected | worker |
| Active Mild Infected | worker | On Leave Mild Infected | worker |
| Recovered and Immune | worker | Severe Infection Rate | worker / day |
| Mild Infection Rate | worker / day | Leave Rate | worker / day |
| Severe Infected Recovery Rate | worker / day | Active Mild Infected Recovery Rate | worker / day |
| On Leave Mild Infected Recovery Rate | worker / day | Perceived Infection Rate | worker / day |
| Effect of Infection Rate on L.F. | - | Leave Fraction | 1 / day |
| Active Inf. Frac. Among Act. Workers | - | Perceived Active Inf. Frac. in Ent. | - |
| Effect of Active Inf. Frac. on Contacts | - | Contacts in Enterprise | contact / (worker $\times$ day) |
| Infectivity | worker / contact | Infection Fraction in Enterprise | 1 / day |
| External Infection Enterprise | 1 / day | Total Infection Fraction | 1 / day |

## Appendix C. Policy Implementation Additional Parameters and Equations

$$\text{Fraction to be Granted Leave} = \max(\text{Perceived Active Infected Fraction in Enterprise - Minimum Infected Fraction for Granting Leave}, 0) \times \text{Granting Leave Coefficient} \quad (3a)$$

$$\text{Management Granting Leave Fraction} = \max(0,\ \min(\text{Fraction to be Granted Leave, Maximum Granting Leave Fraction})\text{-Leave Fraction}) \quad (3b)$$

$$\text{Granted Leave Rate} = \text{Management Granting Leave Fraction} \times \text{Active Mild Infected} \quad (3c)$$