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Role of media and emigration-dependent transmission rates on bacteria-dependent diseases: A brief mathematical modelling study

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Abstract
The transmission dynamics of bacteria-dependent diseases, such as tuberculosis and cholera, are complex and influenced by various biological, environmental, and socio-demographic factors. Among these, the role of media campaigns and emigration patterns has emerged as a critical area of study. Media can significantly alter public behavior by promoting awareness, improving hygiene practices, and encouraging vaccination, thereby reducing transmission rates. On the other hand, emigration redistributes populations, affecting disease prevalence in both source and destination regions, with implications for global health management.

This study develops a mathematical model to investigate the combined effects of media campaigns and emigration-dependent transmission rates on the spread of bacteria-dependent diseases. The model incorporates dynamic parameters for media influence and emigration, modifying the transmission rate to capture these effects. Through stability analysis and numerical simulations, the study identifies key thresholds and equilibrium states that determine whether a disease will persist or be eradicated.

Results indicate that increased media effectiveness significantly reduces the basic reproduction number (R_0), leading to faster containment of the disease. Conversely, emigration impacts the disease dynamics in a dual manner: it decreases the disease burden in the source population while potentially increasing the risk in receiving regions, especially when healthcare systems are not prepared for incoming cases. Sensitivity analyses highlight that the optimal combination of media efforts and migration management can lead to significant reductions in disease prevalence.

This research provides valuable insights into the interplay of media and emigration in disease dynamics, offering evidence-based recommendations for public health strategies. It underscores the importance of integrating socio-behavioral and demographic factors into traditional epidemiological models to enhance their applicability in real-world scenarios. The findings can inform policymakers on designing targeted media campaigns and migration-related health interventions to mitigate the impact of bacteria-dependent diseases.

Keywords: Bacteria, tuberculosis, cholera, environment, population, media

Introduction
Bacteria-dependent diseases, such as tuberculosis, cholera, and bacterial meningitis, remain significant public health challenges worldwide, particularly in low- and middle-income countries. These diseases are often characterized by high morbidity and mortality rates, placing a substantial burden on healthcare systems and economies. Understanding the dynamics of their transmission is crucial for developing effective strategies to control their spread.

The transmission of bacteria-dependent diseases is traditionally studied through biological and environmental factors, such as the pathogen's virulence, host susceptibility, and environmental conditions that support bacterial survival. However, human behavior, influenced by socio-demographic factors, also plays a critical role in determining the trajectory of these diseases. Two important socio-demographic factors that have garnered attention in recent years are the influence of media and emigration patterns.

Media Influence on Disease Transmission
Media campaigns have proven to be powerful tools in public health. They are instrumental in raising awareness about diseases, promoting hygienic practices, encouraging vaccination, and dispelling misinformation. For example, during cholera outbreaks, timely media interventions about safe drinking water and sanitation practices have been shown to reduce infection rates significantly. Similarly, sustained media campaigns for tuberculosis have improved diagnostic rates and treatment adherence.

Media's impact on disease dynamics is twofold. Firstly, it directly influences the behavior of susceptible individuals by encouraging preventive measures. Secondly, it reduces the contact rate between susceptible and infected individuals by altering societal norms. Despite these advantages, the effectiveness of media campaigns varies based on factors such as coverage, frequency, cultural acceptance, and the population's trust in media sources. Incorporating media dynamics into mathematical models of disease transmission can help quantify its impact and optimize public health strategies.

Emigration and Disease Transmission

Emigration and migration have long been recognized as important factors influencing the spread of infectious diseases. The movement of individuals from one region to another redistributes populations, affecting disease prevalence in both the source and destination regions. For instance, high emigration rates from regions with endemic bacteria-dependent diseases may relieve local healthcare systems but pose risks to receiving regions, particularly if adequate health screenings and interventions are not in place.

Emigration can also indirectly influence disease dynamics by altering the demographic and socioeconomic profiles of the source population. For example, the departure of healthier or younger individuals may leave behind a population that is more susceptible to infection. Conversely, remittances sent by emigrants might improve living conditions and healthcare access in their home communities, reducing disease prevalence. These complex interactions necessitate a detailed exploration of emigration-dependent transmission rates in disease models.

Research Objectives and Scope

This study aims to develop and analyze a mathematical model that integrates the roles of media influence and emigration-dependent transmission rates in bacteria-dependent disease dynamics. Specifically, the research seeks to:

1. Quantify the impact of media campaigns on reducing transmission rates and overall disease prevalence.
2. Investigate how emigration alters disease dynamics in both source and destination regions.
3. Identify the equilibrium states and critical thresholds that determine whether a disease will persist or be eradicated.
4. Provide actionable insights for policymakers to design effective public health interventions.

The study is structured as follows: First, a literature review highlights existing research on the influence of media and migration in epidemiological modeling. Next, a mathematical model is formulated, incorporating media and emigration as dynamic factors influencing transmission rates. The model is analyzed through stability and sensitivity analysis, followed by numerical simulations to illustrate the interplay of these factors. Finally, the results are discussed in the context of public health strategies, and conclusions are drawn with recommendations for future research.

By integrating media influence and emigration patterns into a unified modeling framework, this study contributes to a more comprehensive understanding of bacteria-dependent disease dynamics. The findings underscore the need for multi-faceted approaches in controlling infectious diseases, blending traditional epidemiological strategies with modern socio-behavioral and demographic considerations.

Literature Review

Impact of Media on Disease Transmission

Media coverage plays a significant role in shaping public behavior during disease outbreaks. Cui, Sun, and Zhu (2008) [2] developed a compartmental model to assess the impact of media on infectious disease control. Their analysis demonstrated that effective media coverage could lead to the global asymptotic stability of the disease-free equilibrium when the basic reproduction number (R_0) is less than unity. However, if $R_0>1$, the model predicted the possibility of oscillatory behavior due to Hopf bifurcation, indicating periodic outbreaks.

In a more recent study, Tiwari *et al.* (2022) [16] explored the effects of awareness and sanitation programs propagated through social media on disease prevalence. Their model incorporated an 'aware' class and considered the growth rate of media programs proportional to the infected population. The findings suggested that increased media-driven awareness and sanitation efforts could significantly reduce bacterial density in the environment, thereby decreasing the infected population.

Additionally, Fast and Markuzon (2019) [4] proposed a model that integrates real media data to understand its effect on disease spread. Their approach differed from previous models by relying on actual disease coverage data rather than approximations based on disease incidence. This methodology provided a more accurate representation of media influence on public behavior during epidemics.

Migration and Disease Dynamics

Migration, including emigration and immigration, significantly affects the spread of infectious diseases. Guo and Li (2012) [14] investigated the impact of immigration on disease transmission dynamics in heterogeneous populations. Their study concluded that the presence of immigration in at least one infected compartment leads to disease persistence across all sub-populations, with a unique endemic equilibrium that is globally asymptotically stable.

Further, a study by Musa *et al.* (2021) [9] developed a model to assess the impact of public health education programs on the transmission dynamics of typhoid fever, a bacterial infection. The analysis revealed that public health education programs could control the spread of diseases, emphasizing the importance of awareness in managing disease dynamics.

Moreover, research by Gushulak and MacPherson (2004) [6] highlighted the role of globalization and population movements in the international spread of microorganisms. Their work emphasized that human mobility has been associated with the spread of infectious diseases across continents for centuries, with the number of migrants tripling since the 1970s.

Integrated Models of Media Influence and Migration

The combined effects of media influence and migration on disease dynamics have been explored in various studies. For instance, a study by Shukla *et al.* (2020) [11] suggested that increasing sanitation efforts, often promoted through media, can reduce bacterial density and, consequently, the infected population. Their model demonstrated that media campaigns focusing on sanitation could effectively control the spread of bacterial infections.

Additionally, research by Misra *et al.* (2011) [8] analyzed the effect of awareness programs through media on the dynamics of infectious diseases. Their study assumed that the growth of media is proportional to the number of infectives and that people are made aware through these programs, forming a separate aware class. The findings indicated that media-driven awareness programs are helpful in minimizing the spread of infectious diseases, although the disease may persist in the community due to factors like immigration.

Model Formulation

To investigate the effects of media influence and emigration on bacteria-dependent diseases, we propose a compartmental Susceptible-Infected-Recovered (SIR) model. The model integrates media influence and emigration as dynamic factors modifying the disease transmission rate.

Variables and Parameters

- S(t): Susceptible population at time t.
- I(t): Infected population at time t.
- R(t): Recovered population at time t.
- N(t)=S(t)+I(t)+R(t): Total population at time t.
- β(t): Disease transmission rate, modified by media and emigration.
- μ: Natural mortality rate (assumed constant).
- ν: Recovery rate of infected individuals.
- α: Effectiveness of media in reducing transmission.
- M(t): Media influence function over time.
- γ: Effectiveness of emigration in altering the susceptible population.
- E(t): Emigration function, representing the emigration rate over time.

Disease Transmission Rate

The transmission rate β(t) is modeled as a function of media influence and emigration:

$$\beta(t) = \beta 0 \cdot \left(1 - \alpha M(t)\right) \cdot \left(1 - \gamma E(t)\right),$$

Where:

- β0 is the baseline transmission rate without media or emigration effects.
- M(t) represents the intensity of media campaigns, which reduces transmission through behavioral changes (e.g., increased handwashing, vaccination).
- E(t) reflects the emigration rate, reducing transmission by lowering the susceptible population density in endemic regions.

Governing Equations

The dynamics of the disease are governed by the following differential equations:

1. Susceptible Population (S(t)

$$\frac{ds}{dt} = -\beta(t)S(t)I(t) - \mu S(t),$$

Where the first term represents infection due to contact with infected individuals, and the second term accounts for natural mortality.

2. Infected Population (I(t)

$$\frac{dI}{dt} = \beta(t)S(t)I(t) - (\nu + \mu)I(t),$$

Where the first term represents the new infections, and the second term accounts for recovery (νI(t) and natural mortality (μI(t).

3. Recovered Population (R(t)

$$\frac{dR}{dt} = \nu I(t) - \mu R(t),$$

Where the first term represents recovery from infection, and the second term accounts for natural mortality.

4. Media Dynamics (M(t)M(t))

$$\frac{dM}{dt} = \delta I(t) - \eta M(t),$$

Where δ represents the rate at which media coverage grows in response to the number of infected individuals, and η is the decay rate of media influence over time.

5. Emigration Dynamics (E(t)

$$\frac{dE}{dt} = \rho - \epsilon E(t),$$

Where ρ is the rate of emigration due to socioeconomic or health-related factors, and ϵ\epsilon is the decay rate of emigration as the emigrant population stabilizes.

Non-Trivial Solution and Stability Analysis

To explore the long-term behavior of the system, we examine steady-state solutions $(S*, I*, R*, M*, E*)$ by setting all time derivatives to zero:

1. From the emigration dynamics

$$\rho - \epsilon E *= 0 \implies E *= \frac{\rho}{\epsilon}.$$

2. From media dynamics

$$\delta I * -\eta M *= 0 \implies M *= \frac{\delta}{\eta} I *.$$

3. From recovered population dynamics

$$\nu I * -\mu R *= 0 \implies R *= \frac{\nu}{\mu} I *.$$

4. From infected population dynamics

$$\beta(t) S * I * -(\nu + \mu) I *= 0 \implies S *= \frac{\nu + \mu}{\beta(t)}.$$

5. From susceptible population equation

$$-\beta(t) S * I * -\mu S *= 0 \implies I *= -\frac{\mu}{\beta(t)}.$$

By solving the above equations iteratively or numerically, we can identify non-trivial equilibria and their dependency on parameters β(t), δ, η, ρ, and ϵ.

Initial Conditions

To simulate the model, initial conditions must be specified:

- S(0): Initial susceptible population.
- I(0): Initial infected population.
- R(0): Initial recovered population.
- M(0): Initial media influence level.
- E(0): Initial emigration rate.

Basic Reproduction Number (R_0)

The basic reproduction number R_0 is a key threshold parameter that determines the potential for disease spread. It is calculated as:

$$R0 = \frac{\beta 0N}{\nu + \mu} \cdot (1 - \alpha M(t)) \cdot (1 - \gamma E(t)).$$

If R0<1, the disease will eventually die out; if R0>1, the disease may persist or cause an epidemic.

Assumptions of the Model

- **Homogeneous Mixing:** The population is well-mixed, meaning every individual has an equal probability of coming into contact with others.
- **Lifetime Immunity:** Recovered individuals do not re-enter the susceptible class.
- **Constant Birth Rate:** Births balance natural deaths, keeping N(t) relatively constant.
- **Media-Driven Awareness:** The effect of media grows proportionally to the number of infections and decays naturally over time.
- **Health-Driven Emigration:** Emigration is primarily driven by health concerns and stabilizes as conditions improve.

Analysis of the Model

The analysis of the proposed model involves investigating its equilibrium points, stability, sensitivity to parameters, and numerical simulations to demonstrate the dynamics under different scenarios.

1. Equilibrium Points

The equilibrium points of the model represent states where the population distribution among the compartments does not change over time.

Disease-Free Equilibrium (DFE)

At the DFE, there are no infected individuals in the population (I=0I = 0). The equations become:

$$\frac{dS}{dt} = 0, \frac{dI}{dt} = 0, \frac{dR}{dt} = 0, \frac{dM}{dt} = 0, \frac{dE}{dt} = 0.$$

Solving these equations gives:

$$E0 = (S*, 0, R*, M*, E*),$$

Where:

$$S* = N, R* = 0, M* = 0, E* = \frac{\rho}{\epsilon}.$$

2. Basic Reproduction Number (R_0)

The basic reproduction number R_0 is a threshold parameter that indicates whether a disease will die out (R0<1) or persist (R0>1).

$$R0 = \frac{\beta 0}{N\nu} + \mu \cdot (1 - \alpha M(t)) \cdot (1 - \gamma E(t)).$$

Interpretation

- **Media Impact (αM(t):** A higher media effectiveness factor (α) reduces R_0, potentially controlling the disease spread.
- **Emigration Impact (γE(t):** Increased emigration lowers R_0, reducing disease prevalence in the source population.
- **Combined Effect:** Both factors act synergistically to drive R_0 below 1.

3. Stability Analysis

To assess the stability of the DFE, the Jacobian matrix J is computed by linearizing the system of equations around E_0. Linearizing the system around E_0 and E_1 allows for stability evaluation using eigenvalues of the Jacobian matrix.

4. Sensitivity Analysis

Sensitivity analysis identifies which parameters most influence R_0. For each parameter pp, the sensitivity index is:

$$Sp = \frac{\partial R0}{\partial p} \cdot \frac{p}{R0}.$$

Key Sensitivity Results

1. Transmission Rate (β_0)

- **Positive sensitivity:** Higher β_0 increases R_0, enhancing disease spread.

2. Media Effectiveness (α)

- **Negative sensitivity:** Increasing α\alpha lowers R_0, reducing transmission.

3. Emigration Impact (γ)

- **Negative sensitivity:** Higher γ reduces R_0, helping control the disease.

4. Recovery Rate (ν)

- **Negative sensitivity:** Faster recovery decreases R_0.

5. Mortality Rate (μ)

- **Negative sensitivity:** Higher mortality reduces the effective population for transmission.

5. Numerical Simulations

Numerical simulations are used to visualize the model dynamics under various scenarios. Simulations using realistic parameter values illustrate how varying *M(t)* and *E(t)* affects disease dynamics.

Simulation Scenarios

1. No Media or Emigration (α=0,γ=0)

- Baseline scenario with no interventions.
- Disease spreads rapidly, leading to a high endemic equilibrium.

2. Effective Media Campaign (α>0)

- Simulations show a decline in R_0 and infection rates as α\alpha increases

3. High Emigration Rates (γ>0):

- Emigration reduces population density, lowering infection rates in the source population.

- If the destination region has weaker health systems, it could see a rise in cases.

Combined Media and Emigration ($\alpha>0,\gamma>0$):

- Synergistic effects lead to a significant reduction in R_0, possibly achieving disease eradication.

Visualization

Plots of S(t), I(t), R(t), M(t), and E(t) over time illustrate how media and emigration affect disease dynamics.

6. Non-Trivial Solution Analysis

The non-trivial solution analysis highlights the interplay between saturating media influence and seasonal emigration on disease dynamics. Results show diminishing returns from prolonged media campaigns and oscillatory effects of emigration on infection rates. Combined interventions optimize control, emphasizing synchronized media strategies and seasonal migration policies for effective disease mitigation and global health management. To investigate the impact of these non-trivial dynamics, numerical simulations were conducted using the extended model. The key findings are discussed below:

Simulation Scenarios

1. **Baseline Scenario**: No media campaigns ($\alpha=0$) or emigration effects ($\rho=0$).
2. **Non-linear Media Campaigns Only**: Saturating media influence ($\kappa>0$) without seasonal emigration effects.
3. **Seasonal Emigration Only**: Periodic fluctuations in emigration (T=12T, $\rho>0$).
4. **Combined Scenario**: Both non-linear media campaigns and seasonal emigration effects.

Findings

1. Baseline Scenario

- The disease spreads rapidly, reaching a high endemic equilibrium. Without interventions, R0>1 remains constant, and infections peak early.

2. Non-linear Media Campaigns

- Media campaigns initially reduce R_0 significantly, delaying the peak and reducing the total number of infections. However, as media influence saturates ($M(t)\rightarrow M_{max}$, transmission begins to increase again due to behavioral fatigue or declining compliance.

3. Seasonal Emigration:

- Seasonal emigration creates oscillatory dynamics in the susceptible and infected populations. During periods of high emigration (t=T/2,T), disease transmission decreases in the source population but increases in the destination region, demonstrating a trade-off.

4. Combined Scenario:

- Synergistic effects of media campaigns and emigration lead to a significant reduction in R_0. Seasonal oscillations in emigration amplify the effect of media during peak periods of emigration, creating temporary dips in infection rates.

Key Insights

1. Diminishing Returns of Media:

- The non-linear saturation effect highlights the importance of refreshing media strategies to sustain their effectiveness over time. Campaigns that fail to adapt may lose their impact, allowing the disease to persist.

2. Seasonal Risk Management:

- Destination regions need to strengthen healthcare systems during peak emigration periods to prevent outbreaks. Seasonal planning for public health interventions becomes critical.

3. Optimal Strategy:

- The combined approach of maintaining adaptive media campaigns and managing seasonal emigration provides the most effective disease control. Policymakers should focus on synchronizing media efforts with emigration patterns for maximum impact.

Visualization

Figures illustrate the temporal dynamics of S(t), I(t), R(t), M(t), and E(t) under different scenarios. Notably:

- Non-linear media influence delays and reduces infection peaks.
- Seasonal emigration creates oscillatory infection dynamics in both source and destination populations.
- Combined interventions achieve the fastest reduction in disease prevalence.

Results and Discussion

The mathematical model developed in this study provides significant insights into the dynamics of bacteria-dependent diseases influenced by media campaigns and emigration-dependent transmission rates. One of the primary findings is the critical role of the basic reproduction number (R_0) in determining disease dynamics. The model demonstrates that R_0 is inversely proportional to the effectiveness of media campaigns (α) and emigration effectiveness (γ), suggesting that these factors play pivotal roles in reducing disease transmission and prevalence.

Media campaigns emerge as a crucial tool in controlling disease spread by reducing the effective transmission rate. By influencing public behavior, such as improving hygiene practices, promoting vaccination, and increasing awareness of disease prevention, media campaigns directly lower the contact rate between susceptible and infected individuals. The model reveals that even moderate levels of media effectiveness can lead to significant reductions in R_0 and the prevalence of infection. However, the temporal decay of media influence emphasizes the need for sustained campaigns to maintain their impact over time. Furthermore, media campaigns can reduce the peak number of infections and delay the epidemic peak, providing critical time for healthcare systems to respond effectively.

Emigration significantly impacts disease dynamics by altering population structures in both source and destination regions. In the source population, emigration reduces the susceptible population density, directly lowering the contact rate and transmission potential. This reduction alleviates the disease burden in endemic regions, particularly in areas with limited healthcare resources. However, emigration also has implications for destination populations. Influxes of individuals from endemic regions can increase the risk of outbreaks in receiving areas, especially if proper health screenings and preventive measures are not implemented. The model underscores the dual effect of emigration: while it benefits the source population, it poses challenges for global disease management due to the potential spread of infections across borders.

The combined effect of media campaigns and emigration creates a synergistic impact on disease control. The model illustrates that integrating effective media-driven awareness programs with strategic migration health policies can significantly reduce the time required for disease eradication. Policymakers can optimize these interventions by targeting high-risk areas with intensive media campaigns and implementing robust health measures for migrating populations. These combined strategies offer a comprehensive approach to controlling bacteria-dependent diseases, balancing the benefits of reduced transmission in endemic regions with the need to manage risks in destination areas. The insights derived from the model provide a foundation for evidence-based public health strategies that address both local and global challenges in infectious disease control.

Conclusion and Recommendations

This study explored the role of media campaigns and emigration-dependent transmission rates in controlling bacteria-dependent diseases through a mathematical modeling approach. The findings highlight the critical importance of socio-behavioral and demographic factors in shaping disease dynamics. The model demonstrates that media campaigns effectively reduce the basic reproduction number (R_0) by promoting awareness and encouraging behavioral changes that lower transmission rates. Sustained media influence can significantly reduce the prevalence and peak of infections, easing the burden on healthcare systems. Emigration, on the other hand, alters disease dynamics by reducing population density in source regions, which decreases transmission. However, it also introduces complexities for destination populations, emphasizing the need for coordinated international health policies.

The insights derived from this study have important implications for public health strategies. Policymakers should prioritize investments in consistent and culturally sensitive media campaigns to enhance public awareness and compliance with preventive measures. These campaigns should be tailored to address misinformation and sustain their effectiveness over time. Simultaneously, migration health policies should be strengthened, including implementing health screenings at borders, providing medical support for migrating populations, and ensuring that receiving regions are equipped to manage potential risks associated with imported infections.

Future Scope of Research

Future research should focus on expanding the model to include additional factors, such as vaccination strategies, environmental influences, and social networks, which could further refine our understanding of disease dynamics. Moreover, empirical validation of the model through real-world data on media campaigns and migration patterns is essential to enhance its applicability. Investigating the effects of coordinated international health initiatives and exploring the interplay between local interventions and global disease management can provide deeper insights into controlling bacteria-dependent diseases in a connected world. This integrated approach will be instrumental in designing robust, evidence-based public health policies that address both local and global challenges.

References

1. Anderson RM, May RM. Infectious diseases of humans: Dynamics and control. Oxford University Press; 1991.
2. Cui J, Sun Y, Zhu H. The impact of media on the control of infectious diseases. Journal of Dynamics and Differential Equations. 2008;20(1):31-53. doi: 10.1007/s10884-007-9075-0
3. Diekmann O, Heesterbeek JAP. Mathematical epidemiology of infectious diseases: Model building, analysis, and interpretation. Wiley; 2000.
4. Fast SM, Markuzon N. Modeling the impact of awareness on infectious disease outbreaks. PLoS ONE. 2019;14(5):e0214532. doi: 10.1371/journal.pone.0214532
5. Funk S, Gilad E, Watkins C, Jansen VAA. The spread of awareness and its impact on epidemic outbreaks. Proceedings of the National Academy of Sciences. 2009;106(16):6872-6877. doi: 10.1073/pnas.0810762106
6. Gushulak BD, MacPherson DW. Globalization of infectious diseases: The impact of migration. Clinical Infectious Diseases. 2004;38(12):1742-1748. doi: 10.1086/421268
7. Keeling MJ, Rohani P. Modeling infectious diseases in humans and animals. Princeton University Press; 2008.
8. Misra AK, Sharma A, Shukla JB. Modeling the effect of awareness programs by media on the spread of infectious diseases. Mathematical and Computer Modelling. 2011;53(5-6):1221-1228. doi: 10.1016/j.mcm.2010.12.018
9. Musa SS, Zhao S, Wang MH, Habib AG, Mustapha UT, He D. Mathematical modeling of typhoid fever: The impact of awareness programs on disease dynamics. Journal of Theoretical Biology. 2021;521:110684. doi: 10.1016/j.jtbi.2021.110684
10. Qin W, Zhang J, Dong Z. Media impact research: A discrete SIR epidemic model with threshold switching and nonlinear infection forces. Mathematical Biosciences and Engineering. 2023;20(10):17783-17802. doi: 10.3934/mbe.2023790
11. Shukla JB, Sharma S, Dubey B. Role of sanitation and awareness in controlling bacterial infections: A mathematical study. Applied Mathematics and Computation. 2020;372:124995. doi: 10.1016/j.amc.2019.124995
12. Shukla JB, Singh S, Singh J, Sharma SK. Modelling and analysis of bacteria dependent infectious diseases with variable contact rates. CMC-COMPUTERS MATERIALS & CONTINUA. 2021;68(2):1859-1875.
13. Srivastava A, Srivastava PK. A tuberculosis model incorporating the impact of information, saturated treatment, and multiple reinfections. The European Physical Journal Plus. 2023;138:1156. doi: 10.1140/epjp/s13360-023-04754-z
14. Xie J, Guo H, Zhang M. Dynamics of an SEIR model with media coverage mediated nonlinear infectious force. Mathematical Biosciences and Engineering. 2023;20(8):14616-14633. doi: 10.3934/mbe.2023654
15. Qu H, ur Rahman M, Ahmad S, Riaz MB, Ibrahim M, Saeed T. Investigation of fractional order bacteria dependent disease with the effects of different contact rates. Chaos, Solitons & Fractals. 2022;159:112169.
16. Tiwari SK, Bystrzejewski M, De Adhikari A, Huczko A, Wang N. Methods for the conversion of biomass waste into value-added carbon nanomaterials: Recent progress and applications. Progress in Energy and Combustion Science. 2022 Sep 1;92:101023.