Appendix A

Total distance for three depots (C subset)

	*D*1	*D*2	*D*3
PTP mode	357.278	288.473	202.642
MMTS mode	119.3851	145.0218	88.4474
Mixed mode	187.36958	164.4879	126.0311

Total timeliness for three depots (C subset)

	*D*1	*D*2	*D*3
PTP mode	1	1	1
MMTS mode	0.88821901	0.83309162	0.75788615
Mixed mode	0.97178651	0.89720673	0.94884224

Total distance for three depots (R subset)

	*D*1	*D*2	*D*3
PTP mode	452.153	293.746	240.466
MMTS mode	233.8722	215.4168	132.5380
Mixed mode	238.6701	248.54435	178.3513

Total timeliness for three depots (R subset)

	*D*1	*D*2	*D*3
PTP mode	1	1	1
MMTS mode	0.662748	0.452693	0.777507
Mixed mode	0.816888	0.820834	0.905773

M. Liu et al., *Epidemic-logistics Modeling: A New Perspective on Operations Research*, https://doi.org/10.1007/978-981-13-9353-2

Total distance for three depots (RC subset)

	*D*1	*D*2	*D*3
PTP mode	234.556	288.473	131.7881
MMTS mode	109.0158	137.5527	65.3893
Mixed mode	141.13521	181.61341	72.29127

Total timeliness for three depots (RC subset)

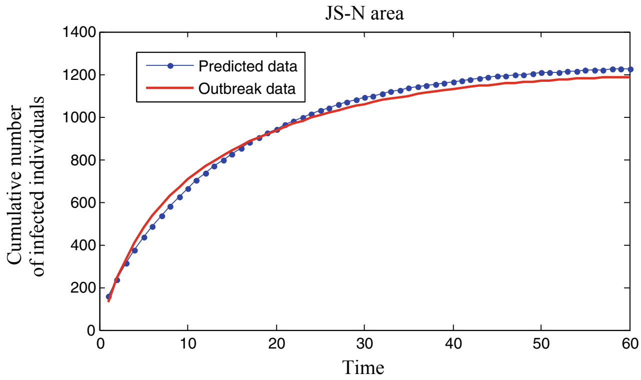
	*D*1	*D*2	*D*3
PTP mode	1	1	1
MMTS mode	0.830251	0.87731	0.872961
Mixed mode	0.936154	0.914882	0.90525

Appendix B

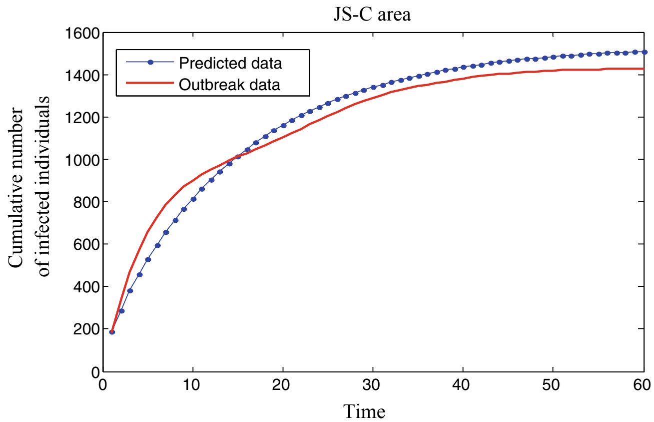
B.1 Model Validation

Following the verification process in Büyüktahtakın et al. [1], we validate our predicted data against the actual outbreak data in terms of the cumulative number of infected individuals on these days (from July 1st to December 27th), which includes a planning horizon of 180 days and contains 60 time-series data. Figure B.1 shows that our predicted data is slightly underestimated at the initial 15 time-series data and then marginally overestimated than the actual outbreak data in later. The paired-t-test results in Table B.1 prove that our model provides statistically similar results with respect to the outbreak data for the time period (from July 1st, 2009 to December 27th, 2009). As we all know, the paired-t-test, sometimes called the dependent sample t-test, is a statistical procedure used to compare the mean difference between two sets of observations. Since all p-values in Table B.1 are greater than 0.05, it illustrates that there is no significant difference between the predicted data and the actual outbreak data.

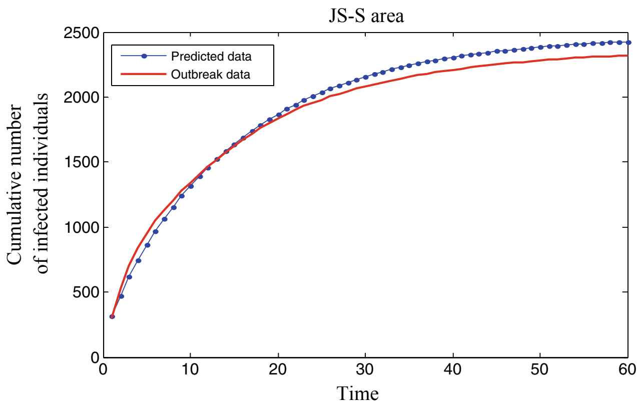
M. Liu et al., *Epidemic-logistics Modeling: A New Perspective on Operations Research*, https://doi.org/10.1007/978-981-13-9353-2



(a) JS-N area



(b) JS-C area



(c) JS-S area

Fig. B.1 Comparison of the cumulative number of infected individuals between the predicted data and the outbreak data [1]

Table B.1 Statistical test of our predicted data and outbreak data [1]

	Area	Mean		Two-tailed paired-t-test	
		Outbreak data	Predicted data	t-stat	*p*-value
Infected areas	JS-N	19.78	20.35	−0.1476	0.8826
	JS-C	23.81	24.57	−0.2932	0.8125
	JS-S	40.42	38.23	−0.1793	0.8355

B.2 Optimization Results With Different Budget Sizes

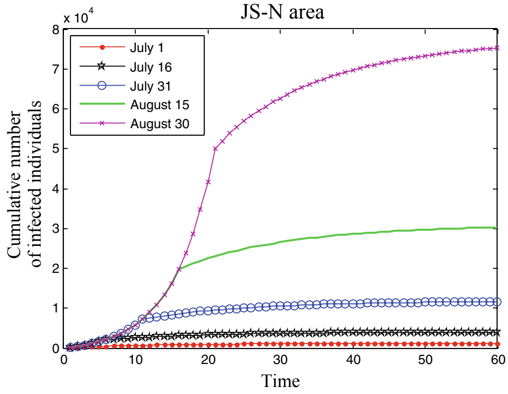
The columns of Table B.2 report the objective value, affected areas, optimal budget allocations, cumulative capacity, cumulative number of infected individuals and cumulative number of hospitalized individuals in each affected area, by solving our model with different budget limitations.

Table B.2 Optimization results with different budget sizes [1]

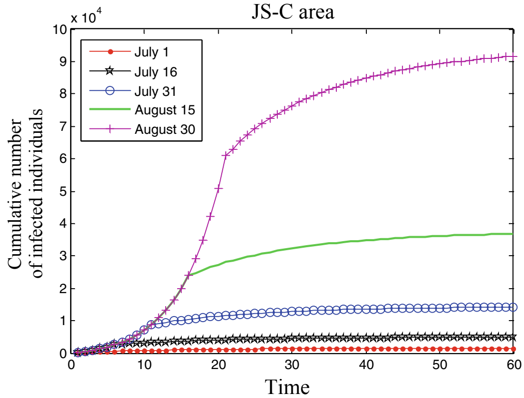
Budget (Million)	Objective	Affected area	Budget allocation	Capacity	Infected	Hospitalized
100	44,412,018	JS-N	22.9 M (22.9%)	1911	10,931,678	1474
		JS-C	28.9 M (28.9%)	2253	13,933,064	1738
		JS-S	48.2 M (48.2%)	3768	19,552,069	2907
		Total	100 M	7932	44,416,812	6120
150	10,902,400	JS-N	34.2 M (22.8%)	2903	2,983,946	2240
		JS-C	45.3 M (30.2%)	3635	3,216,222	2804
		JS-S	70.5 M (47.0%)	5359	4,717,945	4135
		Total	150 M	11,897	10,918,113	9179
200	853,285	JS-N	46.8 M (23.4%)	3895	239,426	3005
		JS-C	56.4 M (28.2%)	4475	264,531	3453
		JS-S	96.8 M (48.4%)	7685	395,144	5930
		Total	200 M	16,056	899,101	12,388
250	2821	JS-N	59.2 M (23.7%)	4396	5218	4178
		JS-C	73.6 M (29.4%)	5943	6590	5153
		JS-S	117.2 M (46.9%)	8908	10,298	6310
		Total	250 M	19,247	22,106	15,641

B.3 Impact of Different Intervention Starting Dates

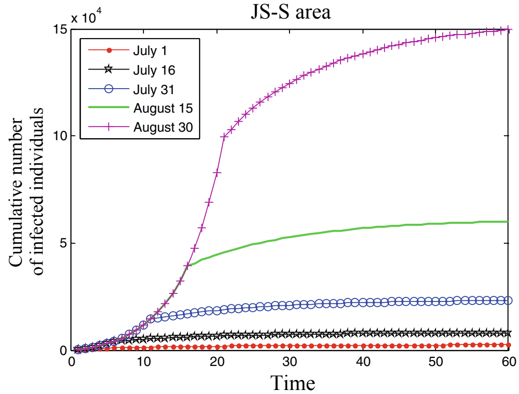
The impact of different intervention starting dates on the number of infected individuals is shown in Fig. B.2. Although all intervention strategies can help reduce the number of infections and lessen the exponential growth of the disease [1], one can see that the earlier the intervention starts, the fewer the infected individuals there are. It is worth mentioning that starting intervention on August 30 is too late because it leads to an outstandingly higher number of infected individuals when compared to the other four scenarios. Such result is consistent with Büyüktahtakın et al. [1], which suggests that the number of infected cases can



(a) JS-N area



(b) JS-C area



(c) JS-S area

Fig. B.2 Impact of different intervention starting dates [1] increase significantly if starting intervention is too late, even with ample emergency budget and strong intervention efforts. Therefore, this result implies us that applying an early intervention strategy is particularly important when response to an unexpected epidemic outbreak.

Reference

Büyüktahtakın İE, Des-Bordes E, Kıbış EY. A new epidemics-logistics model: insights into controlling the Ebola virus disease in West Africa. Eur J Oper Res. 2018;265(3):1046–63.